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 role of high school educational inputs in developing skills relevant to college coursework. I estimate high school teacher value added on ACT scores using administrative data from North Carolina. I then evaluate how exposure to teachers with high ACT score value added impacts college enrollment and performance. I find that ACT score value added varies substantially across math and English teachers, indicating that some generate larger gains in ACT performance. Exposure to teachers with high ACT score value added increases on-time 4-year college enrollment and enrollment in selective 4-year colleges, decreases 2-year college enrollment, and improves 4-year college performance. A one standard deviation increase in math ACT score value added increases the likelihood of completing a 4-year college degree within 5 years of high school completion by 8% due to increased 4-year college enrollment, increased enrollment in selective 4-year colleges with high completion rates, and improved college performance. My results suggest that high school teachers have significant scope to influence the production of college-relevant 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 are a crucial transition period in children's lives. During this period of late adolescence, children make pivotal decisions about whether and where to attend college while completing their academic preparation for college coursework. The stakes of the college enrollment decision and the transition to college coursework are underscored by extensive prior evidence that college degree attainment shapes later life outcomes, including economic mobility (Card, 1999; Chetty et al., 2020). Despite the importance of the college transition years for later life outcomes, little is known about how educational inputs during this period prepare children for college success.

In this paper, I study the role of high school teachers in the production of college-relevant skills. Teachers are foundational for children's development. Indeed, a large body of literature documents the multifaceted effects of teachers during elementary and middle school (Bacher-Hicks and Koedel, 2023), with a smaller body of evidence documenting the role of high school teachers (e.g. Jackson, 2014, 2018). Yet, the impacts of teachers during the college transition years and the persistence of these impacts once students enter college are not well understood.

I begin by estimating the impacts of 11^{th} grade teachers on students' 11^{th} grade ACT scores. 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 then estimate the impacts of exposure to teachers with high ACT score value added on college enrollment and college performance. To capture heterogeneous effects of ACT score value added and substitution patterns between 2-year and 4-year colleges, I model college enrollment using a nested logit model in which students choose between 2-year college, 4-year college, or no college and between heterogeneous colleges within the 4-year college nest. To disentangle the direct effects of ACT score value added on college performance from indirect effects through selection into particular colleges, I employ a selection correction procedure from Lee (1983). This procedure uses the nested logit model to predict selection into each college in the data, with peers' college enrollment patterns serving as an instrument that shifts the propensity to enroll without affecting college performance.

I utilize detailed administrative data on the universe of public high school students in North Carolina linked with enrollment records from the University of North Carolina (UNC) System, which includes all public 4-year colleges and universities in North Carolina and is among the largest public university systems in the United States. In North Carolina, the ACT test is administered in public high schools during the school day, free of charge, to all 11$^{\text{th}}$ 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. State-level universal admissions testing policies have rapidly increased in prevalence over the past two decades (Cook and Turner, 2019), generating state-level longitudinal data with a college admissions test score for each student. This new data environment enables my paper's novel contribution in estimating teacher value added on college admissions test scores.

ACT score value added varies substantially across teachers and has positive impacts on both college enrollment and college performance, measured by freshman year GPA, remedial math course-taking, freshman dropout, and college completion. My results suggest that ACT score value added reflects the accumulation of transferable college-relevant skills and therefore has long-run benefits beyond the signalling value of a higher ACT score. 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 math teacher with value added one standard deviation above the mean increases math ACT scores by 0.08 standard deviations, approximately 0.5 points on the 36-point ACT test scale. While math ACT score value added has larger impacts on 4-year college enrollment and 4-year college performance, English ACT score value added has larger impacts on enrollment in selective 4-year colleges. 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 1.23 percentage points or 7% relative to the full sample 4-year enrollment rate, decreases 2-year college enrollment by 1.53 percentage points or 4%, and decreases freshman college dropout rates by 0.5 percentage points or 6%. Assignment to an English teacher with ACT score value added one standard deviation above the mean increases enrollment in selective state flagship universities, conditional on 4-year college enrollment, by 1.93 percentage points or 8%.

ACT score value added substantially increases the likelihood that a student completes a 4-year college degree within 5 years of high school graduation, taking together positive impacts on 4-year college enrollment, enrollment in selective 4-year colleges with high completion rates, and college performance conditional on whether and where a student enrolls. Assignment to a math teacher with ACT score value added one standard deviation above the mean increases the 4-year college degree attainment rate by 1.16 percentage points or 8% of the full sample mean. Increased 4-year college enrollment explains 68% of the degree attainment effect, while increased enrollment in selective 4-year colleges with high completion rates and improved college performance play smaller roles.

Comparing my results to prior studies, the estimated standard deviations of ACT score value added are similar in magnitude to prior estimates of high school teacher value added (Jackson, 2014) and smaller in magnitude than estimates of teacher value added in earlier grades (e.g. Chetty et al., 2014a), consistent with dynamic complementarities in skill production and exposure to multiple teachers reducing the scope for individual teachers to influence test score growth among older students. Importantly, I find that ACT score value added is only weakly correlated with traditional standardized test score value added measures and noncognitive value added measures. My results highlight the multidimensional nature of teacher quality, with important policy implications for teacher evaluation. In particular, evaluation policies based on one dimension of teacher skill may overlook important aspects of teacher quality.

The 1.23 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, while Hyman (2017) finds that mandating the ACT test in Michigan increased 4-year college enrollment by 1.9 percentage points.

ACT score value added has larger impacts than a purely random 1-point composite

ACT score increase induced by rounding, which increases 4-year college enrollment by 0.44 percentage points and has no effect on college persistence (Haggag et al., 2024). Larger impacts of ACT score value added on college persistence, relative to a random ACT score increase, further suggest that the benefits of ACT score value added extend beyond the signalling value of a higher ACT score for college admissions and reflect the accumulation of transferable college-relevant skills.

This work bridges two long-standing bodies of literature: a broad multidisciplinary literature on child skill development, and an empirical literature on the determinants of college choice and college persistence. I bridge these literatures by evaluating the role of teachers in child skill production during the college transition period, when children's skills interact crucially with their college choices to determine their long-run outcomes.

By bridging the child development and college choice literatures, this paper makes two main contributions. First, I estimate teacher value added on college admissions test scores, generating a new measure of teacher quality which distinct from traditional value added measures. Prior studies of teacher value added measure cognitive skill outcomes using state standardized test scores, which are unobservable to colleges (Bacher-Hicks and Koedel, 2023). College admissions test scores, unlike state standardized test scores, are observable to colleges and therefore directly impact college enrollment and selectivity. In my setting, college admissions tests are also the last standardized assessment administered to all students before high school graduation, providing a final opportunity to measure students' preparedness for college on a common scale. Second, I estimate the effects of K-12 teacher value added on academic performance in college, complementing existing studies which estimate effects on college enrollment and adult earnings but do not speak to the transferability of skills between K-12 and college classrooms (Chetty et al., 2014b; Jackson, 2018; Backes et al., 2024; Lavy and Megalokonomou, 2024).[1]

The economics literature on child development seeks to identify the technology of child skill formation from early childhood through adolescence (Cunha and Heckman, 2007; Attanasio et al., 2022). I contribute to the education production function branch of this litera-

[1]Prior literature has evaluated the relationship between other educational inputs and college completion, including school quality (Deming et al., 2014; Totty, 2020) and peer quality (Bifulco et al., 2014).

ture, which evaluates the role of schooling inputs (Todd and Wolpin, 2003), particularly K-12 teachers. Prior work has shown large and multifaceted effects of teachers during elementary school (e.g. Rockoff, 2004; Rivkin et al., 2005; Hanushek and Rivkin, 2006; Kane and Staiger, 2008). Less is known about the impacts of teachers during high school (e.g. Jackson, 2014, 2018; Mansfield, 2015).[2] Yet, recent evidence points to adolescence as a second crucial period for child development, particularly the development of advanced cognitive skills (Steinberg, 2014; National Academies of Sciences, Engineering, and Medicine, 2019; Hoxby, 2021). This evidence underscores the need for additional research on skill production during adolescence, a period termed the "missing middle" between early childhood and realized adult outcomes (Almond et al., 2018) during which the education production function is not well-specified. I contribute to this gap in the literature by providing novel estimates of the effects of teachers during late adolescence.[3]

A large body of prior work seeks to understand the predictors of college enrollment and college choice (e.g. Long, 2007; Page and Scott-Clayton, 2016). Less is known about college persistence and graduation among marginal students (Hoxby, 2004; Bound and Turner, 2011; Zimmerman, 2014; Castleman and Long, 2016; Hyman, 2020). Understanding predictors of college persistence is a policy-relevant concern, as college completion rates in the U.S. have stagnated in recent decades (Lee and Shapiro, 2023). Weak academic preparation is a leading explanation for poor college persistence; however, interventions designed to boost college-relevant skills through remedial college coursework (Bettinger et al., 2013a) and high school curriculum supports (Xu et al., 2022) have been met with limited success. I contribute to this gap in the literature by evaluating whether, by improving students' ACT scores, high value added teachers develop skills that transfer across high school and college classrooms to improve college persistence.

[2]To my knowledge, published high school value added studies in the U.S. context are limited to those cited above along with Aaronson et al. (2007), Koedel (2009), Cook and Mansfield (2016), Liu and Loeb (2021), and Backes et al. (2024). Dozens of prior studies estimate elementary school teacher value added (reviewed in Bacher-Hicks and Koedel, 2023).

[3]The National Academies of Sciences, Engineering, and Medicine defines late adolescence as ages 16 to 18 (National Academies of Sciences, Engineering, and Medicine, 2019). The American Academy of Pediatrics defines late adolescence as ages 18 to 21 (`https://www.healthychildren.org/English/ages-stages/teen/Pages/Stages-of-Adolescence.aspx`). 11$^{\text{th}}$ grade students in the United States are typically ages 16 to 17.

The paper proceeds as follows. Section 2 describes the linked K-12 and postsecondary administrative data from North Carolina. Section 3 discusses the value added framework and estimates. Section 4 presents the nested logit model of college enrollment and the selection-corrected analysis of college performance. Section 5 concludes.

2 Data

2.1 K-12 Data

I leverage 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). 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 11$^{\text{th}}$ grade students, allowing me to estimate the impacts of 11$^{\text{th}}$ grade teachers on students' ACT scores without needing to account for non-random selection into ACT-taking.[4] The test is administered during the spring semester, on or near March 1$^{\text{st}}$. This universal college admissions testing regime, along with the linkage between detailed K-12 and postsecondary education records, makes North Carolina an ideal setting in which to study 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

[4] My sample of 11$^{\text{th}}$ grade ACT-takers includes approximately 93% of 11$^{\text{th}}$ grade students in the corresponding North Carolina public school cohorts. Thus, although the ACT test is mandatory, ACT participation is below 100% due to testing exemptions and student absences. The 93% ACT-taking rate in my sample indicates that many schools fall short of the state-mandated 95% ACT participation threshold. Detailed information on ACT testing exemptions and school-level participation requirements for the most recent academic year can be found here: https://www.dpi.nc.gov/documents/accountability/testing/north-carolina-test-coordinators-handbook/open.

formed as the rounded average of each section score. I evaluate separately students' math ACT scores and average English and reading ACT scores. Hereafter, I use "English ACT" to refer to the average of a student's English and reading ACT scores.

I leverage NC DPI data on student demographics, ACT scores, lagged standardized test scores, and course enrollments linked with teacher identifiers, demographics, experience, and educational credentials to estimate teacher value added on ACT scores. My sample consists of North Carolina public high school students who took the 11^{th} grade ACT test between 2014 and 2018, corresponding to the high school graduating classes of 2015-2019.[5] I restrict the sample as follows.

I restrict the English value added estimation sample to students matched with their 11^{th} grade English teacher. I restrict the math value added estimation sample to students matched with their 11^{th} grade math teacher. I match students who took different courses within the same subject in the fall and spring semesters with their fall semester teacher to maximize the amount of exposure prior to taking the ACT test. I match students who took different courses within the same subject concurrently with their teacher in the least advanced course.[6] For example, a student who takes Algebra 2 in the fall semester and Precalculus in the spring semester is assigned to their Algebra 2 teacher. A student who takes full-year courses in Algebra 2 (course code 2024) and Precalculus (course code 2070) concurrently is also assigned to their Algebra 2 teacher.

I restrict the 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), representing approximately 80% of 11^{th} grade students. This sample restriction excludes very advanced students and remedial students, who may be taking a wide range of different math courses during 11^{th} grade.

[5] 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 analyses of college performance outcomes.

[6] I define the least advanced course as the course with the lowest numeric course code. Lower numeric course codes typically correspond to core courses rather than electives.

2.2 College Data

I link K-12 data with enrollment records from all sixteen public 4-year colleges and universities in North Carolina, provided by the University of North Carolina (UNC) System. The UNC System includes all public 4-year colleges and universities in North Carolina. It is among the oldest and largest public university systems in the United States and includes five Historically Black Colleges and Universities (HBCUs) and one Historically American Indian University (UNC Pembroke). Selectivity and quality vary significantly across institutions within the UNC System. I match students who took the 11$^{\text{th}}$ grade ACT test between 2015 and 2018, corresponding to 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.[7] The UNC system enrollment records include semester-level enrollment status as well as course-level enrollments, final grades, and earned credits.[8] The UNC system graduation records include degree and major information for both undergraduate and graduate degrees. I restrict my analysis to on-time college enrollment during the summer or fall semester following high school graduation.

Approximately 70% of on-time 4-year college enrollments among North Carolina public high school graduates are 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), provided by NC DPI. This survey is administered to all North Carolina public high school students during the spring of 12$^{\text{th}}$ 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 at-

[7] I match a subset of the full sample with college enrollment records to capture on-time college enrollment because college enrollment data begins in 2016.

[8] Admissions data is not available; therefore, my analysis will not separately consider college acceptance outcomes and enrollment outcomes conditional on acceptance.

tend a public or private institution and whether they plan to enroll in-state or out-of-state.[9]

I utilize UNC system data, supplemented with high school graduation survey data, to evaluate college outcomes of interest, including college enrollment, college choice, and college performance (measured by freshman year GPA, remedial college algebra course-taking, dropout during or after freshman year, and 5-year 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).

2.3 Descriptives

Table 1 presents summary characteristics for the 493,582 North Carolina public high school students who took the 11$^{\text{th}}$ grade ACT test between 2014 and 2018. After imposing track restrictions and excluding students who are not matched with a teacher, are missing a valid subject-specific ACT score, or are missing covariates, my English value added estimation sample includes 412,678 students and my math value added estimation sample includes 339,324 students. After excluding the 2014 ACT-taking cohort and excluding students who are not matched with English and math teacher value added estimates or are missing covariates, my college outcomes estimation sample includes 272,096 students.[10] 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$^{\text{th}}$ 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. 20.7% 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. Among students who enroll in the UNC system, 9.2% drop out during or after freshman year and 70.8% graduate with a bachelor's

[9] Appendix K describes the alignment between high school graduation survey data on in-state 4-year public college enrollment and UNC system administrative data. Prior work linking K-12 and higher education outcomes in North Carolina typically relies on the high school graduation survey data (e.g. Jackson, 2014, 2018), which overreports UNC system enrollment relative to administrative data and does not include enrollment in specific colleges.

[10] Appendix K demonstrates that the characteristics of my estimation samples are similar to those of the full sample of 11$^{\text{th}}$ grade students and provides further detail on variable and sample construction.

degree or higher within 5 years of initial enrollment.

Table 2 presents summary characteristics for the teachers in my sample. The students in my sample are matched with 5,518 math teachers and 5,635 English teachers. 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. Sample attrition arises from teachers either leaving the teaching profession in North Carolina or transferring to courses in other grade levels. Teachers are matched with approximately 60 to 70 11$^{\text{th}}$ grade students in the sample, on average. Students are distributed 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$^{\text{th}}$ grade students take the ACT test, my sample is restricted to a subset of the students in 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.[11] There is also a wide range of student performance across institutions, as measured by GPA, remedial college algebra course-taking, dropout, and 5-year completion rate. Cross-institution differences in student performance are partially driven by differences in student body composition but may also be attributed to institutional policies such as grading curves and student support programs. Thus, students' expected performance in college may vary substantially with their choice of institution within the UNC system.

Figures 1 and 2 demonstrate that ACT score distributions overlap substantially between some, but not all, colleges. A 25$^{\text{th}}$ percentile ACT math score at UNC Chapel Hill, the highly selective state flagship university, is equivalent to a 75$^{\text{th}}$ percentile score at moderately selective Appalachian State University, indicating some overlap in the schools' ACT score distributions. On the other hand, a 25$^{\text{th}}$ percentile score at Appalachian State is several points higher than the 75$^{\text{th}}$ percentile score across all less-selective Historically Black Colleges and Universities in the sample. Thus, marginal improvements in ACT scores may shift

[11] 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.

students from moderately selective to highly selective colleges, but may have little effect on enrollment in the least selective institutions.

Table 1: Student Summary Statistics by Estimation Sample

	Mean (SD)
Economically Disadvantaged	0.386
Female	0.507
Black	0.247
Hispanic	0.125
ACT Composite	18.61
	(5.160)
ACT Math	19.03
	(4.820)
ACT English	18.07
	(5.997)
Math Teacher Match	0.937
English Teacher Match	0.946
Math and English Teacher Match	0.919
Intend to Enroll in 2-Year College	0.351
Intend to Enroll in 4-Year Private/Out-of-State College	0.132
Enrolled in UNC On-Time (After High School)	0.207
Freshman UNC GPA	2.960
	(0.801)
Freshman UNC Dropout	0.0920
Graduated from UNC within 5 Years	0.708
Observations	493582

UNC GPA, dropout, graduation conditional on UNC enrollment

Table 2: Teacher Summary Statistics

	English Mean (SD)	Math Mean (SD)
Holds Graduate Degree	0.434	0.380
	(0.496)	(0.485)
Female	0.778	0.646
	(0.415)	(0.478)
Nonwhite	0.182	0.204
	(0.386)	(0.403)
Experience (Years)	11.66	12.51
	(9.027)	(9.942)
Years in Sample	2.489	3.067
	(1.459)	(1.418)
Switched Schools	0.125	0.183
	(0.331)	(0.387)
Number of 11$^{\text{th}}$ Grade Students	72.88	61.11
	(106.0)	(72.73)
Number of Sections with 11$^{\text{th}}$ Grade Students	6.225	8.122
	(6.570)	(7.423)
Observations	5635	5518

Table 3: College Summary Statistics

	Student Count	Math ACT Mean	English ACT Mean	Acceptance Rate	Freshman GPA Mean	College Algebra	Freshman Dropout	5-Year Completion
State Flagship								
UNC Chapel Hill	10611	27.02	27.71	0.305	3.312	0.145	0.0261	0.930
NC State	13333	26.28	26.00	0.504	3.308	0.00586	0.0402	0.855
UNC Charlotte	11537	23.08	22.30	0.633	3.127	0.491	0.0792	0.745
UNC Wilmington	6273	23.07	23.17	0.610	3.205	0.605	0.0660	0.801
Appalachian State	10549	22.70	22.93	0.664	3.168	0.203	0.0590	0.798
UNC Asheville	1970	22.38	23.68	0.785	2.933	0.0312	0.117	0.669
UNC School of the Arts	227	22.20	24.50	0.344	3.306	0.0373	0.0621	0.773
East Carolina	13029	20.82	20.53	0.690	2.764	0.534	0.0796	0.673
Western Carolina	6662	20.55	20.47	0.403	2.902	0.316	0.103	0.623
UNC Greensboro	9284	20.10	20.48	0.586	2.812	0.369	0.133	0.612
Historically Minority Serving								
UNC Pembroke	3669	18.40	18.03	0.744	2.486	0.643	0.159	0.470
NC A&T	5508	18.33	17.39	0.605	2.569	0.478	0.161	0.512
Winston-Salem State	3075	17.16	16.26	0.585	2.618	0.640	0.146	0.513
Fayetteville State	1920	17.12	16.14	0.604	2.543	0.706	0.158	0.403
Elizabeth City State	939	17.10	15.97	0.700	2.554	0.628	0.168	0.468
NC Central	3157	17.07	16.07	0.659	2.360	0.693	0.140	0.454
4-Year Private/Out of State	48891	21.19	20.84					
2-Year College	132255	17.25	16.00					
No College	116500	17.60	16.28					
Observations	272096	271959	271795	99809	90654	98994	97996	57259

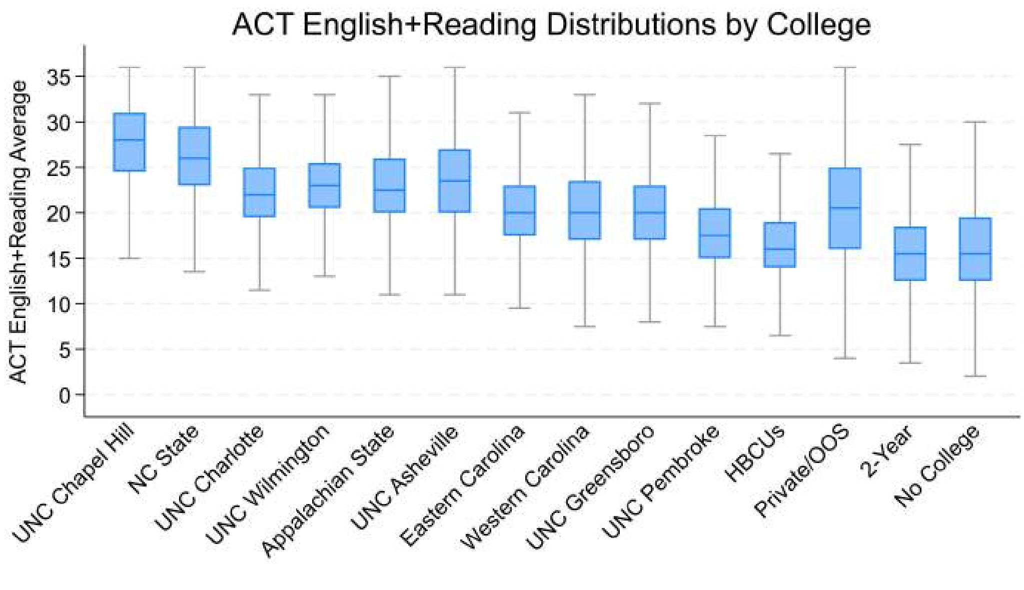
Columns (1),(2),(3),(5),(6),(7),(8) calculated using estimation sample of North Carolina public high school (in-state) students

Column (4) calculated using 2015 IPEDS data downloaded from the Urban Institute Data Explorer, including both in-state and out-of-state students

Elizabeth City State, Fayetteville State, NC A&T, NC Central, and Winston-Salem State are HBCUs

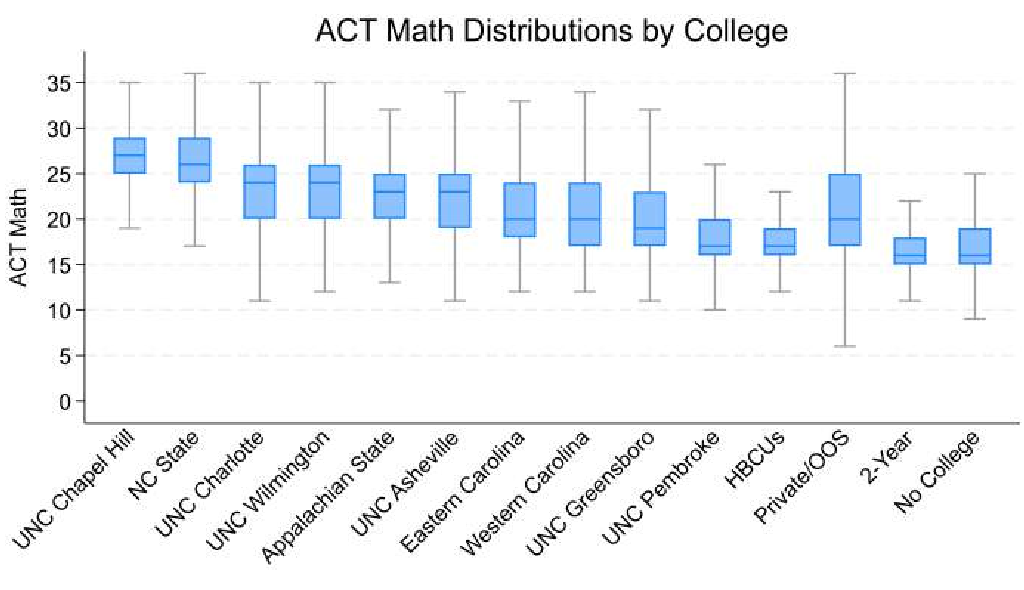
UNC Pembroke is a historically American Indian University

Figure 1: English Skill Distributions by College



Box represents 25th–75th percentiles, line represents median, whiskers represent $1.5 \times IQR$
HBCUs include NC A&T, Winston-Salem State, Fayetteville State, Elizabeth City State, NC Central

Figure 2: Math Skill Distributions by College



Box represents 25th–75th percentiles, line represents median, whiskers represent $1.5 \times IQR$
HBCUs include NC A&T, Winston-Salem State, Fayetteville State, Elizabeth City State, NC Central

3 Estimating ACT Score Value Added

3.1 Value Added 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 using a linear value added model. I assume that teacher assignment is independent from students' expected 11^{th} grade ACT performance after controlling for lagged student achievement and observable characteristics as follows.

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 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 Equation (1).

$$\text{ACT}_{ijkst} = \beta_{0k} + \beta_{1k}\text{EOC}_{it-1} + \beta_{2k}X_{it} + \beta_{3k}Z_{it} + \theta_{jk}T_{jkt} + \gamma_{ks} + \alpha_{kt} + \epsilon_{ijkst} \tag{1}$$

Here, ACT_{ijkst} is the subject k ACT score of student i assigned to teacher j in school s and year t. EOC_{it-1} is a vector of lagged end-of-course test scores.[12] X_{it} is a vector of student-level and classroom-level controls.[13] Z_{it} is a vector of controls for 11^{th} grade math and English courses and course levels (standard, honors, or college-level).[14] Most high schools in the United States do not explicitly label courses of study; yet, students are often placed

[12] 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.

[13] X_{it} includes 8^{th} grade end-of-grade (EOG) math, English, and science test scores, math track, economically disadvantaged status, race/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.

[14] Appendix K describes the mapping of high school course codes to course controls.

into different courses based on academic achievement (Betts, 2011). Z_{it} accounts for implicit tracking practices by restricting comparison to students taking the same 11^{th} grade courses at the same level. Additionally, X_{it} accounts 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).

γ_s and α_t are school and cohort fixed effects, respectively. High school fixed effects are identified separately from teacher fixed effects due to the presence of teacher "switchers" who move schools during the sample period (Mansfield, 2015).[15] T_{jkt} are vectors of subject k 11^{th} grade teacher indicator variables, respectively. θ_{jk} are the parameters of interest, representing the causal effects of teacher j of subject k on subject k ACT scores.

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 the ACT scores of students 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 toward an empirical prior of zero, the mean teacher effect. This shrinkage accounts for the fact that 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 closer 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

[15] While it is not standard to include school fixed effects when estimating teacher value added in elementary and middle school, nearly all prior studies of high school teacher value added include fixed effects for schools (Bacher-Hicks and Koedel, 2023). While high school fixed effects narrow the variation used to identify teacher value added, the larger size of high schools relative to lower grades makes identification feasible. High school fixed effects account for non-random student and teacher sorting across schools, which may be more relevant in high school than in lower grades (Bacher-Hicks and Koedel, 2023). Including high school fixed effects diminishes the utility of common forecast unbiasedness tests (e.g. Chetty et al., 2014a) because average bias from nonrandom sorting to teachers within schools is zero by construction at the school level.

student ACT scores are stationary; that is, the means of the teacher quality distribution and the (normalized) student ACT score distribution are constant throughout the sample period and the correlation 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$^{\text{th}}$ grade ACT performance after accounting for the covariates included in the model. I evaluate this assumption empirically by running several balance tests in the spirit of Rothstein (2010), with results in Table 4.

First, I regress 10$^{\text{th}}$ grade unweighted GPA, residualized on value added model covariates, on 11$^{\text{th}}$ grade teacher fixed effects to understand whether teacher assignment is predictive of lagged student academic achievement after conditioning on model covariates. An F-test for joint significance of the teacher fixed effects suggests that the relationship is marginally statistically significant; however, the magnitude of the fixed effects is small. A one standard deviation increase in 11$^{\text{th}}$ grade English teacher fixed effects increases residualized 10$^{\text{th}}$ grade GPA by 0.23 GPA points or roughly half of a standard deviation, while a one standard deviation increase in 11$^{\text{th}}$ grade math teacher fixed effects increases residualized 10$^{\text{th}}$ grade GPA by 0.09 GPA points or roughly one quarter of a standard deviation. 11$^{\text{th}}$ grade math teacher assignment is less correlated with residualized 10$^{\text{th}}$ grade GPA than 11$^{\text{th}}$ 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. Repeating the exercise without residualizing 10$^{\text{th}}$ grade GPA suggests that value added model covariates account for a substantial share of nonrandom student-teacher sorting.

I compare the results of the conditional and unconditional balance tests with a "placebo" balance test regressing the length of a student's last name, residualized on value added model covariates, on 11$^{\text{th}}$ grade teacher fixed effects. An F-test for joint significance of the teacher fixed effects suggests that the relationship is also marginally statistically significant, despite student last names being unrelated to the teacher assignment process. The marginally significant conditional balance test and placebo balance test results likely reflect over-rejection of the null hypothesis in F-tests with a large number of fixed effects and relatively small within-cell sample sizes. Appendix A presents results of an additional permutation-based balance test adapted from Abrams et al. (2012) and Landon (2024), which addresses over-rejection of the null hypothesis in F-tests with a large number of fixed effects and relatively small within-cell sample sizes.[16] Appendix B describes the course scheduling algorithm used by North Carolina public high schools to create students' course schedules, which provides further support for the quasi-random nature of teacher assignment after conditioning on a student's course choices. Appendix C demonstrates robustness of value added estimates to various modeling assumptions.

Table 4: Balance Tests: Joint Significance of Teacher Assignment

	(1) English	(2) Math
Residualized GPA		
R^2	0.0493	0.0550
F-Statistic	3.213	2.905
SD of Teacher Fixed Effects	0.228	0.0912
SD of Outcome	0.442	0.441
GPA		
R^2	0.292	0.345
F-Statistic	25.55	26.28
SD of Teacher Fixed Effects	0.570	0.386
SD of Outcome	0.717	0.717
Placebo: Last Name Length		
R^2	0.0166	0.0194
F-Statistic	1.043	0.989
SD of Teacher Fixed Effects	0.765	0.285
SD of Outcome	2.532	2.532
Observations	227221	227045

F-Statistics from OLS regressions of GPA or placebo outcome on 11$^{\text{th}}$ grade teacher fixed effects

[16] I simulate the random assignment of teachers to classrooms within school-cohort cells and calculate the standard deviation of mean 10$^{\text{th}}$ grade student absences, residualized on value added model covariates, across the teachers in the sample. I then repeat the process 100 times, generating 100 simulated measures of dispersion capturing sampling variation in classroom average ability under random teacher assignment. Finally, I compare the true standard deviation of teacher-mean residualized student absences to the simulated distribution. For both math and English, I find that the true standard deviation falls just outside the range of simulated standard deviations, suggesting a limited role for student-teacher sorting in this setting after accounting for value added model covariates.

The estimation procedure is as follows. First, I residualize subject ACT scores on the set of covariates included in the value added model:

$$\hat{\epsilon}_{ijkst} = \text{ACT}_{ijkst} - \hat{\beta}_0 - \hat{\beta}_1 \text{EOC}_{it-1} - \hat{\beta}_2 X_{it} - \hat{\beta}_3 Z_{it} - \hat{\gamma}_s - \hat{\alpha}_t \tag{2}$$

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

$$\hat{\theta}_{j,-t} = \psi_t' \bar{\epsilon}_{j,-t} \tag{3}$$

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 $\hat{\theta}_{j,-t}$ 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 $\overline{e}_{cjt}$, 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

Table 5 summarizes the distributions of shrunken leave-year-out value added estimates. The estimated standard deviation of English teacher ACT score value added is 0.0610. The estimated standard deviation of math teacher ACT score value added is slightly larger, 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 0.0610 standard deviations. Assignment to a comparably skilled math teacher increases a student's predicted math ACT score by 0.0796 standard deviations, approximately 0.5 points on the 36-point ACT test scale. ACT score value added has out-of-sample predictive power, as demonstrated by a simple forecast test shown in Appendix D.

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). The estimated standard deviations of teacher value added on ACT scores are similar in magnitude to prior estimates of high school teacher value added on standardized test scores (Jackson, 2014) and smaller in magnitude than estimates of teacher value added in elementary and middle school (e.g. Chetty et al. (2014a)). This is consistent with the notion that variation in teacher value added decreases as students age because individual teachers become less influential for cognitive skill development (Cunha and Heckman, 2007), a standard deviation in test scores captures increasing cognitive skill dispersion as course content becomes more advanced (Cascio and Staiger, 2012), and students are exposed to more teachers simultaneously. Decomposing the variance of ACT score value added into between-school and within-school components, following Chetty et al. (2014a), reveals substantial variation both within and across high schools.[17]

Table 5: Estimated Distributions of Teacher Value Added

	Estimated Standard Deviation
English	0.0610
Math	0.0796

Estimated standard deviation is the square root of the estimated covariance in mean residuals from equation (2) across classrooms, within teachers

ACT score value added is distinct from observable teacher qualifications. Observable teacher characteristics, including race/ethnicity, gender, experience, and education, predict approximately 1-2% of the variation in value added estimates across teachers. Appendix F provides additional detail on the relationships between ACT score value added and observable teacher characteristics.

ACT score value added is also distinct from teacher value added on traditional standardized test score measures and teacher value added on noncognitive student outcomes. To test the relationship between ACT score value added and teacher value added on traditional

[17] Results of the value added variance decomposition are shown in Appendix E.

standardized test score measures, I estimate 9^{th} grade math teacher value added on 9^{th} grade Algebra 1 end-of-course (EOC) test scores and 10^{th} grade English teacher value added on 10^{th} grade English 2 end-of-course (EOC) test scores. Results are shown in Appendix G. I find a positive but relatively low within-math teacher correlation of 0.0715 between ACT score value added and Algebra 1 EOC score value added and a within-English teacher correlation of 0.0146 between ACT score value added and English 2 EOC score value added. To test the relationship between ACT score value added and teacher value added on noncognitive student outcomes, I estimate 11^{th} grade math and English teacher value added on total 11^{th} student absences.[18] Results are shown in Appendix G. I find a negative within-math teacher correlation of -0.0701 between math ACT score value added and noncognitive value added and a negative within-English teacher correlation of -0.0275 between English ACT score value added and noncognitive value added.

The low within-teacher correlations between EOC score value added, noncognitive value added, and ACT score value added are 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 for the low correlation between EOC and ACT value added is that the ACT test measures different latent constructs than EOC tests; in particular, the ACT test is designed to measure general aptitude and college readiness, while EOC tests evaluate mastery of subject-specific content. Teachers may reasonably differ in their effectiveness across these domains (Papay, 2011). Additionally, EOC tests are designed to assess course-specific knowledge in alignment with North Carolina curriculum standards, while the ACT does not directly align with the North Carolina high school curriculum. Thus, teacher value added across EOC and ACT tests may differ based on how strictly teachers adhere to state curricular standards and how much classroom time is spent on state test preparation. Other potential explanations include test timing, score standardization, and teacher test preparation incentives (Papay,

[18] Student absences are a measure of school participation behavior. School participation behaviors may be influenced by students' noncognitive and cognitive skill levels as well as factors such as family responsibilities, particularly among older high school students. I follow prior literature in using behaviors, including school absences, as an imperfect proxy for noncognitive skills (e.g. Heckman and Kautz, 2012; Jackson, 2018).

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, EOC test scores factor in to teacher, school, and student accountability measures.

To understand the relative predictive power of ACT score value added versus EOC score and noncognitive value added for long-run outcomes, I estimate OLS regressions of ACT score value added, EOC score value added, and noncognitive value added measures on an indicator for on-time enrollment in 4-year colleges, conditioning on student-level covariates and school and cohort fixed effects. I find that, without conditioning on high school GPA, math EOC score value is more predictive of college enrollment than math ACT score value added. After conditioning on high school GPA, however, math EOC score value added is no longer predictive of college enrollment. This result suggests that the impact of math EOC score value added on college enrollment operates through improvements in high school GPA, while math ACT score value added has positive impacts not captured by GPA alone. Given that ACT scores are observable to colleges during the admissions process while EOC scores are not, this result underscores the distinct relevance of ACT score value added for college outcomes. I find no significant relationship between noncognitive value added and college enrollment in this sample. These results, shown in Appendix F, suggest that teacher value added on ACT scores is not only distinct from traditional test score value added measures and noncognitive value added measures, but also an empirically relevant predictor of long-run postsecondary outcomes despite the smaller variance in ACT score value added relative to teacher value added in earlier grade levels.

4 ACT Score Value Added and College Outcomes

In this section, I estimate the long-run effects of ACT score value added on college enrollment, college choice, and college performance. Evaluating these different postsecondary outcomes will reveal whether ACT score value added reflects the accumulation of skills that are transferable across high school and college classrooms, or the accumulation of non-transferable skills that boost student achievement on the ACT test but do not translate to improvements in postsecondary academic performance.

Examples of non-transferable skills include incentivizing effort on the ACT test and "teaching to the test" by focusing on ACT-specific testing strategies. Even if the skills captured by ACT score value added are non-transferable, we should expect to see impacts of ACT score value added on 4-year college enrollment and the choice of specific 4-year colleges because ACT scores enter directly in college admissions decisions. Thus, ACT scores are valuable as an ability signalling mechanism in the college admissions process regardless of the mapping from the ACT score signal to college-relevant skills.

Examples of transferable skills include encouraging student engagement with school, leading to increased motivation and effort across courses and assessments, teaching general academic skills such as problem-solving and critical reading which are foundational to college coursework, and teaching specific academic content upon which college coursework builds. If ACT score value added measures transferable college-relevant skill accumulation, we should expect to see long-run effects not only on college enrollment and college choice, but also on college performance conditional on whether and where a student enrolls in college.

4.1 Reduced-Form Evidence

Table 6 presents evidence that ACT score value added $\hat{\theta}$ is positively related with 4-year college enrollment and selectivity and negatively related with 2-year college enrollment, even after conditioning on student covariates X_{it},[19] cohort fixed effects α, and high school fixed effects γ as shown in Equation (4).

$$Y_{ist} = \omega_0 + \omega_{1,English}\hat{\theta}_{English-t} + \omega_{1,Math}\hat{\theta}_{Math-t} + \omega_2 X_{it} + \gamma_s + \alpha_t + \epsilon_{ist} \tag{4}$$

The relationship between ACT score value added and 4-year college enrollment is larger for on-time enrollment, suggesting that ACT score value added induces 4-year college enrollment among some students who would have otherwise enrolled in a 2-year college and later transferred to a 4-year institution. While the administrative UNC system enrollment data captures both on-time and lagged enrollment, the survey data on 4-year private or out-

[19]Student covariates are defined as in the value added estimation model (1).

of-state college enrollment and 2-year college enrollment captures only on-time enrollment. Thus, for consistency I restrict all subsequent analysis to on-time college enrollment during the summer or fall semester following high school graduation.

A one standard deviation increase in ACT score value added is associated with a substantially larger increase in 4-year college enrollment than would be implied by a purely random ACT score shock of the same size. Haggag et al. (2024) find that a random 1-point increase in composite ACT score induced by rounding increases 4-year college enrollment by 0.44 percentage points. In contrast, my reduced-form estimates imply that a one standard deviation increase in math ACT score value added increases on-time 4-year college enrollment by 1.89 percentage points. A one standard deviation increase in math ACT score value added corresponds to a 0.0796 standard deviation or 0.356-point increase in math ACT score. Because the composite ACT score is the average of the four section scores (math, English, reading, and science), a 0.356-point increase in math ACT score alone translates to a 0.089-point increase in the composite score ($0.356 \div 4$). Thus, scaling up the 4-year college enrollment effect of math ACT score value added to represent a 1-point increase in composite ACT score yields an enrollment increase of 21.2 percentage points, 48 times larger than the impact of a random ACT score increase. Analogously, scaling up the 4-year college enrollment effect of English ACT score value added to represent a 1-point increase in composite ACT score yields a 4-year college enrollment increase of 3.58 percentage points, 8 times larger than the impact of a random ACT score increase.[20]

This exercise is necessarily speculative: A teacher would need to have ACT score value added 11 (math) or 6 (English) standard deviations above the mean to raise composite ACT scores by 1 point. However, the results highlight that relatively small ACT score increases induced by high value added teachers are associated with substantial increases in 4-year college enrollment. This suggests that the impacts of ACT score value added

[20] A one standard deviation increase in English ACT score value added increases on-time 4-year college enrollment by 0.64 percentage points. A one standard deviation increase in English ACT score value added corresponds to a 0.0610 standard deviation or 0.358-point increase on the English and reading ACT, two of four ACT sections. Because the composite ACT score is the average of the four section scores (math, English, reading, and science), a 0.358-point increase in English and Reading translates to a 0.179-point increase in the composite score ($0.358 \div 2$). Thus, scaling up the 4-year college enrollment effect to represent a 1-point increase in composite ACT score yields a 4-year college enrollment increase of 3.58 percentage points, 8 times larger than the impact of a random ACT score increase.

on college enrollment extend beyond the signalling value of a higher ACT score, operating partly through the accumulation of skills.[21] For example, teachers with high ACT score value added may boost ACT scores by increasing students' cognitive skills, leading to better subsequent grades and higher scores on repeated ACT or SAT attempts, or by increasing students' noncognitive skills such as persistence, leading to higher academic effort and college application quality. These skill improvements will directly increase 4-year college enrollment and, if transferable, could improve college performance as well.

Table 6: ACT Score Value Added and College Enrollment

	(1) 4-Year College Enrollment	(2) On-Time 4-Year College Enrollment	(3) On-Time 2-Year College Enrollment	(4) 4-Year College Acceptance Rate
English ACT Value Added	-0.000384	0.00636	-0.00710	-0.00659**
	(0.00812)	(0.00845)	(0.0121)	(0.00325)
Math ACT Value Added	0.0130***	0.0189***	-0.0207***	-0.00601***
	(0.00312)	(0.00338)	(0.00378)	(0.00157)
Observations	272082	272082	263603	74230
Mean	0.472	0.399	0.348	0.578
R^2	0.353	0.334	0.185	0.228

Standard errors in parentheses, clustered at the high school level

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

Coefficients standardized to reflect 1σ increase in value added

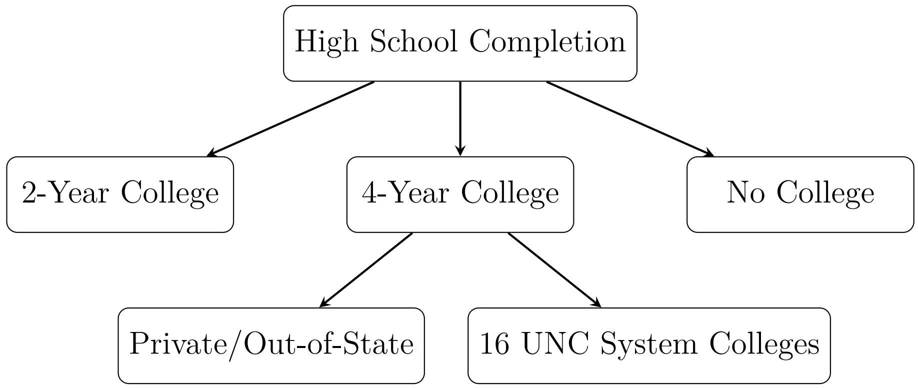
Includes controls for student lagged test scores and demographics X_{it}, high school fixed effects, and cohort fixed effects

4.2 College Outcomes Model

Motivated by reduced-form evidence of the relationship between ACT score value added and college enrollment and selectivity, I model college choice using a nested logit model, with the student's decision problem depicted in Figure 3. The nested structure allows for heterogeneous effects of ACT score value added across students with different characteristics, such as lagged achievement. Additionally, the nested logit model allows for two 4-year colleges to be closer substitutes than a 2-year college and a 4-year college, capturing student substitution patterns across heterogeneous college types.

[21] Controlling for a student's observed ACT score in Equation (4) reduces the association between ACT score value added and college enrollment by roughly 5%, further suggesting that the impacts of ACT score value added on college enrollment extend beyond the signalling value of ACT scores. Because ACT score value added is, by construction, correlated with students' observed ACT scores, this exercise can be interpreted as a mediation-style analysis quantifying the share of the relationship between ACT score value added and college enrollment that can be accounted for by ACT scores. Results are shown in Appendix H.

Figure 3: College Decision Problem



I estimate the nested logit model in two stages.[22] The choice probabilities of college c within the 4-year college nest and of college nest l can be expressed as:

$$\mathbb{P}(Y_i = c \mid \hat{\theta}, X_{it}, s, t, Y_i \in \text{4-year}) \tag{5}$$
$$= \frac{exp(\delta_{0c} + \delta_{1,English,c}\hat{\theta}_{English-t} + \delta_{1,Math,c}\hat{\theta}_{Math-t} + \delta_{2c}X_{it} + \delta_{3c}S_{st} + \alpha_{ct})}{\sum_c exp(\delta_{0c} + \delta_{1,English,c}\hat{\theta}_{English-t} + \delta_{1,Math,c}\hat{\theta}_{Math-t} + \delta_{2c}X_{it} + \delta_{3c}S_{st} + \alpha_{ct})}$$

$$\mathbb{P}(Y_i \in l \mid \hat{\theta}, X_{it}, s, t) \tag{6}$$
$$= \frac{exp(\kappa_{0l} + \kappa_{1,English,l}\hat{\theta}_{English-t} + \kappa_{1,Math,l}\hat{\theta}_{Math-t} + \kappa_{2l}X_{it} + \rho IV_{ist} + \gamma_{ls} + \alpha_{lt})}{\sum_l exp(\kappa_{0l} + \kappa_{1,English,l}\hat{\theta}_{English-t} + \kappa_{1,Math,l}\hat{\theta}_{Math-t} + \kappa_{2l}X_{it} + \rho IV_{ist} + \gamma_{ls} + \alpha_{lt})}$$

where 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, and ρ therefore represents the degree of similarity between choices within the 4-year college nest.[23] The coefficient on the inclusive value term, ρ, is identified from individual-level variation in the inclusive value term, generated by the inclusion of school–cohort covariates in the within-nest choice of 4-year college c. School-cohort covariates are excluded from the choice of nest l, which

[22] Due to the additive separability of the nested logit log-likelihood function, estimating the model in two stages is equivalent to estimating the model in one stage using maximum likelihood estimation. Estimating the model in two stages is less efficient but more computationally tractable.

[23] If $\rho = 1$, the model reduces to a multinomial logit model without nesting.

includes only time-invariant school fixed effects.

$$IV_{ist} = \log(\sum_{c} exp(\delta_{0c} + \delta_{1,English,c}\hat{\theta}_{English-t} + \delta_{1,Math,c}\hat{\theta}_{Math-t} + \delta_{2c}X_{it} + \delta_{3c}S_{st} + \alpha_{ct})) \quad (7)$$

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, and l indexes college nests, which include 2-year college, 4-year college, and no college.[24] In the absence of data on college admissions decisions, I assume that each student's choice set includes all colleges in the data. Therefore, my estimates will encompass the impacts of ACT score value added on both college admissions outcomes and college enrollment decisions conditional on admission.

$\hat{\theta}_{k-t}$ is a "leave-year out" estimate of subject k ACT score value added.[25][26] X_{it} is a vector of student-level covariates defined in the value added estimation model shown in Equation (1), and α are cohort-choice fixed effects. γ are high school-choice fixed effects, accounting for cross-high school differences in the propensity to enroll in each nest, and S_{st} is a vector of high school-cohort level controls, including the share of students in the prior graduating class attending each college in the UNC system.[27] These lagged peer college enrollment shares are included in the college choice equation but will be excluded from the college performance

[24]"No college" includes the 4.75% of students who do not graduate high school on time.

[25]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 (0.1015).

[26]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 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.

[27]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. I do not allow high school fixed effects to enter the choice of specific 4-year college c because high school-by-college fixed effects are not well identified outside of very large high schools.

equation. This exclusion restriction will allow me to identify the effects of ACT score value added on college performance, correcting for selection into specific colleges on unobservable student characteristics. Error terms are type 1 extreme value (Gumbel) distributed. I allow all coefficients to vary across 4-year colleges c and nests l; that is, all model covariates are allowed to impact the likelihood of enrollment differently across colleges.

Within the 4-year college nest, I normalize the coefficients on choice $c =$ UNC Chapel Hill to 0. Across nests, I normalize the coefficients on $l =$ no college to 0. Coefficient estimates on $l =$ 2-year college from Equation (6) will therefore reflect the likelihood of attending a 2-year college, relative to not attending college. Coefficient estimates on $l =$ 4-year college from Equation (6) will reflect the likelihood of attending UNC Chapel Hill, relative to not attending college, and coefficient estimates from Equation (5) will reflect the likelihood of attending 4-year college c, relative to UNC Chapel Hill. To obtain coefficient estimates reflecting the likelihood of attending each 4-year college c relative to not attending college, I first multiply estimates from Equation (5) by the estimate of ρ from Equation (6). I then add the coefficient estimates on $l =$ 4-year college from Equation (6), which reflect the likelihood of attending UNC Chapel Hill.

After estimating the nested logit model of college choice, I evaluate the effects of ACT score value added on college performance measures, including freshman year GPA, remedial math course-taking (measured by enrollment in an introductory college algebra course during any semester of college), persistence (measured by dropout during or after freshman year), and graduation within 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 depicted in Equation (6), 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 depicted in Equation (5), 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 which directly improves student performance in college, conditional on whether and where a student enrolls within the UNC system. Channels one and two are consistent with either interpretation of ACT score value added; that is, whether ACT score value added measures the accumulation of skills that are transferable or non-transferable between high school and college. This is because ACT scores factor in to college admissions decisions, and therefore a higher ACT score will improve college enrollment outcomes on the margin regardless of the skills measured by an ACT score. Channel three, on the other hand, will only be present if ACT score value added measures the accumulation of skills that transfer across high school and college classrooms.

To disentangle these three channels and isolate the direct effects of ACT score value added on college performance, I generalize the Heckman selection correction procedure to a nested logit college selection model, using methods from Lee (1983).[28] The Lee (1983) selection correction has been previously applied in empirical education literature to study, for example, the wage returns to college quality (Brewer et al., 1999), the effects of student characteristics on years of completed schooling (Hilmer, 2001), and the competitive behavior of for-profit universities (Kofoed, 2015).

I model college performance as follows:

$$\begin{aligned} College\_Performance_{icst} &= \pi_0 + \pi_{1English}\hat{\theta}_{English-t} + \pi_{1Math}\hat{\theta}_{Math-t} + \pi_2 X_{it} \\ &\quad + \gamma_s + \alpha_t + \tau_c + u_{icst} \end{aligned} \tag{8}$$

Here, $\hat{\theta}$, X_{it}, γ_s, α_t, and τ_c are defined as in Equations (5) and (6). In particular, the college performance equation includes high school fixed effects γ_s but does not account for time-varying high school characteristics such as the share of students in the prior graduating class attending each college in the UNC system. This exclusion restriction implies that time-varying within-high school peer enrollment patterns impact students' college choices, but do

[28]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). Appendix J shows that the results are qualitatively similar when applying the selection correction method from Dahl (2002), which requires a less restrictive assumption on the error structure but does not nest the Heckman selection correction.

not impact college performance.[29] Appendix I demonstrates that the results are robust to using an alternative set of instruments, indicators for which college is nearest to a student's high school, conditional on the distance to the nearest college.

The outcome $College\_Performance_{icst}$ is observed only when a student chooses some college choice c in the UNC system. I omit students at UNC School of the Arts from the college performance equations. UNC School of the Arts offers only Bachelor of Fine Arts degrees and Bachelor of Music degrees; therefore, college performance measures are not directly comparable to performance at the other comprehensive academic institutions in the UNC System.

I make the standard conditional independence assumption: $\hat{\theta} \perp u \mid X, s, t, c$. I assume that u follows a normal distribution with mean zero and that the first stage nested logit error terms η_c follow a generalized extreme value (GEV) distribution. The crucial 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 selection equation, such that choice c is chosen when $\epsilon_c < 0$. J is a function of the CDF of ϵ_c.[30] This distributional assumption implies that the correlation between unobservable characteristics driving the choice of alternative c against any other alternative and unobservable characteristics driving college performance takes the same sign across all colleges c.

The distributional assumptions are consistent with the generalized Roy model of Willis and Rosen (1979), which posits that individuals select the college which yields the highest life cycle utility. The utility maximizing college is not necessarily the college performance maximizing college due to nonpecuniary preferences and the imperfect mapping between college performance and lifetime earnings. However, because those with larger benefits to attending a particular college have a higher probability of being observed in that college, the Roy model implies that unobservable characteristics driving the choice of college c and unobservable characteristics driving college performance will be positively correlated at each

[29] This exclusion restriction provides exogenous variation in students' propensities to attend college and to attend each specific college in the data, so that identification in the Lee selection correction model is not based solely on nonlinearities in the nested logit selection equation.

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

college c.

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 to obtain selection terms s_c corresponding to each college in the UNC system, as a function of the nested logit choice probabilities $P_c = P_{c|\text{4-year college}} P(\text{4-year college})$.

$$s_c = \frac{\phi(J_{\epsilon_c}(0 \mid \Gamma))}{F_{\epsilon_c}(0 \mid \Gamma)} = \frac{\phi(\Phi^{-1}(P_c))}{P_c} \tag{9}$$

I then estimate the college performance equation using an OLS regression, controlling for selection terms s_c to account for cross-college differences in selection.[31]

$$\begin{aligned} College\_Performance_{icst} &= \pi_0 + \pi_{1English}\hat{\theta}_{English-t} + \pi_{1Math}\hat{\theta}_{Math-t} + \pi_2 X_{it} \\ &+ \gamma_s + \alpha_t + \tau_c + \sum_c \pi_c \mathbb{1}(enroll\_in\_c)s_c + u_{icst} \end{aligned} \tag{10}$$

Appendix H demonstrates that the lagged enrollment instruments are highly predictive of enrollment at each college in the UNC system. In particular, coefficient estimates reveal that a student is significantly more likely to attend a particular college if a higher share of 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.

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

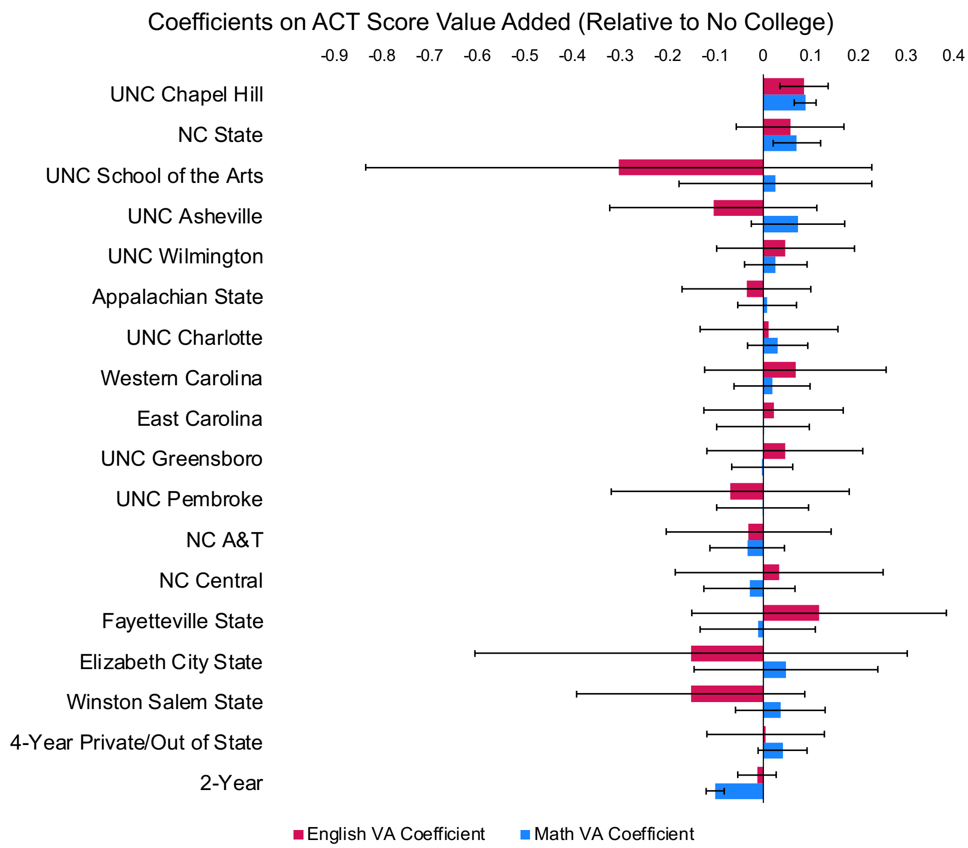
[31] Appendix H demonstrates that the results are qualitatively similar when probit regressions are estimated for binary outcomes. Although results are robust to different functional form assumptions on the college performance equation, the Lee (1983) selection correction method is a "logit-OLS two-stage estimation method."

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). Appendix H demonstrates 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, providing evidence in support of the exclusion restriction. Intuitively, the enrollment instruments are unlikely to affect college performance because I leverage within-high school shifts in college enrollment patterns over time, rather than cross-high school differences that might reflect overall school quality or student body composition. Moreover, the enrollment instruments are unlikely to capture benefits to college performance from attending college with a larger group of friends from high school because I leverage lagged enrollment patterns from the prior cohort, rather than contemporaneous peer composition.

4.3 Results

Figure 4 presents the estimated coefficients of ACT score value added on enrollment in 4-year and 2-year colleges, relative to the outside option of no college, ordering 4-year colleges by selectivity. Coefficients indicate that math ACT score value added significantly increases enrollment in the two 4-year state flagship universities, UNC Chapel Hill and NC State, and significantly decreases enrollment in 2-year colleges. Impacts on the propensity to enroll in less-selective 4-year colleges, relative to the outside option of no college, are not significantly different from 0. Impacts of English ACT score value added are qualitatively similar but smaller in magnitude and less precisely estimated.

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



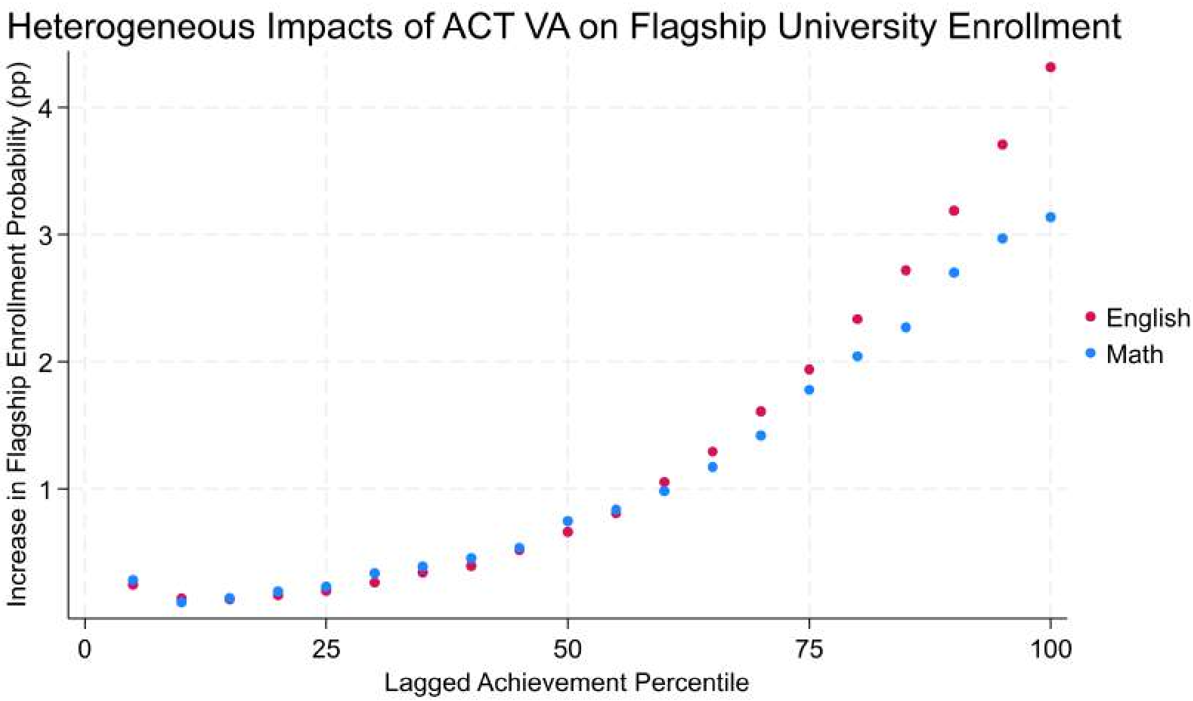
Coefficients standardized to reflect the effects of a 1σ increase in teacher value added.
Error bars represent 95% confidence intervals.
Coefficient estimates with standard errors reported in Appendix H.
Coefficients normalized relative to no college enrollment.
Standard errors bootstrapped with 100 replications to adjust for two-stage nested logit estimation procedure.

To summarize the magnitude of effects on enrollment in selective state flagship universities, conditional on 4-year college enrollment, I calculate for each student the predicted probability of state flagship enrollment when assigned to a teacher with average ACT score value added versus a teacher with ACT score value added one standard deviation above the mean, holding all other covariates at their true values. Moving from a math teacher with average ACT score value added to a math teacher with ACT score value added one standard deviation above the mean increases the probability of 4-year state flagship enrollment by 1.63 percentage points (7% relative to the flagship enrollment rate conditional on 4-year enrollment). An analogous change in English teacher value added increases the probability of 4-year state flagship enrollment by 1.93 percentage points (8%).

The logit structure of the college enrollment model allows for the marginal effects of ACT score value added on college enrollment to vary with student characteristics. Figure 5 plots the difference in predicted 4-year state flagship enrollment probability when assigned to a teacher with average ACT score value added versus a teacher with ACT score value added one standard deviation above the mean, averaged over students in each ventile of the subject-specific lagged achievement distribution who attended college.[32] The impacts of math ACT score value added on 4-year state flagship enrollment are largest for students above the 90th percentile of the lagged achievement distribution, who are likely on the margin of qualifying for admission to highly selective institutions.

[32] I measure lagged achievement using Algebra 1 EOC scores for math value added and English 2 EOC scores for English value added.

Figure 5: Heterogeneous Impacts of ACT Score Value Added on College Enrollment



To summarize changing enrollment patterns across all 4-year colleges in the sample, I calculate for each student the predicted probability of enrollment in each college c when assigned to a teacher with average ACT score value added versus a teacher with ACT score value added one standard deviation above the mean. I use these estimates to form an "expected acceptance rate" weighted by predicted college-specific choice probabilities, shown in Equation (11).[33] Moving from an English teacher with average ACT score value added to an English teacher with ACT score value added one standard deviation above the mean decreases the expected acceptance rate of a student's enrolled college, conditional on 4-year college enrollment, by 1 percentage point. The same change in math teacher value added decreases expected acceptance rate by 0.05 percentage points. Decreases in expected acceptance rate further suggest that students exposed to teachers with high ACT score value

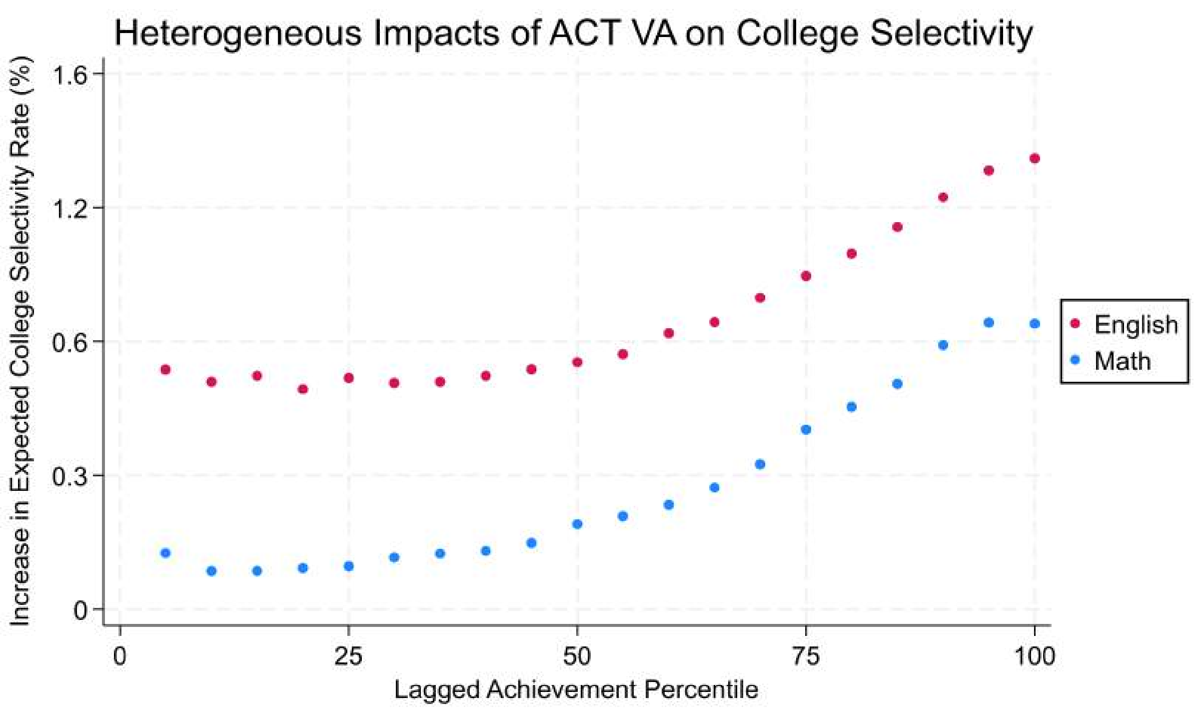
[33] Because I do not observe enrollment in specific private and out-of-state universities, I do not observe the acceptance rate for private and out-of-state enrollment. Therefore, I omit private and out-of state universities from the expected acceptance rate calculation and divide Equation (11) by $1 - P_{i17st}$ where $c = 17$ indexes private and out-of-state university enrollment.

added attend more selective, higher quality 4-year colleges on average.

$$\text{Expected Acceptance Rate}_{icst} = \sum_{c=1}^{16} \hat{P}_{icst}(\hat{\theta}_{English-t}, \hat{\theta}_{Math-t}) \times \text{Acceptance Rate}_c \tag{11}$$

Figure 6 plots the difference in 4-year college selectivity, measured using expected acceptance rate, when assigned to a teacher with average ACT score value added versus a teacher with ACT score value added one standard deviation above the mean, averaged over students in each ventile of the subject-specific lagged achievement distribution who attended college.[34] I find that the impacts of ACT score value added on 4-year college selectivity are again largest for students above the 90$^{\text{th}}$ percentile of the lagged achievement distribution.

Figure 6: Heterogeneous Impacts of ACT Score Value Added on College Enrollment



To summarize the magnitude of effects on 2-year and 4-year college enrollment, I calculate for each student the predicted probability of 2-year and 4-year college enrollment when assigned to a teacher with average ACT score value added versus a teacher with ACT score

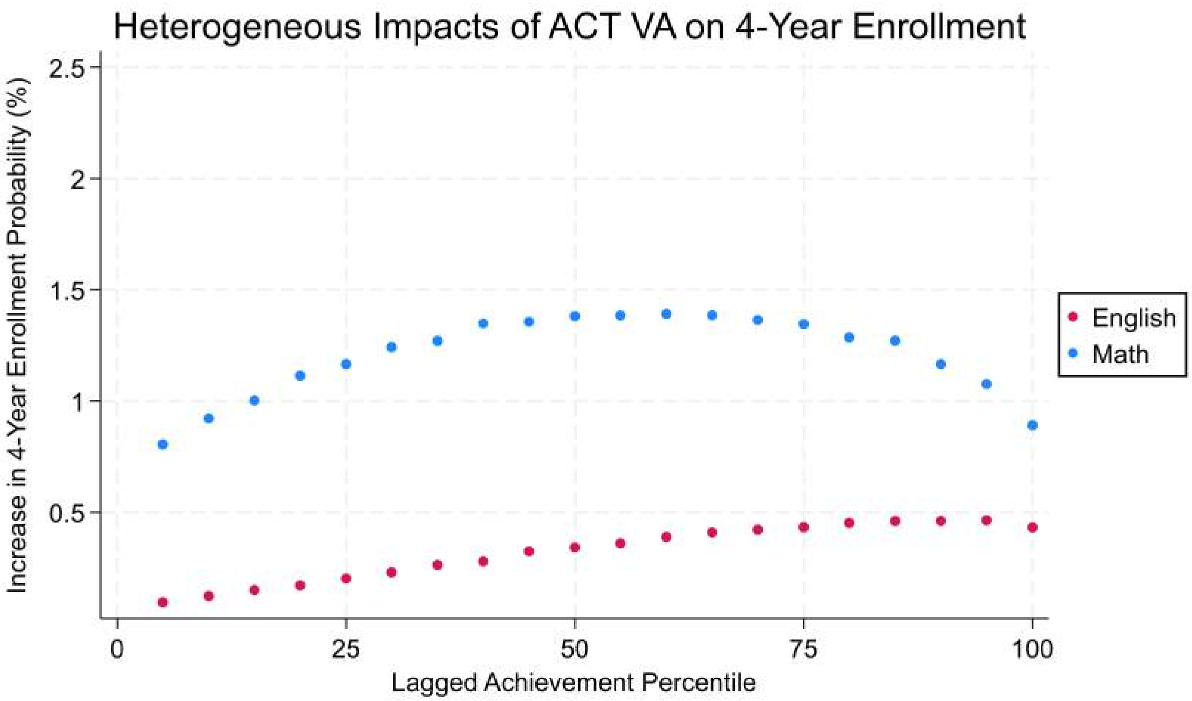
[34] I measure lagged achievement using Algebra 1 EOC scores for math value added and English 2 EOC scores for English value added.

value added one standard deviation above the mean. Moving from a math teacher with average ACT score value added to a math teacher with ACT score value added one standard deviation above the mean increases the probability of 4-year college enrollment by 1.23 percentage points (7% relative to the full sample 4-year enrollment rate) and decreases the probability of 2-year college enrollment by 1.53 percentage points (4% relative to the full sample 2-year enrollment rate). An analogous change in English teacher value added increases the probability of 4-year college enrollment by 0.39 percentage points (2%) and decreases the probability of 2-year college enrollment by 0.30 percentage points ($< 1\%$).

In a nested logit model, the S-shape of the logit curve implies that students' choice of college nest (4-year, 2-year, or no college) will be most responsive to changes in ACT score value added at moderate levels of lagged achievement, unless changes in the within-nest probabilities at high or low achievement levels are large enough to dominate. This property of the logit model is conceptually appealing: Students with very low lagged achievement levels may be less responsive on the margin of 4-year college enrollment, because many of these students will not be qualified for 4-year college admission regardless of achievement gains made in 11$^{\text{th}}$ grade. Conversely, students with very high lagged achievement levels may be less responsive because their decision to apply to college is made prior to 11$^{\text{th}}$ grade and their achievement levels have already exceeded the threshold required for 4-year college admission. Figure 7 plots the difference in predicted 4-year college enrollment probability when assigned to a teacher with average ACT score value added versus a teacher with ACT score value added one standard deviation above the mean, averaged over students in each ventile of the subject-specific lagged achievement distribution.[35] The impacts of math ACT score value added on 4-year college enrollment are largest for students between the 50$^{\text{th}}$ and 75$^{\text{th}}$ percentiles of the lagged achievement distribution, who are likely on the margin of qualifying for 4-year college admission. In contrast, the impacts of English ACT score value added are largest for students above the 75$^{\text{th}}$ percentile, indicating that increased attractiveness of the 4-year college nest driven by access to more selective colleges plays a dominant role in increasing overall 4-year college enrollment.

[35] I measure lagged achievement using Algebra 1 EOC scores for math value added and English 2 EOC scores for English value added.

Figure 7: Heterogeneous Impacts of ACT Score Value Added on College Enrollment



Appendix H presents the estimated effects of ACT score value added on enrollment in specific 4-year colleges, separating the College of Engineering at NC State University from the rest of NC State University. Unlike students at other institutions in the UNC System, freshman applicants to NC State are admitted specifically to one of the university's twelve colleges based on the intended major indicated on their application. In particular, students intending to major in engineering are admitted separately to the College of Engineering, suggesting that math ACT score value added may have different effects on College of Engineering enrollment. Indeed, I find a positive effect of math ACT score value added on enrollment in the College of Engineering at NC State, relative to the outside option of enrollment in UNC Chapel Hill and conditional on 4-year college enrollment.

Table 7 presents estimates from the college performance equation with and without the selection correction. Both selection-corrected and reduced-form estimates indicate that ACT score value added improves a host of college performance measures, including freshman year GPA in both STEM and non-STEM courses, enrollment in a college algebra course,[36] dropout during or after freshman year, and college completion within 5 years of initial enrollment. Compared to reduced-form estimates, effects of math ACT score value added on freshman year GPA, college algebra course-taking, 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 toward 0. Multiple empirical results confirm the presence of selection bias in reduced-form estimates. First, an F-test demonstrates that the selection correction terms enter the college performance equation significantly. Second, coefficients on several measures of student achievement in the college performance equation increase in magnitude after applying the correction procedure. Results are shown in Appendix H.

After correcting for selection, coefficient estimates indicate that a one standard deviation increase in math ACT score value added increases freshman GPA by 0.027 GPA points, 3% of a standard deviation. The impact of math ACT score value added on GPA is larger for STEM courses. A one standard deviation increase in math ACT score value added reduces college algebra course-taking by 2.9 percentage points and reduces dropout by 0.05 percentage points. Effects on college algebra course-taking and dropout translate to declines of 8% and 6%, respectively, relative to the full sample means. Effects of math ACT score value added on 5-year college completion rates are positive but statistically insignificant.[37] While the effects of English ACT score value added on college performance are less precisely

[36] I use enrollment in a college algebra course to proxy for remedial math course placement, although classifications of math courses as remedial, credit acceptance policies, and math course requirements for degree completion vary across institutions within the UNC system. Several institutions use math ACT scores as one metric to determine students' initial math placement (see, for example, the math placement policy at UNC Charlotte: https://pages.charlotte.edu/math-placement/faq/). Thus, exposure to teachers with high math ACT score value added could allow students to place out of remedial math courses and more easily complete degree requirements on time.

[37] A 5-year completion rate is unavailable for the 2018 ACT-taking cohort, the youngest cohort in my sample, decreasing sample size and statistical power for this outcome.

estimated, they are largely similar in magnitude to the effects of math ACT score value added. Notable exceptions include freshman year STEM GPA and enrollment in a college algebra course, outcomes that likely depend more heavily on skills taught by math teachers and are not impacted by English ACT score value added.[38] These results suggest that subject-specific ACT score value added measures capture not only improvements in student motivation and other general academic skills relevant to the college classroom, but also the accumulation of subject-specific cognitive skills.

Table 7: Impacts of ACT Score Value Added on College Performance

	GPA	STEM GPA	Non-STEM GPA	College Algebra	Dropout	Completion
A. No Correction						
English ACT VA	0.0221	0.00522	0.0200	0.00901	-0.00774	0.00400
	(0.0186)	(0.0281)	(0.0197)	(0.0123)	(0.00677)	(0.0120)
Math ACT VA	0.0262***	0.0276**	0.0253***	-0.0276***	-0.00458*	0.00446
	(0.00713)	(0.0107)	(0.00741)	(0.00489)	(0.00274)	(0.00491)
B. Correction						
English ACT VA	0.0233	0.00872	0.0206	0.00809	-0.00844	0.00307
	(0.0185)	(0.0247)	(0.0182)	(0.00997)	(0.00717)	(0.0143)
Math ACT VA	0.0272***	0.0292***	0.0261***	-0.0287***	-0.00494*	0.00399
	(0.00742)	(0.00998)	(0.00730)	(0.00416)	(0.00253)	(0.00487)
Observations	69661	49558	68060	73559	73559	57138
Mean	2.981	2.786	3.114	0.364	0.0863	0.707
R^2 (No Correction)	0.261	0.241	0.255	0.269	0.0432	0.146
R^2 (Correction)	0.262	0.243	0.256	0.274	0.0437	0.148

Panel A: standard errors in parentheses, clustered at the high school level
Panel B: standard errors in parentheses, bootstrapped with 100 replications to adjust for two-stage selection correction procedure
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$
Coefficients standardized to reflect 1σ increase in value added
Includes controls for student lagged test scores and demographics X_{it}, high school fixed effects, cohort fixed effects, college fixed effects

Taken together, my results suggest that 11$^{\text{th}}$ grade teachers have significant scope to influence the accumulation of skills that are transferable from high school to college classrooms. Assignment to 11$^{\text{th}}$ grade teachers with high ACT score value added has important implications for student success in college, both by shifting college enrollment patterns toward selective 4-year universities and by directly improving student performance, conditional on whether and where students choose to pursue postsecondary education.

[38] Appendix H demonstrates that math ACT score value added has positive effects on STEM major choice, further suggesting a role for subject-specific skill accumulation.

4.4 Decomposing Completion Effects

I have shown that assignment to a teacher with high ACT score value added has positive effects on three channels impacting the probability a student completes a 4-year college degree within 5 years of high school graduation. First, ACT score value added increases on-time enrollment in 4-year colleges. Second, ACT score value added increases enrollment in selective colleges with higher on-time completion rates, conditional on 4-year college enrollment. Third, ACT score value added directly improves student performance in college, conditional on whether and where a student enrolls.

In this analysis, I decompose the overall effect of ACT score value added on college completion, unconditional on college enrollment, into three channels as follows:

$$P(\text{4-year college completion}) = \left(\sum_{c=1}^{15} P(\text{complete college} \mid c) P_{c|\text{4-year college}} \right) P(\text{4-year college}) \tag{12}$$

Here, c indexes colleges,[39] and $P_{c|\text{4-year college}}$ is the probability of enrolling in college c conditional on 4-year college enrollment. Each component of Equation (12) can be predicted as a function of ACT score value added. I predict $\hat{P}(\text{complete college} \mid c)$ at each college c using estimates from the college performance Equation (10).[40] I predict $\hat{P}_{c|\text{4-year college}}$ using estimates from the second stage nested logit Equation (5). I predict $\hat{P}(\text{4-year college})$ using estimates from the nested logit equation (6).

I generate each of these predicted probabilities for the full sample of students, including students who do not enroll in a 4-year college, to generate a counterfactual 4-year college completion rate.[41] I hold all other covariates at their true values and calculate counterfactual probabilities when ACT score value added equals 0 (the mean) versus 1 (one standard deviation above the mean). I repeat the exercise separately for English value added, holding math value added at its true values, and for math value added, holding English value added

[39] Because I do not include private and out-of-state colleges and UNC School of the Arts in my college performance analysis, I omit these college from the completion rate summation and divide Equation (12) by $1 - P_{i16st} - P_{i17st}$ where $c = 16$ indexes UNC School of the Arts enrollment and $c = 17$ indexes private and out-of-state college enrollment. Both probabilities can be predicted a function of ACT score value added analogously to the other components of Equation (12).

[40] I hold selection correction terms fixed when predicting counterfactual values of $\hat{P}(\text{complete college} \mid c)$ as a function of ACT score value added.

[41] I omit students from the 2018 ACT-taking cohort because a 5-year completion rate is unavailable.

at its true values.

I substitute these counterfactual probabilities into Equation (12) to calculate the difference in counterfactual 4-year college completion rate when students are assigned to a teacher with average ACT score value added versus ACT score value added one standard deviation above the mean. I find that a one standard deviation increase in English ACT score value added increases the predicted full sample 4-year college completion rate by 0.43 percentage points, while a one standard deviation increase in math ACT score value added increases the predicted college completion rate by 1.16 percentage points.

To decompose the total change in predicted 4-year college completion into three channels, I repeat the exercise allowing only one channel to vary at a time. First, I allow $\hat{P}$(4-year college) (channel 1) to vary when value added equals 0 versus 1, holding the other two predicted probabilities fixed at the true covariate values. Second, I allow $\hat{P}_{c|\text{4-year college}}$ (channel 2) to vary when value added equals 0 versus 1, holding the other two predicted probabilities fixed at the true covariate values. Third, I allow $\hat{P}(\text{complete college} \mid c)$ (channel 3) to vary when value added equals 0 versus 1, holding the other two predicted probabilities fixed at the true covariate values. To calculate the share of the completion effect explained by each channel, I divide the channel-specific changes in completion by the total change in completion when allowing all three channels to vary. The residual share can be explained by interactions between the three channels of interest.[42]

Figure 8 demonstrates that increases in 4-year college enrollment explain the largest share of the completion effect. Roughly 47% of the effect of English ACT score value added on 4-year college completion and 68% of the effect of math ACT score value added on college

[42]Let f represent $\hat{P}(\text{complete college} \mid c)$ as a function of value added v, g represent $\hat{P}_{c|\text{4-year college}}$, and h represent $\hat{P}$(4-year college). Equation (12) can be written as

$$\begin{aligned}
\Delta &= \sum_{c=1}^{15} \big[f_c(1) g_c(1) h(1) - f_c(0) g_c(0) h(0) \big] \\
&= \sum_{c=1}^{15} \Big[\underbrace{(f_c(1) - f_c(0))\, g_c(v)\, h(v)}_{\Delta_f} + \underbrace{f_c(v)\, (g_c(1) - g_c(0))\, h(v)}_{\Delta_g} + \underbrace{f_c(v)\, g_c(v)\, (h(1) - h(0))}_{\Delta_h} \\
&\quad + \big(f_c(1) - f_c(v)\big)\big(g_c(1) - g_c(v)\big) h(v) + \big(f_c(1) - f_c(v)\big) g_c(v) \big(h(1) - h(v)\big) \\
&\quad + f_c(v) \big(g_c(1) - g_c(v)\big)\big(h(1) - h(v)\big) + \big(f_c(1) - f_c(v)\big)\big(g_c(1) - g_c(v)\big)\big(h(1) - h(v)\big) \Big]
\end{aligned} \tag{13}$$

completion is driven by increases in 4-year college enrollment, with the remainder divided between changes in college choice and improvements in college performance.

I next repeat the decomposition exercise among students with different levels of lagged achievement, with results shown in Figures 9 and 10. I measure lagged achievement using terciles of the Algebra 1 EOC score distribution for math value added and terciles of the English 2 EOC score distribution for English value added. The total effects of both English and math ACT score value added on 4-year college completion are smallest among students with low lagged achievement (tercile 1) and largest among students with high lagged achievement (tercile 3). Increases in 4-year college enrollment explain a larger share of the completion effect among students with low lagged achievement, while changes in college choice and improvements in college performance explain a larger share of the completion effect among students with high lagged achievement. This is likely because students with low lagged achievement are on the margin of enrolling in a 4-year college, while students with high lagged achievement are on the margin of enrolling in selective colleges and performing well in college coursework.

Figure 8: Completion Decomposition Analysis

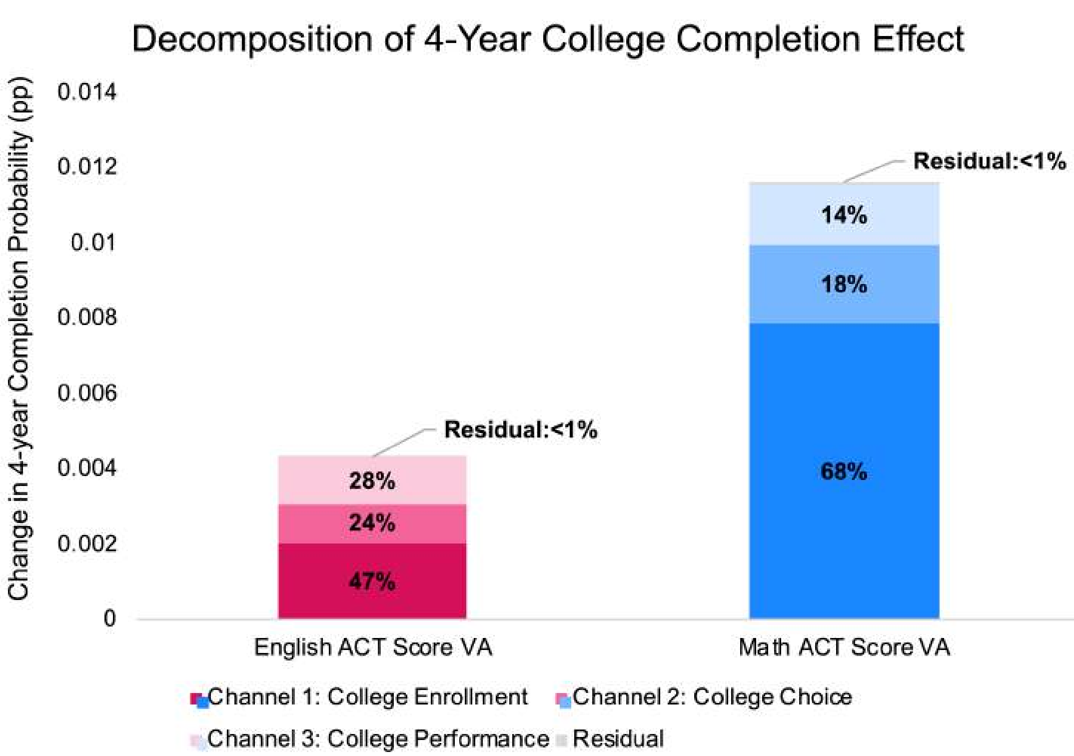


Figure 9: Completion Decomposition Analysis by Lagged English Achievement

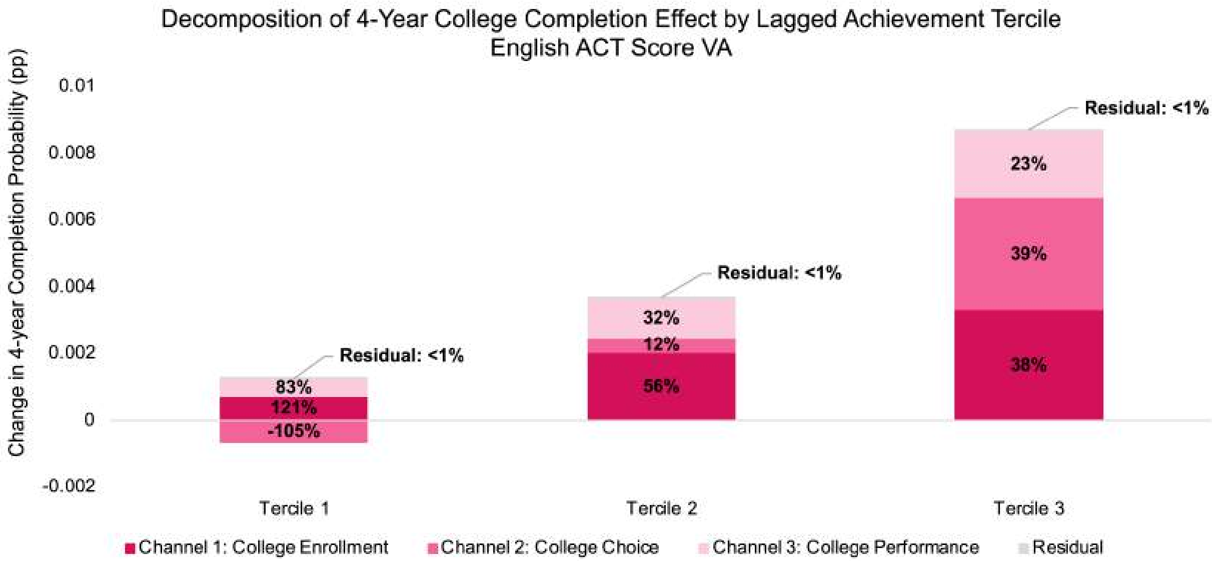
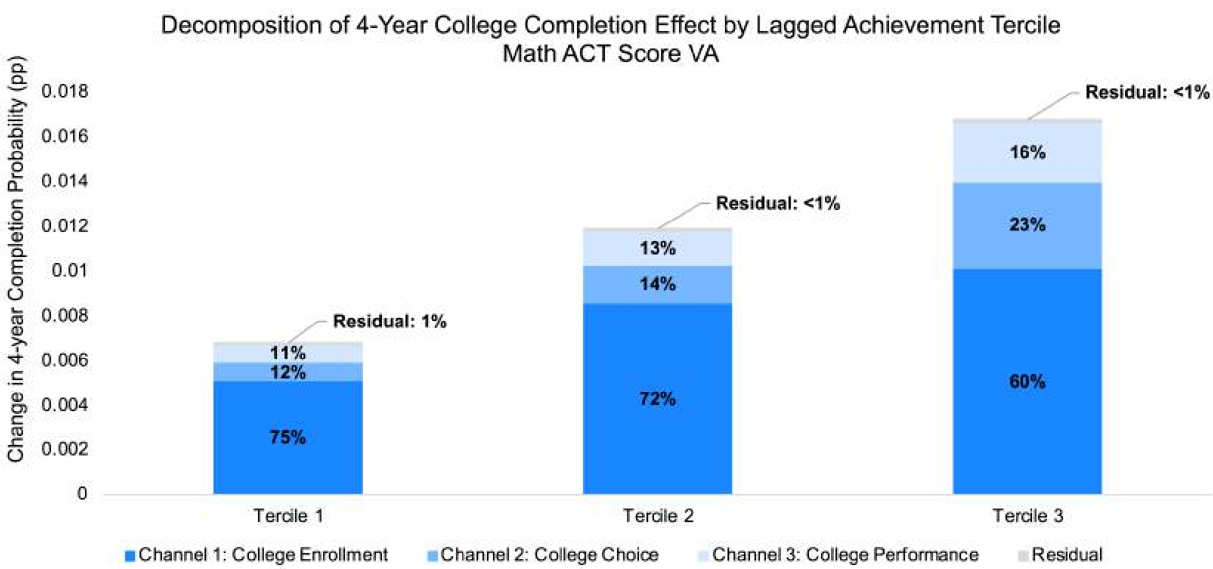


Figure 10: Completion Decomposition Analysis by Lagged Math Achievement



5 Conclusion

My results provide new evidence on the importance of high school teachers for students' later life success. I find that teachers have significant scope to influence students' life trajectories during the transition years between high school and college, which coincide with a critical period of adolescent development. Quantifying and investing in the multifaceted contributions of teachers is a timely and policy-relevant concern, as declines in teacher satisfaction have been accelerating in recent years (Kraft and Lyon, 2024).

Leveraging detailed administrative data from North Carolina, I provide novel estimates of teacher value added on college admissions test scores or "ACT score value added." Using a nested logit model in which students choose whether to attend a 2-year or 4-year college and which 4-year college to attend, I find positive impacts of ACT score value added on 4-year college enrollment and selectivity.

I find that quasi-random assignment to a teacher with high value added on the ACT test has positive impacts not only on ACT scores and college enrollment, but on a host of college performance measures. Students assigned to English or math teachers with high ACT score value added earn higher freshman college GPAs, are less likely to drop out during or after freshman year, and are more likely to graduate within five years of initial college enrollment. Moreover, students assigned to math teachers with high ACT score value added earn higher freshman GPAs in STEM courses and are less likely to enroll in a remedial college algebra course, suggesting an important role for subject-specific cognitive skill accumulation. Positive impacts on college performance are robust to accounting for selection into enrollment in specific colleges using a selection correction method from Lee (1983), suggesting that improvements in college performance are driven by direct improvements in college-relevant skills in addition to changing patterns of college enrollment.

This paper speaks 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 find that marginal increases in ACT scores, induced by quasi-random shocks to teacher quality, are predictive of college performance, suggesting that ACT scores are a useful measure of skills relevant to college coursework.

Taken together, my results suggest that ACT score value added captures college-relevant skills with economically significant long-run benefits extending into adulthood. The role of teachers in shaping children's skill development during late adolescence thus merits further attention. Future work should evaluate the impacts of high school teachers on other dimensions of skill which may improve college enrollment and performance, moving beyond traditional skill measures to assess noncognitive skills relevant to college enrollment and performance, such as cooperation, persistence, or self-discipline. Future work should also consider whether high school teachers impact college outcomes beyond academic performance, such as college major and course choice. Quantifying the multifaceted effects of teachers during adolescence can fill crucial gaps in our understanding of child development and help children flourish during the transition to adulthood.

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Appendix

A Permutation Test of Random Teacher Assignment

I adapt a permutation-based balance test from Abrams et al. (2012) and Landon (2024). This procedure addresses over-rejection of the null hypothesis in F-tests with a large number of fixed effects and relatively small within-cell sample sizes. I simulate the random assignment of teachers to classrooms within school-cohort cells and calculate the standard deviation of mean student 10^{th} grade (lagged) absences, residualized on value added model covariates, across the teachers in the sample. I then repeat the process 100 times, generating 100 simulated measures of dispersion capturing sampling variation in classroom average ability under random teacher assignment. Finally, I compare the true standard deviation of teacher-mean residualized student absences to the simulated distribution. For both math and English, I find that the true standard deviation falls just outside the range of simulated standard deviations, suggesting a limited role for student-teacher sorting in this setting after accounting for value added model covariates.

Figure A1: English Permutation Test

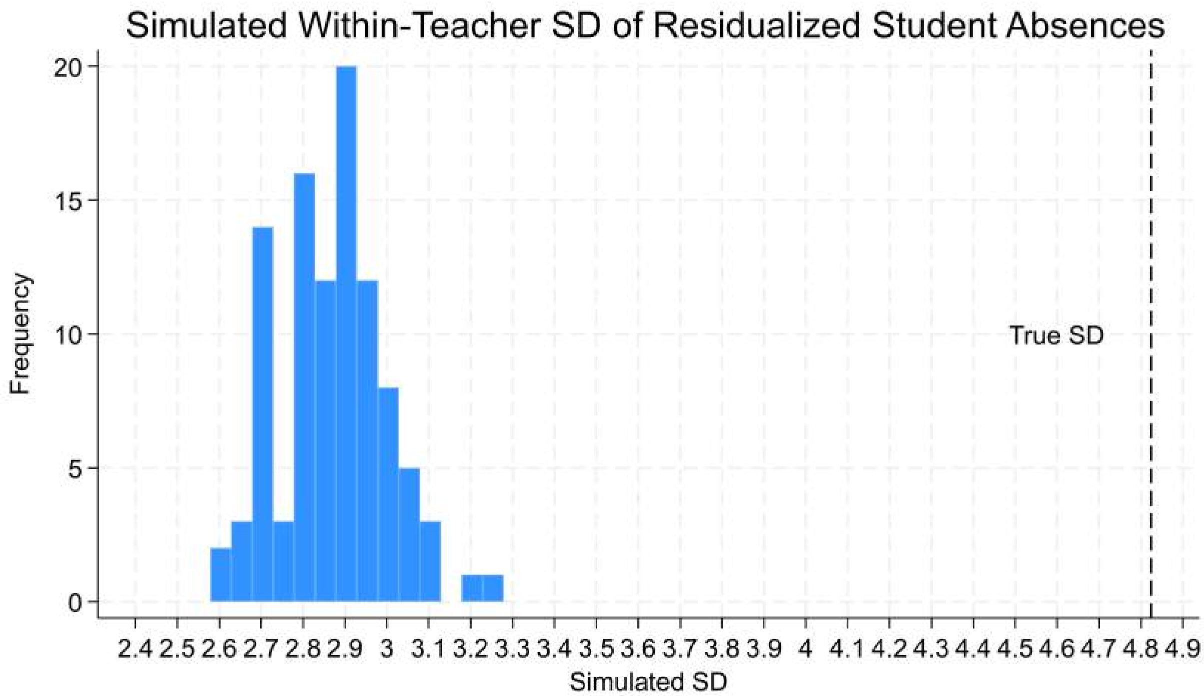
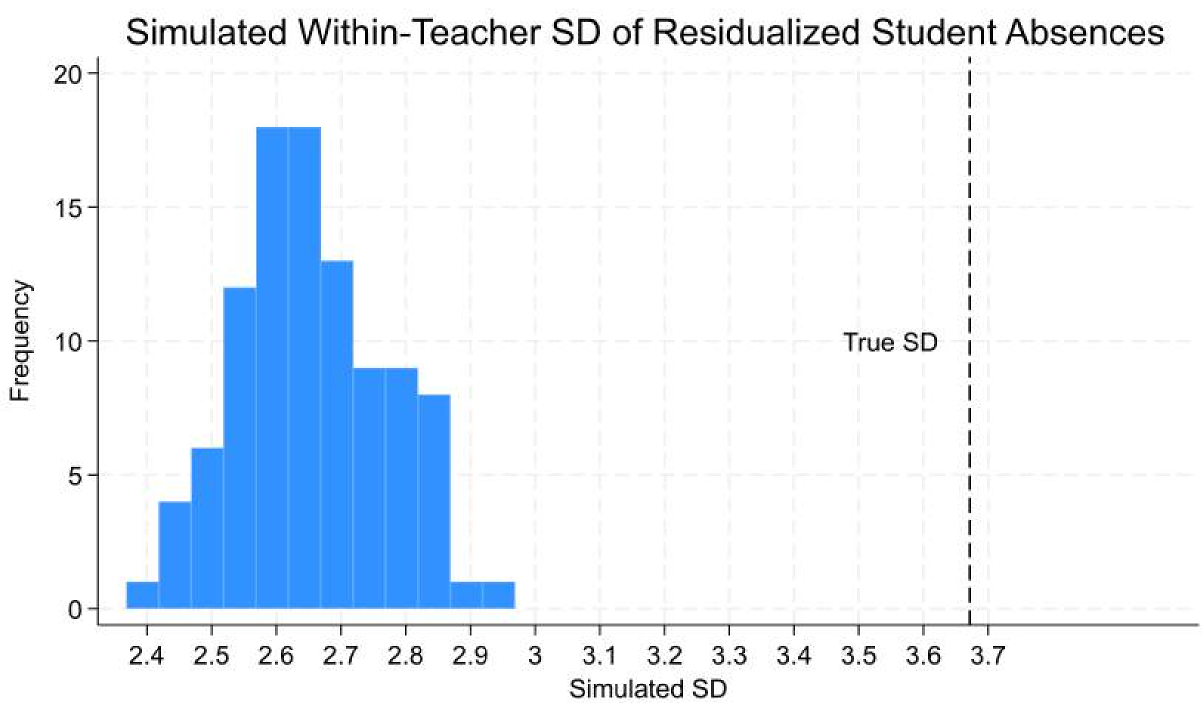


Figure A2: Math Permutation Test



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 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. 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.

C ACT Score Value Added Specification

Figures A3 and A4 present the empirical distributions and estimated standard deviations of ACT score value added across several alternative specifications to Equation (1). Tables A1 and A2 demonstrate within-teacher correlations across value added measures. Removing controls for which 11$^{\text{th}}$ grade math and English courses a student is enrolled in increases the standard deviation of ACT score value added by only 0.0009 for English and 0.0114 for math, suggesting a limited role for student-course sorting to drive the variance in ACT score value added estimates after accounting for lagged student achievement. The larger change in math value added after removing course controls is consistent with the wider variety of 11$^{\text{th}}$ grade math course offerings relative to English, allowing for greater sorting. The within-teacher correlations across value added specifications with and without course controls are over 0.9 for both English and math teachers. Removing high school fixed effects increases the standard deviation of ACT score value added by 0.0452 for English and 0.0353 for math, suggesting that teacher quality varies substantially across high schools. Removing high school fixed effects reduces the within-teacher correlation across value added specifications to 0.190 for English teachers and 0.612 for math teachers, suggesting that high school fixed effects play an important role in determining the ordinal ranking of teachers used throughout my analysis.

Estimating Equation (1) using OLS, rather than an empirical Bayes estimator, roughly doubles the standard deviation of both English and math ACT score value added in the absence of shrinkage accounting for measurement error. This suggests that the shrunken empirical Bayes estimates used in my main specification are comparatively conservative, speaking to concerns over the utility of empirical Bayes methods under nonrandom teacher assignment (Guarino et al., 2015).

Additionally, I estimate English teacher value added on English ACT scores only, rather than the average of English and reading ACT scores, given prior evidence finding that the English and math sections of the ACT have the greatest predictive power for long-run outcomes (Bettinger et al., 2013b). I find that the standard deviation of English teacher value added on English ACT scores is very similar to the main specification, and that the within-teacher correlation between the two specifications is 0.845. This result suggests that including both English and reading ACT scores in the outcome of my main specification leads to substantively similar results. To understand cross-subject spillovers, I estimate English teacher value added on math ACT scores and math teacher value added on English and reading ACT scores. I find that the standard deviation of cross-subject English teacher value added on math ACT scores is similar in magnitude to within-subject English teacher value added, while cross-subject math teacher value added on English ACT scores is smaller in magnitude than within-subject math teacher value added. One potential explanation for larger cross-subject spillovers of English teachers is that English ACT score value added reflects the accumulation of skills, such as critical reading, which are transferable across subjects. Another potential explanation is that English teacher value added reflects even more general human capital accumulation in the form of noncognitive skills such as motivation. A more thorough discussion of cross-course spillovers, general human capital accumulation, and mechanisms including noncognitive skill formation, is outside the scope of this paper and should be explored in future work.[43]

Table A3 demonstrates that impacts on college enrollment, estimated using the two-stage nested logit estimation procedure in Equation (6) and standardized to represent a one standard deviation change in value added, are qualitatively similar across specifications but differ in magnitude. In particular, effects of ACT score value added on 4-year college enrollment are much larger when value added is estimated using OLS without shrinkage, suggesting that my main estimates are comparatively conservative. Table A4 demonstrates that impacts on college dropout, estimated using Equation (8) without selection correction, are similar in both sign and magnitude across specifications. This suggests a limited role for modeling assumptions in explaining the relationship between ACT score value added and college performance.

[43]Cross-course spillover effects could, alternatively, reflect student-teacher sorting on unobserved ability which improves performance across multiple sections of the ACT test.

Figure A3: English ACT Score Value Added Specifications

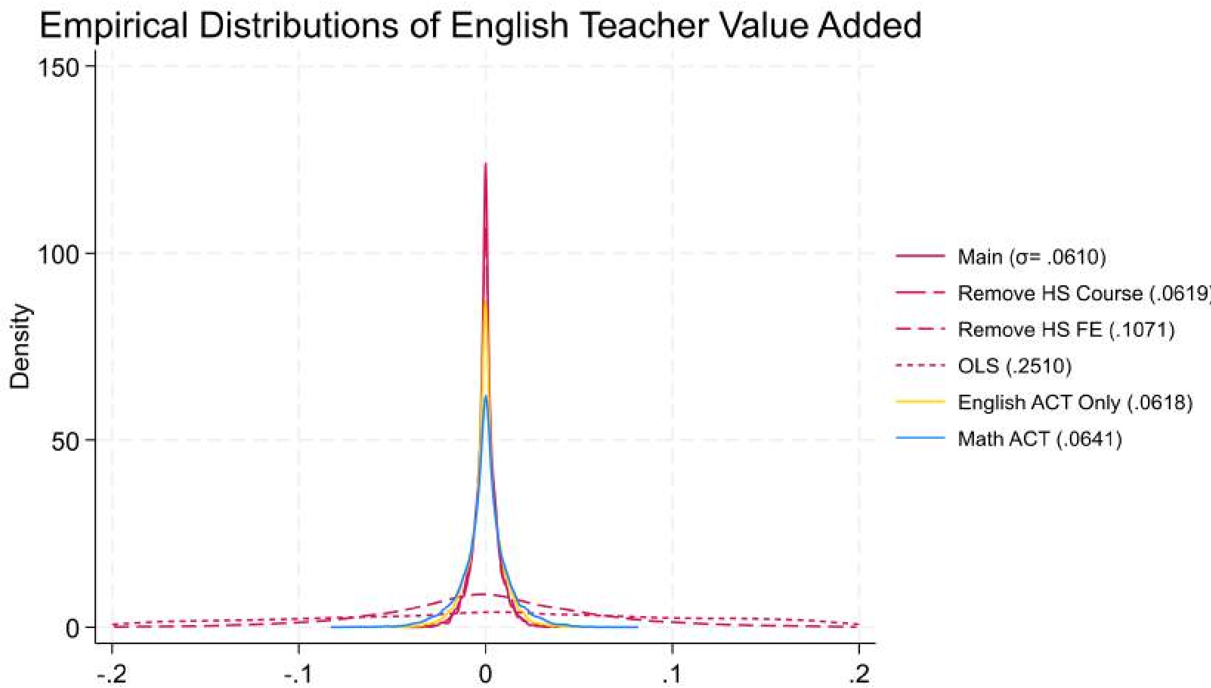


Figure A4: Math ACT Score Value Added Specifications

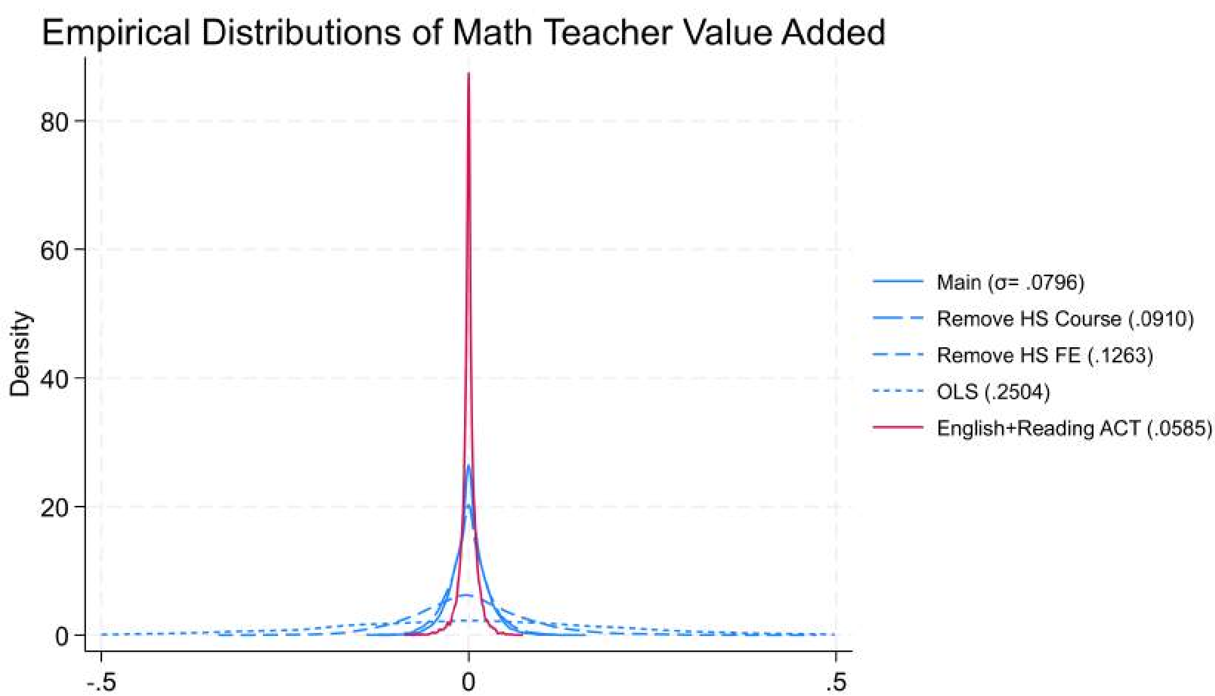


Table A1: English ACT Score Value Added Correlations

	(1)	(2)	(3)	(4)	(5)	(6)
(1) Main	1					
(2) Remove HS Course	0.939***	1				
(3) Remove HS FE	0.190***	0.217***	1			
(4) OLS	0.0169	0.0380***	0.223***	1		
(5) English ACT Only	0.845***	0.834***	0.287***	0.0715***	1	
(6) Math ACT	0.415***	0.389***	0.0868***	0.0150	0.421***	1
Observations	10545					

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table A2: Math ACT Score Value Added Correlations

	(1)	(2)	(3)	(4)	(5)
(1) Main	1				
(2) Remove HS Course	0.920***	1			
(3) Remove HS FE	0.612***	0.623***	1		
(4) OLS	0.274***	0.282***	0.282***	1	
(5) English and Reading ACT	0.0828***	0.0537***	-0.0884***	-0.0754***	1
Observations	11276				

t statistics in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table A3: Impacts of ACT Score Value Added on College Enrollment by Specification

	(1) Main	(2) Remove HS Course	(3) Remove HS FE	(4) OLS
4-Year College Enrollment				
Standardized English ACT VA	0.0855	0.0587	0.0391*	0.221***
	(0.0712)	(0.0630)	(0.0213)	(0.0275)
Standardized Math ACT VA	0.0887***	0.0502**	0.0652***	0.150***
	(0.0222)	(0.0211)	(0.0163)	(0.0189)
Inclusive Value Term	0.320***	0.319***	0.316***	0.356***
	(0.0313)	(0.0315)	(0.0319)	(0.0344)
2-Year College Enrollment				
Standardized English ACT VA	-0.0121	0.0172	-0.0472**	-0.0430*
	(0.0845)	(0.0738)	(0.0186)	(0.0243)
Standardized Math ACT VA	-0.101***	-0.0928***	-0.0785***	-0.0600***
	(0.0230)	(0.0224)	(0.0163)	(0.0193)
Observations	272096	272192	272124	317308

Standard errors in parentheses

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

Table A4: Impacts of ACT Score Value Added on College Dropout by Specification

	(1) Main	(2) Remove HS Course	(3) Remove HS FE	(4) OLS
Standardized English ACT VA	-0.00787	-0.00811	-0.00380	-0.00249
	(0.00677)	(0.00616)	(0.00256)	(0.00454)
Standardized Math ACT VA	-0.00535*	-0.00713***	-0.00439**	-0.00570**
	(0.00278)	(0.00272)	(0.00210)	(0.00263)
Observations	78853	78853	78853	78853
Mean	0.0859	0.0859	0.0859	0.0859
R^2	0.0350	0.0350	0.0350	0.0350

Standard errors in parentheses, clustered at the high school level

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

Coefficients standardized to reflect 1σ increase in value added

No selection correction applied

D Out-of-Sample Forecast Test

To test the out-of-sample predictive power of ACT score value added, I randomly assign students within each teacher-year cell to two subsamples of equal size. I then estimate ACT score value added on each subsample and calculate the correlation between teacher-year level value added estimates between the two samples. The correlation is 0.359 for English teachers and 0.440 for math teachers, depicted in Figures A5 and A6.

Figure A5: Split-Sample Forecast Test, Math ACT Score Value Added

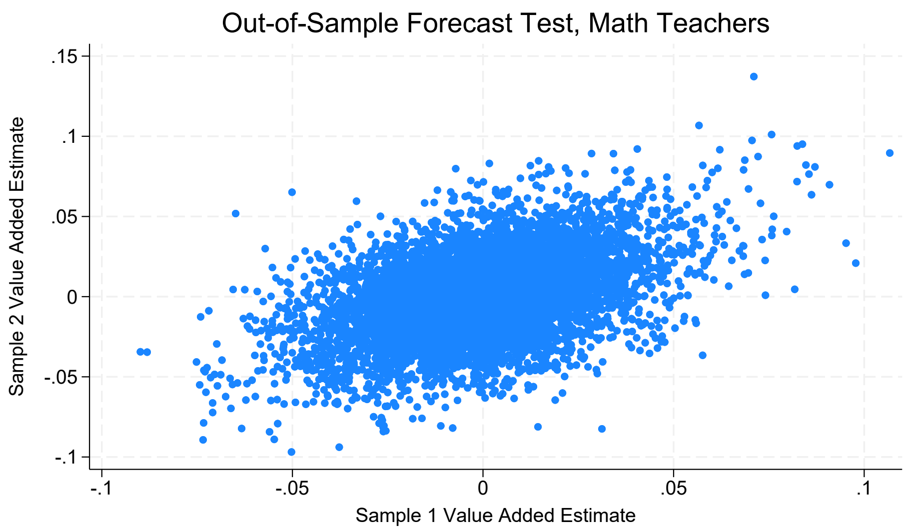
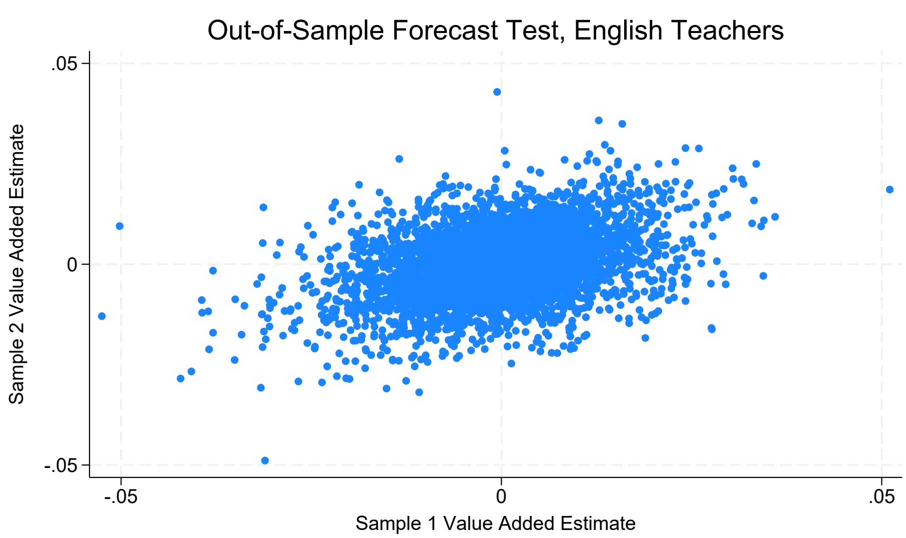


Figure A6: Split-Sample Forecast Test, English ACT Score Value Added



To preserve sample size within each teacher-year cell and obtain a more precise forecast test, I generate two bootstrap student samples with replacement, each equal in size to the true teacher-year cell. I then estimate ACT score value added on each bootstrap sample and calculate the correlation between teacher-year level value added estimates between the two samples. The correlation is 0.630 for English teachers and 0.722 for math teachers, depicted in Figures A7 and A8.

Figure A7: Bootstrap Sample Forecast Test, Math ACT Score Value Added

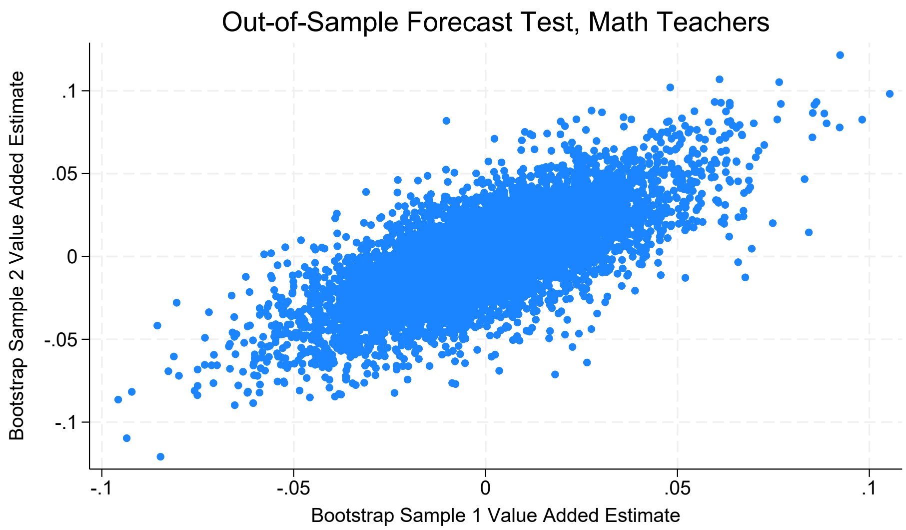
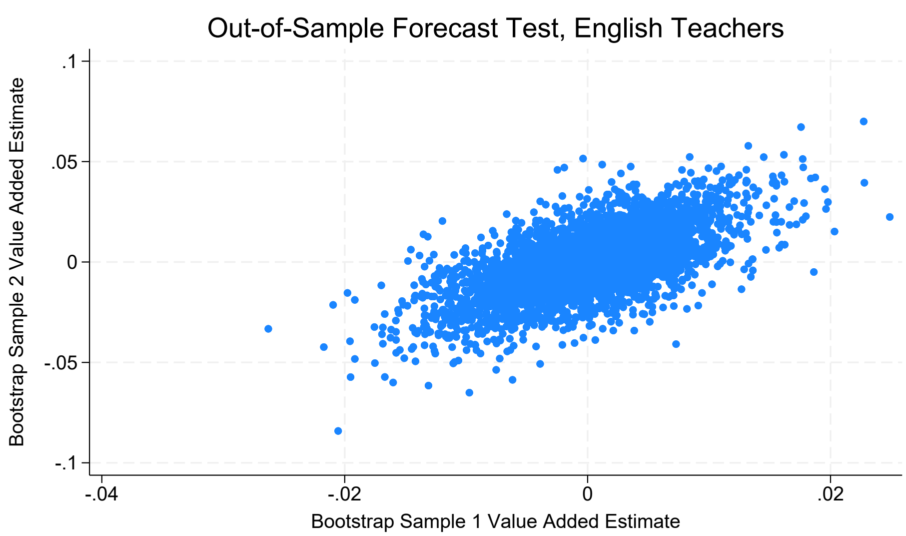


Figure A8: Bootstrap Sample Forecast Test, English ACT Score Value Added



E ACT Score Value Added Variance Decomposition

Decomposing the variance of ACT score value added into between-school and within-school components, following Chetty et al. (2014a), suggests that the majority of variation in ACT score value added is between high schools, yet substantial variation in teacher quality remains within the high schools. To decompose the variance of ACT score value added, I calculate school-level means of shrunken teacher-year level value added estimates weighted by the number of students taught. Then, I calculate the share of the total variance attributable to deviations of school means from the grand mean (between-school) versus deviations of teacher-year estimates from their school mean (within-school). Specifically, I decompose the variance of shrunken teacher-year ACT score value added estimates using the law of total variance, weighting by the number of students taught. The between-school and within-school variance components can be expressed as follows:

$$Var_{\text{between}} = \frac{\sum_s \left(\sum_{j \in s,t} N_{jt} \right) (\bar{\theta}_s - \bar{\theta})^2}{\sum_{j,t} N_{jt}},$$

$$Var_{\text{within}} = \frac{\sum_s \sum_{j \in s,t} N_{jt} \, (\hat{\theta}_{j,-t} - \bar{\theta}_s)^2}{\sum_{j,t} N_{jt}},$$

where $\hat{\theta}_{j,-t}$ is the estimated ACT score value added of teacher j in year t, N_{jt} is the number of students assigned to teacher j in year t, $\bar{\theta}$ is the weighted mean of ACT score value added across all teacher-year observations, and $\bar{\theta}_s$ is the weighted mean of ACT score value added across teacher-year observations in school s.

Table A5 demonstrates that 61.7% of the variance of English ACT score value added and 70.2% of the variance of math ACT score value added is between high schools, leaving roughly one-third of the variation unexplained by cross-school differences.

This variance decomposition exercise relies on the ability to separately identify high school fixed effects and teacher fixed effects, which in turn requires a sufficiently connected network of teacher movers across schools (Mansfield, 2015). If some schools cannot be connected to the broader teacher mobility network through a chain of teacher moves, teacher quality within those schools will partially be absorbed by the estimated high school fixed effects. In such cases, the between-school component of the variance may be overstated, potentially explaining the higher between-school variance share observed in this setting relative to previous studies (Chetty et al., 2014a; Mansfield, 2015, e.g.). The overstating of between-school variance in teacher value added is not a concern when estimating the effects of teacher value added on college outcomes, because all college outcomes models include high school fixed effects, effectively restricting the analysis to within-high school comparisons. I do not perform any counterfactual analysis involving teacher reassignment across high schools, which would require the separate identification of high school and teacher effects across all high schools in the sample.

Table A5: Value Added Variance Decomposition

	Between-School Variance Share	Within-School Variance Share
English	61.7%	38.3%
Math	70.2%	29.8%

F ACT Score Value Added & Teacher Characteristics

Observable teacher characteristics predict approximately 1-2% of the variation in value added estimates across teachers, as demonstrated in Table A6.

Table A6: ACT Score Value Added and Observable Teacher Characteristics

	(1) English	(2) Math
Attended HBCU	-0.00000416	0.000685
	(0.000282)	(0.000969)
Acceptance Rate of Bachelor's Degree Institution	0.00222	-0.0114
	(0.00230)	(0.00873)
Years of Experience	0.00000450	0.000161***
	(0.00000792)	(0.0000259)
Experienced Teacher (>0 Years)	0.000712	-0.00297
	(0.000498)	(0.00204)
Holds Graduate Degree	-0.0000510	0.000398
	(0.000143)	(0.000534)
Female	0.000249	0.00278***
	(0.000165)	(0.000504)
Completed Bachelor's Degree in NC	-0.0000821	-0.000792
	(0.000157)	(0.000600)
N	10076	9922
R^2	0.00573	0.0173

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.

I find a small positive relationship between ACT score value added and teachers' years of experience. Figure A9 demonstrates suggestive evidence that math teachers with fewer than 10 years of experience have lower ACT score value added than more experienced teachers, in line with prior evidence finding that value added increases early in teachers' careers and eventually plateaus (Bacher-Hicks and Koedel, 2023). Figures A10, A11, and A12 demonstrate the relationship between ACT score value added and teachers' educational credentials, as measured by the selectivity of bachelor's degree institution and graduate degree attainment.[44] I find no significant relationship between ACT score value added and teachers' educational credentials.

[44] I define graduate degree attainment to include master's, doctorate, and other advanced degrees.

Figure A9: ACT Score Value Added and Teacher Experience

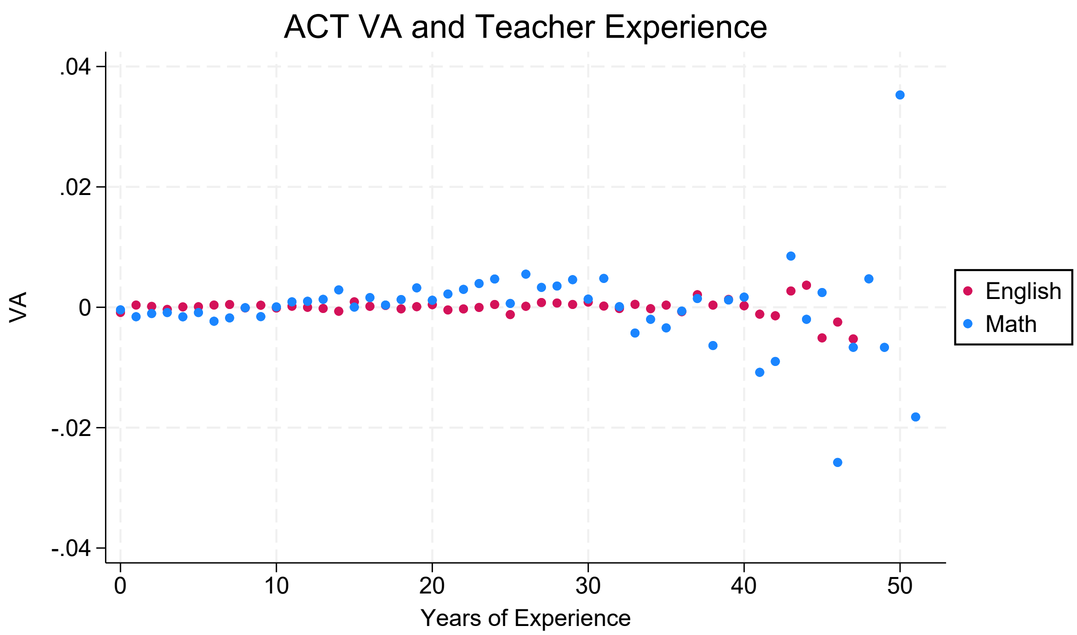


Figure A10: ACT Score Value Added and College Selectivity

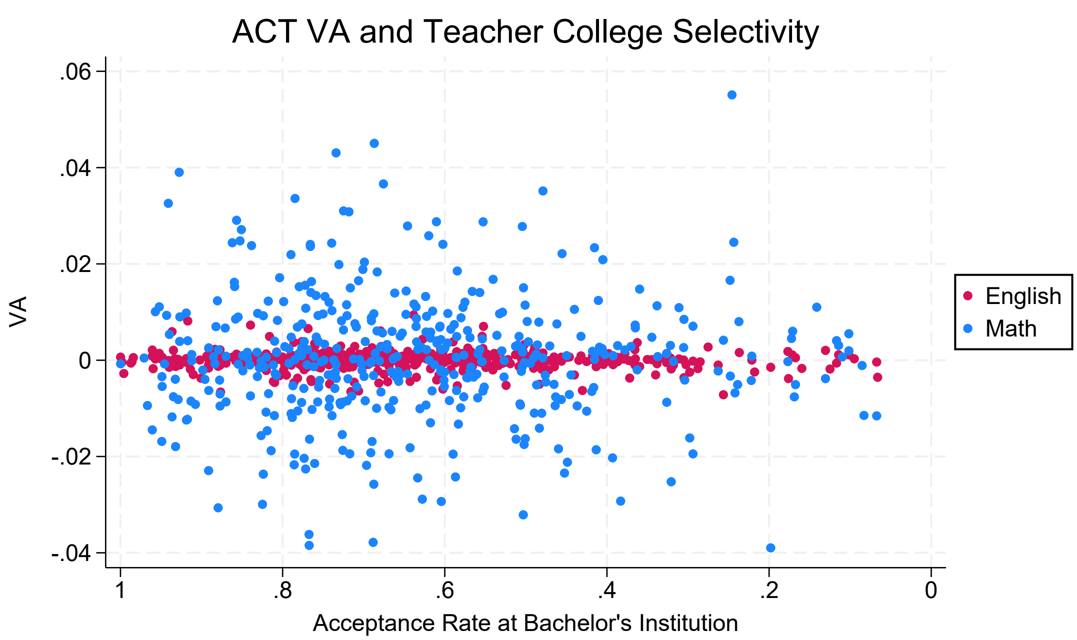


Figure A11: English ACT Score Value Added and Graduate Degree Attainment

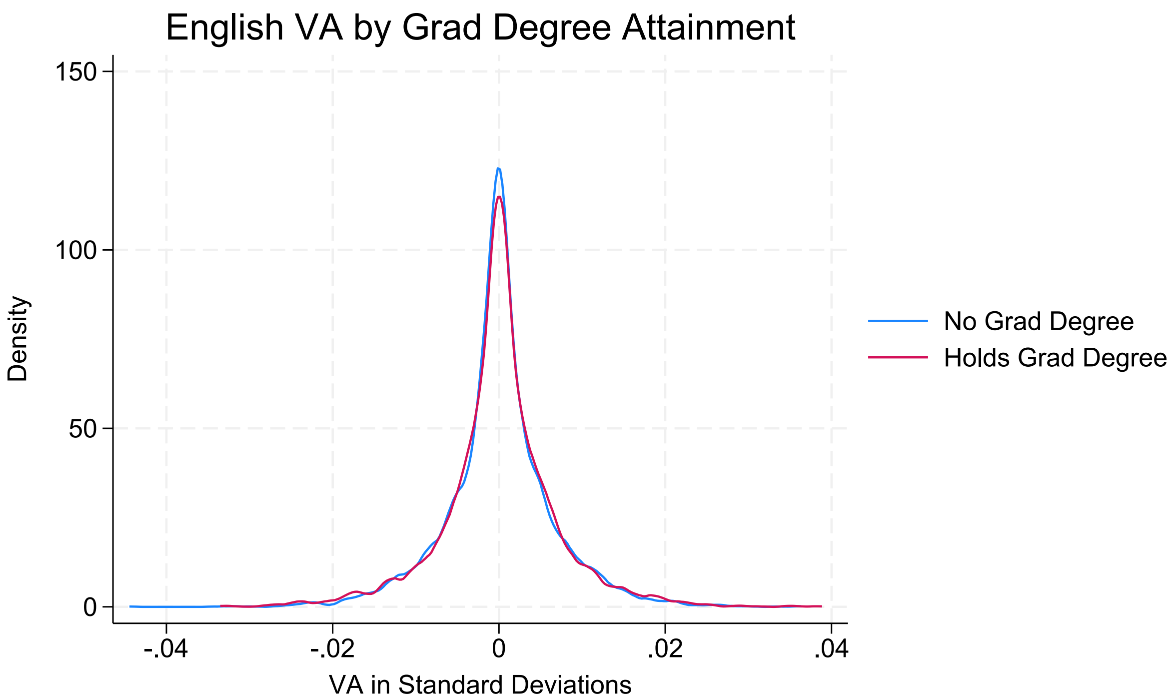
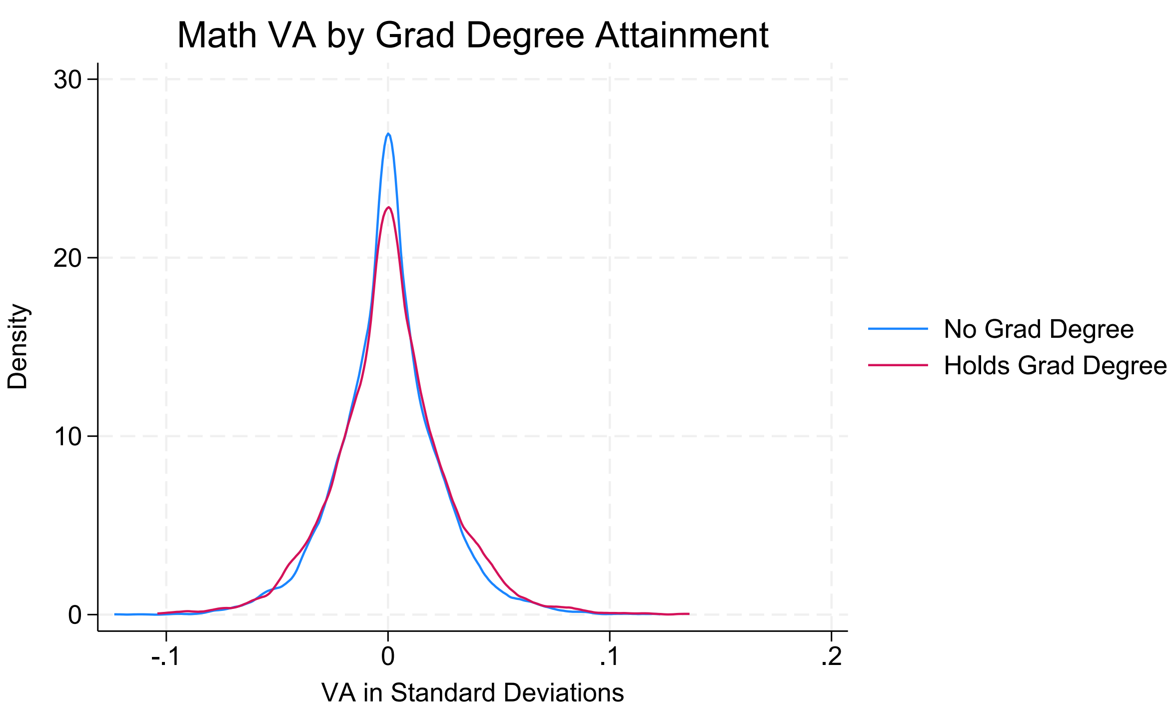


Figure A12: Math ACT Score Value Added and Graduate Degree Attainment



G Teacher Value Added Across Outcomes

G.1 Math Teachers

To test the relationship between ACT score value added and teacher value added on traditional standardized test score measures, I estimate 9$^{\text{th}}$ grade math teacher value added on 9$^{\text{th}}$ grade Algebra 1 end-of-course (EOC) test scores. The estimation sample includes 9$^{\text{th}}$ grade Algebra 1 test-takers from 2013-2018 who are matched with their 9$^{\text{th}}$ grade math teachers.[45] I construct a sample of 438,680 math students using similar procedures to those used in the estimation of ACT score value added.[46] 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.

$$\text{EOC\_Math}_{ijst} = \beta_0 + \beta_1 \text{EOG}_{it-1} + \beta_2 \text{EOG}_{it-2} + \beta_3 X_{it} + \theta_j T_{jt} + \alpha_s + \gamma_t + \epsilon_{ijst} \tag{14}$$

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$^{\text{th}}$ grade lagged end-of-grade (EOG) math, reading, and science test scores and EOG_{it-2} includes the student's 7$^{\text{th}}$ grade EOG math and reading test scores.[47] X_{it} is the same vector of student-level controls included in ACT score value added specifications. T_{jt} is a vector of 9$^{\text{th}}$ 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.[48] Among the 32.21% of

[45] By restricting to 9$^{\text{th}}$ 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 9$^{\text{th}}$ grade Algebra 1 end-of-course test scores.

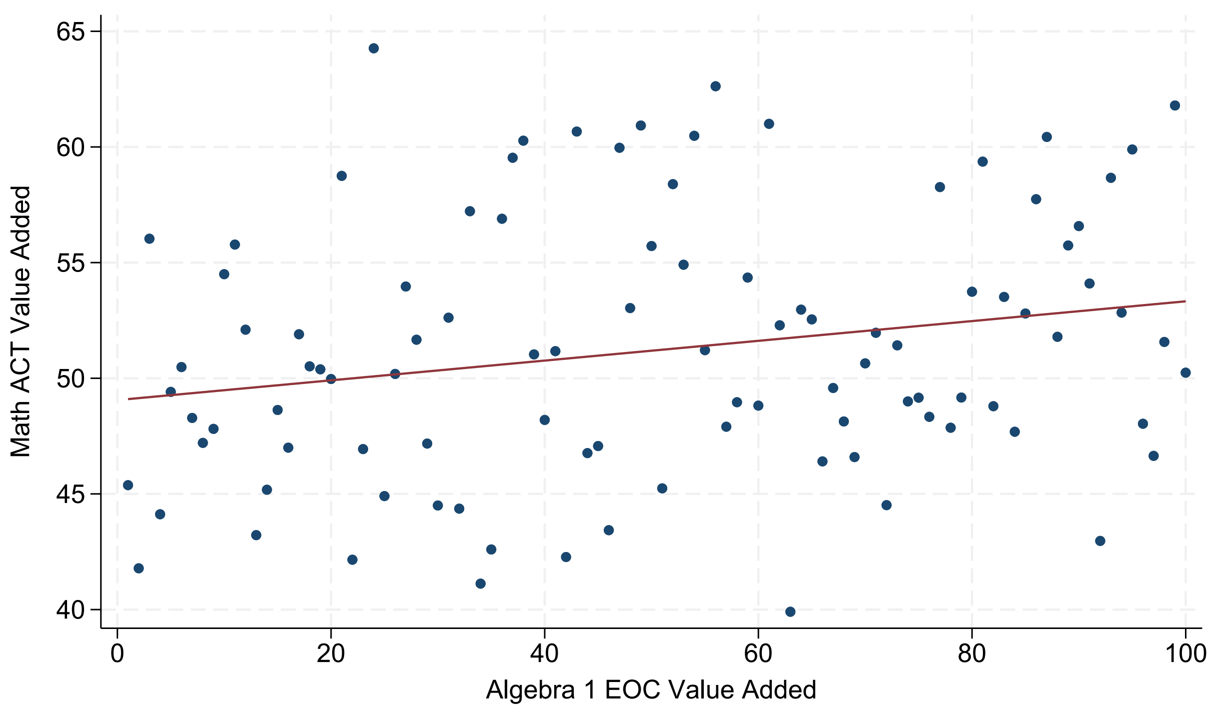
[46] On average, each Algebra 1 teacher is observed in 8 sections with 93 students over 2.76 years. I use students' fall 9$^{\text{th}}$ grade Algebra 1 course enrollments if they are enrolled in different fall and spring Algebra 1 courses and spring enrollments otherwise.

[47] Students with missing 8$^{\text{th}}$ grade math or reading end-of-grade test scores are excluded from the sample. Missing 8$^{\text{th}}$ grade science end-of-grade test scores and missing 7$^{\text{th}}$ 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.

[48] 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

math teachers in my sample who taught both 11$^{\text{th}}$ grade students and 9$^{\text{th}}$ 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 A13 plots the percentiles of Algebra 1 EOC score value added distribution against the mean percentiles of the corresponding teachers' ACT score value added estimates.

Figure A13: Algebra 1 EOC Score Value Added vs ACT Score Value Added Percentiles



To test the relationship between ACT score value added and teacher value added on noncognitive student outcomes, I estimate 11$^{\text{th}}$ grade math teacher value added on total 11$^{\text{th}}$ grade student absences. The estimation sample is the same as the math ACT score value added estimation sample, excluding students with missing values for 10$^{\text{th}}$ or 11$^{\text{th}}$ grade absences. I estimate the following value added model using the Chetty et al. (2014a) esti-

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.

mation procedure, to maintain close comparability with ACT score value added estimates.

$$\text{Absences}_{ijst} = \beta_0 + \beta_1 \text{EOC}_{it-1} + \beta_2 X_{it} + \beta_3 Z_{it} + \beta_4 \text{Absences}_{it-1} + \theta_j T_{jt} + \alpha_s + \gamma_t + \epsilon_{ijst} \quad (15)$$

Here, Absences_{ijst} is the total 11^{th} grade absences of student i assigned to teacher j in school s and year t[49] and Absences_{it-1} is the student's total 10^{th} grade absences. All other variables are defined as in Equation (1).

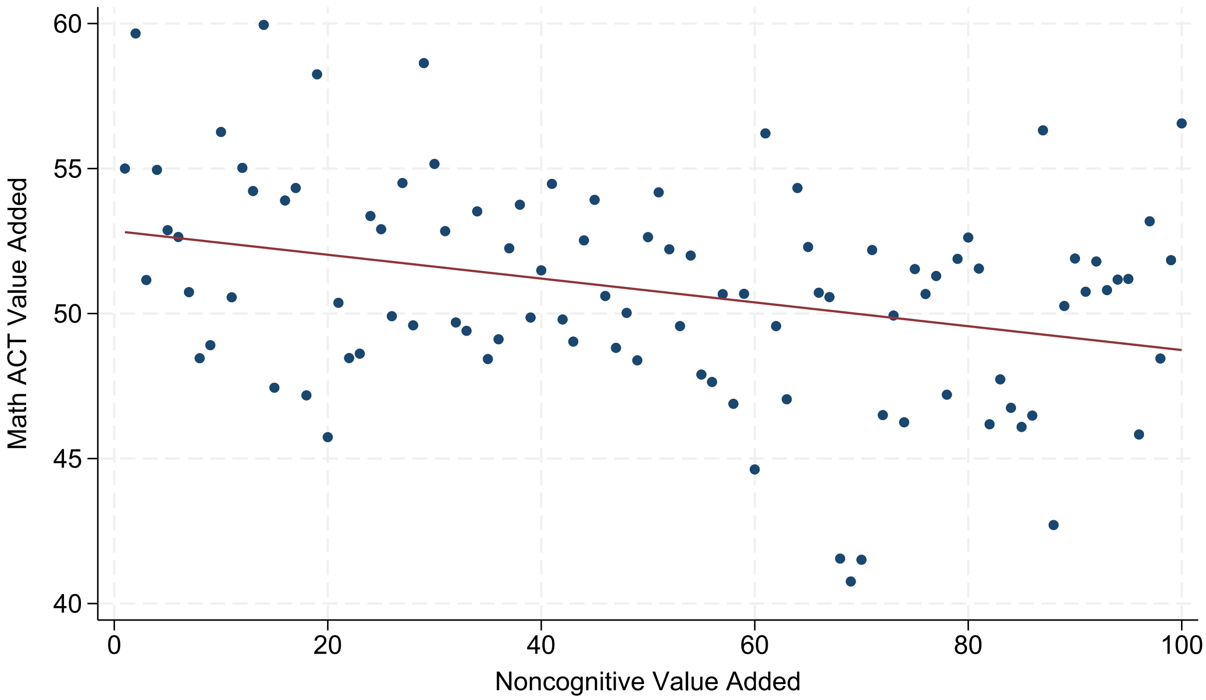
The estimated standard deviation of math teacher value added on student absences is 0.1708, larger than prior estimates found by Jackson (2018) using an earlier sample period and a specification with school-track fixed effects, leveraging a narrower source of identifying variation by comparing students enrolled in the same set of core academic courses.[50] I find a negative within-teacher correlation of -0.0701 between math ACT score value added and noncognitive value added.[51] Figure A14 plots the percentiles of noncognitive value added distribution against the mean percentiles of the corresponding math teachers' ACT score value added estimates.

[49]I transform student absences by taking the log and adding 1, then standardizing log absences to have mean 0 and standard deviation 1 within cohorts following Jackson (2018).

[50]Jackson's preferred estimates incorporate student absences into an index of noncognitive behaviors along with suspensions, GPA, and grade repetition. I focus on absences here because teacher value added on GPA could plausibly reflect both cognitive and noncognitive skill development and teacher value added on suspensions and grade repetition is likely less relevant to students on the margin of college enrollment.

[51]I find a correlation of -0.00524 between math EOC score value added and noncognitive value added which is statistically indistinguishable from 0.

Figure A14: Noncognitive Value Added vs Math ACT Score Value Added Percentiles



To understand the relative predictive power of ACT score value added versus EOC score and noncognitive value added for long-run outcomes, I estimate OLS regressions of ACT score value added, EOC score value added, and noncognitive value added measures on an indicator for on-time enrollment in 4-year colleges, conditioning on student-level covariates and school and cohort fixed effects.[52] I find that, without conditioning on high school GPA, math EOC score value is more predictive of college enrollment than math ACT score value added. After conditioning on high school GPA, however, math EOC score value added is no longer predictive of college enrollment. This result suggests that the impact of math EOC score value added on college enrollment operates through improvements in high school GPA, while math ACT score value added has positive impacts not captured by GPA alone. Given that ACT scores are observable to colleges during the admissions process while EOC scores are not, this result underscores the distinct relevance of ACT score value added for college outcomes.

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

I find no significant relationship between noncognitive value added and college enrollment in this sample.[53] These results suggest that teacher value added on ACT scores is not only distinct from traditional test scores value added measures and noncognitive value added measures, but also an empirically relevant predictor of long-run postsecondary outcomes despite the smaller variance in ACT score value added relative to other value added measures.

Table A7: Impacts of Math ACT, EOC, and Noncognitive Value Added on College Enrollment

	(1)	(2)	(3)	(4)
Math ACT Score Value Added	0.0184			0.0122
	(0.0249)			(0.0243)
Math EOC Score Value Added		0.182***		0.177***
		(0.0627)		(0.0605)
Noncognitive Value Added			-0.00728	-0.00479
			(0.0166)	(0.0159)
N	48662	48662	48662	48662
R^2	0.124	0.125	0.124	0.125

Standard errors in parentheses, clustered at the high school level

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

Coefficients from OLS regression of 4-year college enrollment on value added with covariates

Coefficients standardized to reflect 1σ increase in value added

Sample: 11^{th} grade ACT-takers with nonmissing 10^{th} and 11^{th} grade absences and Algebra 1 EOC scores matched with 9^{th} and 11^{th} grade math teachers. Standard math track only (9^{th} grade Algebra 1 EOC-takers)

[53] These results contrast with Jackson (2018), who finds that 9^{th} grade teacher value added on an index of noncognitive behaviors including absences, suspensions, GPA, and grade repetition predicts intended 4-year college enrollment. This difference could be due to differences in noncognitive outcome measures, differences between self-reported college intentions used in Jackson's study and administrative college enrollment used in my study, or underlying differences in the importance of noncognitive value added between 9^{th} and 11^{th} grade teachers. In particular, it may be the case that improvements in the type of noncognitive skills captured by student attendance are no longer sufficient to improve college attendance on the margin by the time students reach 11^{th} grade.

Table A8: Impacts of Math Value Added on College Enrollment with GPA Control

	(1)	(2)	(3)	(4)
Math ACT Score Value Added	0.0213**			0.0213**
	(0.00873)			(0.00908)
Weighted HS GPA at Graduation	0.281***	0.280***	0.281***	0.280***
	(0.00335)	(0.00339)	(0.00340)	(0.00335)
Math EOC Score Value Added		0.0150		0.00736
		(0.0319)		(0.0329)
Noncognitive Value Added			-0.000549	0.00185
			(0.00720)	(0.00732)
N	45655	45655	45655	45655
R^2	0.347	0.347	0.347	0.347

Standard errors in parentheses, clustered at the high school level

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

Coefficients from OLS regression of 4-year college enrollment on value added with covariates

Coefficients standardized to reflect 1σ increase in value added

GPA control is weighted composite high school GPA at graduation

Sample: 11^{th} grade ACT-takers with nonmissing 10^{th} and 11^{th} grade absences and Algebra 1 EOC scores matched with 9^{th} and 11^{th} grade math teachers. Standard math track only (9^{th} grade Algebra 1 EOC-takers)

G.2 English Teachers

I estimate English teacher value added analogously on 10th grade English 2 end-of-course (EOC) test scores and noncognitive student outcomes. The EOC value added 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.[54] 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.

$$\text{EOC\_English}_{ijst} = \beta_0 + \beta_1 \text{EOG}_{it-2} + \beta_2 \text{EOG}_{it-3} + \beta_3 X_{it} + \beta_4 S_{st} + \theta_j T_{jt} + \alpha_s + \gamma_t + \epsilon_{ijst} \quad (16)$$

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 and reading test scores.[55] 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.

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.[56] Among the 71.14% of English teachers in my sample who taught both 11th grade students and 10th grade students

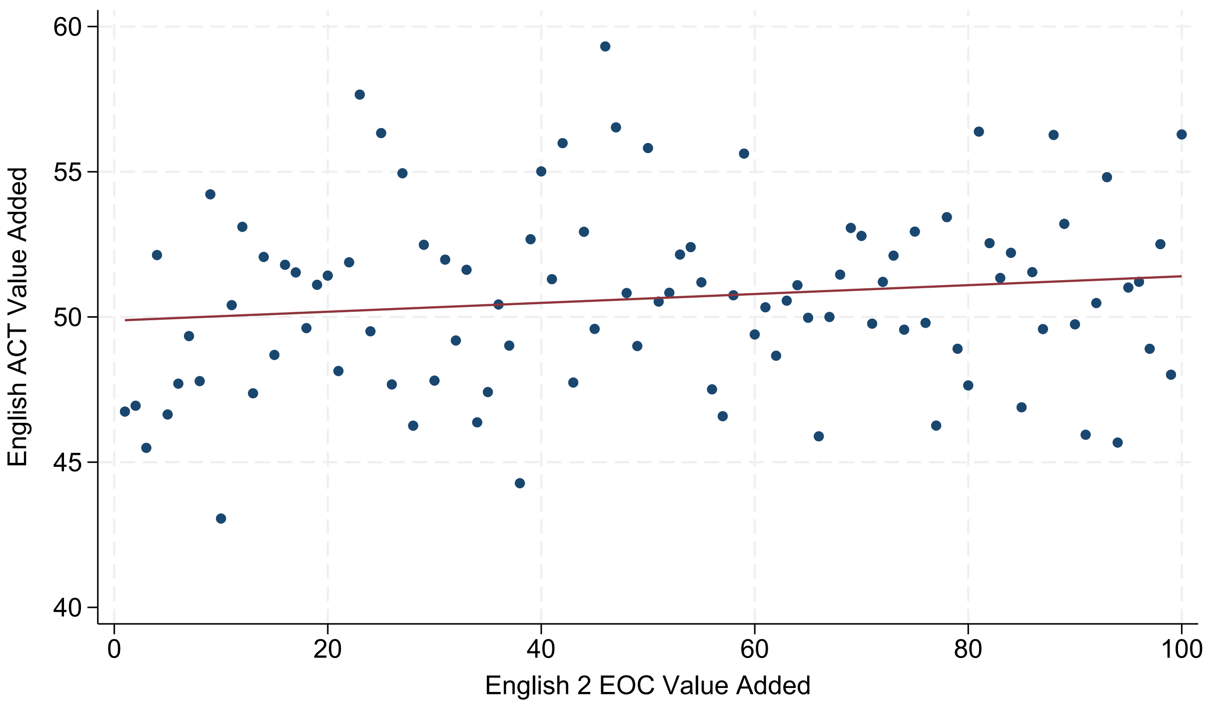
[54] On average, each English teacher is observed in 7 sections with 77 students over 2.54 years. I use students' fall 10th grade English course enrollments if they are enrolled in different fall and spring English courses and spring enrollments otherwise.

[55] 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.

[56] 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 due to differences in English EOC test timing during my sample period. 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.

during the sample period, I find a positive but relatively low correlation of 0.0146 between ACT score value added and English 2 EOC score value added. Figure A15 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 A15: English 2 EOC Score Value Added vs ACT Score Value Added Percentiles



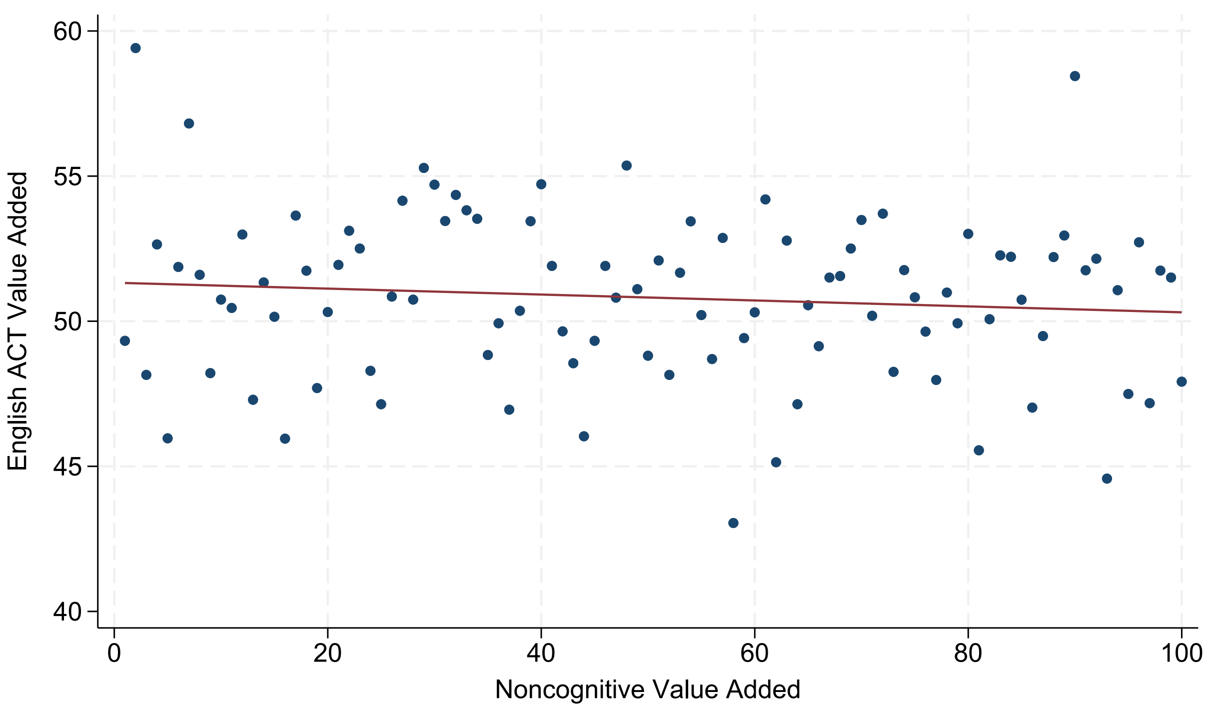
To test the relationship between ACT score value added and teacher value added on noncognitive student outcomes, I estimate 11th grade English teacher value added on total 11th grade student absences. The estimation sample is the same as the English ACT score value added estimation sample, excluding students with missing values for 10th or 11th grade absences. 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.

$$\text{Absences}_{ijst} = \beta_0 + \beta_1 \text{EOC}_{it-1} + \beta_2 X_{it} + \beta_3 Z_{it} + \beta_4 \text{Absences}_{it-1} + \theta_j T_{jt} + \alpha_s + \gamma_t + \epsilon_{ijst} \quad (17)$$

Here, Absences_{ijst} is the total 11th grade absences of student i assigned to teacher j in school s and year t[57] and Absences_{it-1} is the student's total 10^{th} grade absences. All other variables are defined as in Equation (1).

The estimated standard deviation of math teacher value added on student absences is 0.1709, larger than prior estimates found by Jackson (2018) using an earlier sample period and a specification with school-track fixed effects, leveraging a narrower source of identifying variation by comparing students enrolled in the same set of core academic courses.[58] I find a negative within-teacher correlation of -0.0275 between English ACT score value added and noncognitive value added.[59] Figure A16 plots the percentiles of noncognitive value added distribution against the mean percentiles of the corresponding English teachers' ACT score value added estimates.

Figure A16: Noncognitive Value Added vs English ACT Score Value Added Percentiles



[57]I transform student absences by taking the log and adding 1, then standardizing log absences to have mean 0 and standard deviation 1 within cohorts following Jackson (2018).

[58]Jackson's preferred estimates incorporate student absences into an index of noncognitive behaviors along with suspensions, GPA, and grade repetition. I focus on absences here because teacher value added on GPA could plausibly reflect both cognitive and noncognitive skill development and teacher value added on suspensions and grade repetition is likely less relevant to students on the margin of college enrollment.

[59]I find a correlation of 0.000277 between English EOC score value added and noncognitive value added which is statistically indistinguishable from 0.

To understand the relative predictive power of ACT score value added versus EOC score and noncognitive value added for long-run outcomes, I estimate OLS regressions of ACT score value added, EOC score value added, and noncognitive value added measures on an indicator for on-time enrollment in 4-year colleges, conditioning on student-level covariates and school and cohort fixed effects.[60] I find that, with and without conditioning on high school GPA, English EOC score value added is more predictive of college enrollment than English ACT score value added. I find no significant relationship between noncognitive value added and college enrollment in this sample. These results suggest that English teacher value added on ACT scores is distinct from traditional test scores value added measures and noncognitive value added measures, but may be a less quantitatively important predictor of long-run postsecondary outcomes due to the smaller variance in ACT score value added relative to other value added measures.

Table A9: Impacts of English Value Added on College Enrollment

	(1)	(2)	(3)	(4)
English ACT Score Value Added	0.0248			0.0188
	(0.0276)			(0.0277)
English EOC Score Value Added		0.0564***		0.0561***
		(0.0156)		(0.0156)
Noncognitive Value Added			-0.00657	-0.00678
			(0.00935)	(0.00927)
N	135145	135145	135145	135145
R^2	0.0855	0.0866	0.0855	0.0867

Standard errors in parentheses, clustered at the high school level

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

Coefficients from OLS regression of 4-year college enrollment on value added with covariates

Coefficients standardized to reflect 1σ increase in value added

Sample: 11^{th} grade ACT-takers with nonmissing 10^{th} and 11^{th} grade absences and English 2 EOC scores matched with 10^{th} and 11^{th} grade English teachers

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

Table A10: Impacts of English Value Added on College Enrollment with GPA Control

	(1)	(2)	(3)	(4)
Standardized English ACT Value Added	0.0149			0.0130
	(0.0120)			(0.0119)
Weighted HS GPA at Graduation	0.282***	0.282***	0.282***	0.282***
	(0.00216)	(0.00216)	(0.00216)	(0.00216)
English EOC Score Value Added		0.0157***		0.0156***
		(0.00509)		(0.00510)
Noncognitive Value Added			-0.00545	-0.00544
			(0.00402)	(0.00397)
N	126955	126955	126955	126955
R^2	0.363	0.363	0.363	0.363

Standard errors in parentheses, clustered at the high school level

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

Coefficients from OLS regression of 4-year college enrollment on value added with covariates

Coefficients standardized to reflect 1σ increase in value added

GPA control is weighted composite high school GPA at graduation

Sample: 11^{th} grade ACT-takers with nonmissing 10^{th} and 11^{th} grade absences and English 2 EOC scores matched with 10^{th} and 11^{th} grade English teachers

H Supplemental Coefficient Estimates

Table A11 demonstrates that controlling for a student's observed ACT score in Equation (4) reduces the association between ACT score value added and college enrollment by roughly 5%, relative to estimates shown in Table 6. Because ACT score value added is, by construction, correlated with students' observed ACT scores, this exercise can be interpreted as a mediation-style analysis quantifying the share of the relationship between ACT score value added and college enrollment that can be accounted for by ACT scores. The relationship between ACT score value added and college enrollment cannot be fully explained by ACT scores, suggesting that the impacts of ACT score value added extend beyond the signalling value of a higher ACT score.

Table A11: ACT Score Value Added and College Enrollment, OLS Estimates with ACT Score Controls

	(1) 4-Year College Enrollment	(2) On-Time 4-Year College Enrollment	(3) On-Time 2-Year College Enrollment	(4) 4-Year College Acceptance Rate
English ACT VA	-0.00528	0.00101	-0.00364	-0.00518*
	(0.00786)	(0.00815)	(0.0116)	(0.00312)
Math ACT VA	0.00737**	0.0127***	-0.0169***	-0.00486***
	(0.00303)	(0.00322)	(0.00371)	(0.00153)
English ACT Score	0.0114***	0.0118***	-0.00709***	-0.00252***
	(0.000353)	(0.000324)	(0.000342)	(0.000153)
Math ACT Score	0.0110***	0.0123***	-0.00695***	-0.00253***
	(0.000432)	(0.000427)	(0.000420)	(0.000197)
Observations	271749	271749	263319	74222
Mean	0.473	0.399	0.348	0.578
R^2	0.362	0.345	0.189	0.237

Standard errors in parentheses, clustered at the high school level

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

Coefficients standardized to reflect 1σ increase in value added

Includes controls for student lagged test scores and demographics X_{it}, high school fixed effects, and cohort fixed effects

Table A12 presents F-statistics from tests of joint instrument significance in Equation (5), demonstrating that the lagged enrollment instruments are highly predictive of enrollment at each college in the UNC system. In particular, coefficient estimates reveal that a student is significantly more likely to attend a particular college if a higher share of students in the prior cohort of their high school attended that college.

Table A12: Testing Relevance of Lagged Enrollment Instruments

Outcome Equation	F-Statistic
Appalachian State University	23.46
East Carolina University	83.60
Elizabeth City State University	16.12
Fayetteville State University	31.61
NC A&T University	34.84
NC Central University	6.154
UNC Asheville	16.24
UNC Charlotte	24.23
UNC Greensboro	29.02
UNC Pembroke	53.48
UNC Wilmington	85.32
Western Carolina University	27.24
Winston-Salem State University	17.46
NC State University	34.86
UNC School of the Arts	20.23
4-Year Private/Out of State	10.30

F-Statistics from joint tests of instrument significance in multinomial logit model corresponding to equation (5).

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). Table A13 demonstrates 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, providing evidence in support of the exclusion restriction.

Table A13: Exclusion Restriction

	(1) GPA	(2) ACT
Lagged Appalachian State Enrollment Share	-0.201	-1.119**
	(0.126)	(0.490)
Lagged East Carolina Enrollment Share	-0.224	-0.144
	(0.148)	(0.536)
Lagged Elizabeth City State Enrollment Share	-0.0623	0.249
	(0.143)	(0.347)
Lagged Fayetteville State Enrollment Share	-0.215	-0.147
	(0.155)	(0.537)
Lagged NC A&T Enrollment Share	0.0200	-0.0187
	(0.0956)	(0.246)
Lagged NC Central Enrollment Share	0.0750	0.346
	(0.0832)	(0.395)
Lagged NC State Enrollment Share	0.0986	0.348
	(0.151)	(0.470)
Lagged UNC Asheville Enrollment Share	-0.0568	1.054
	(0.260)	(0.936)
Lagged UNC Wilmington Enrollment Share	0.0268	0.0155
	(0.0724)	(0.281)
Lagged UNC Chapel Hill Enrollment Share	0.262	0.676
	(0.163)	(0.554)
Lagged UNC Charlotte Enrollment Share	-0.0988	-0.120
	(0.0797)	(0.272)
Lagged UNC Greensboro Enrollment Share	-0.193*	0.655*
	(0.105)	(0.352)
Lagged UNC Pembroke Enrollment Share	0.173	-0.458
	(0.271)	(0.607)
Lagged Western Carolina Enrollment Share	0.0258	-0.458
	(0.192)	(0.672)
Lagged Winston-Salem State Enrollment Share	-0.108	1.254
	(0.289)	(0.793)
Lagged UNC School of the Arts Enrollment Share	-0.583	-1.788
	(0.982)	(5.279)
Observations	179091	271581
F-Statistic	0.991	1.257

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

Table A14 presents coefficients from the first stage of the two-stage nested logit estimation procedure, corresponding to Figure A17. Tables A15 and A16 presents coefficients from the first stage of the two-stage nested logit estimation procedure, corresponding to Figure

A18. Tables A17, A18, and A19 present college fixed effects, selection term coefficients, and covariate coefficients, respectively, from the college performance equation, corresponding to Equation (10). Multiple empirical results confirm the presence of selection bias in reduced-form estimates. First, an F-test demonstrates that the selection correction terms enter the college performance equation significantly. Second, coefficients on several measures of student achievement in the college performance equation increase in magnitude after applying the correction procedure.

Tables A20 and A21 demonstrate that the results are qualitatively similar when probit regressions are used to estimate the college performance equation for binary outcomes, including enrollment in a college algebra course, dropout during or after freshman year, and college completion within 5 years of initial enrollment. Figure A19 demonstrates the estimated effects of ACT score value added on enrollment in specific 4-year colleges, separating the College of Engineering at NC State University from the rest of NC State University. I find a positive effect of math ACT score value added on enrollment in the College of Engineering at NC State, relative to the outside option of enrollment in UNC Chapel Hill.

Table A22 demonstrates that math ACT score value added increases the likelihood that a student intends to major in STEM during his or her first semester of college and the likelihood of completing a STEM major. 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).[61] I do not apply the selection correction procedure to major choice results because the choice of college and the choice of major are likely made jointly based on college-specific major availability. Thus, attempting to disentangle the direct effects of ACT score value added on major choice from indirect effects through college choice may not be informative. Future work should further explore the role of high school teachers in students' choice of colleges and majors.

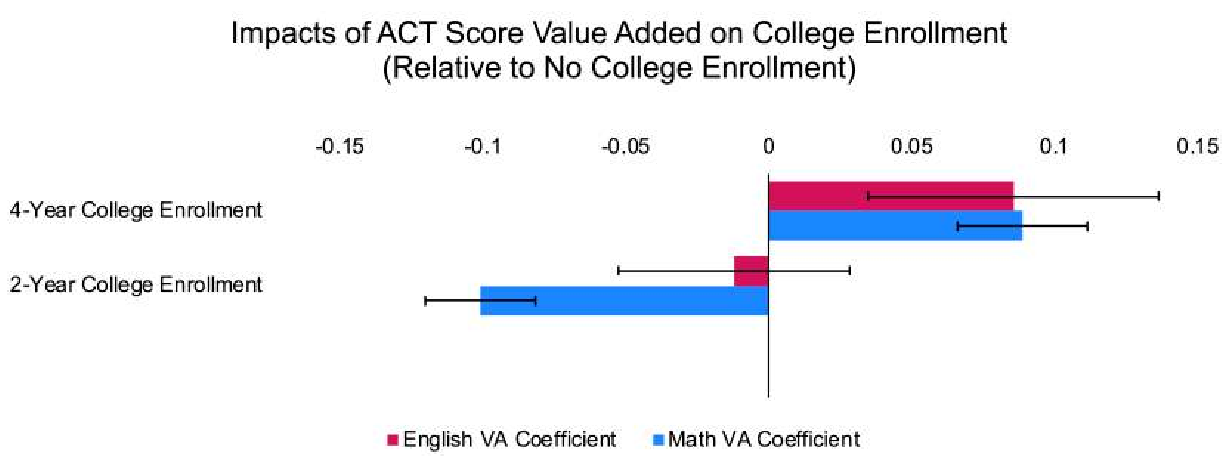
[61]I classify the following CIP codes as STEM: 03, 11, 14, 15, 26, 27, 40, 41, and 51.

Table A14: First Stage Nested Logit Coefficients

4-Year College Enrollment	
Standardized English ACT Value Added	0.0855
	(0.0507)
Standardized Math ACT Value Added	0.0887***
	(0.0227)
Inclusive Value Term	0.320***
	(0.0576)
2-Year College Enrollment	
Standardized English ACT Value Added	-0.0121
	(0.0404)
Standardized Math ACT Value Added	-0.101***
	(0.0193)
Observations	272096

Standard errors in parentheses, bootstrapped with 100 replications to adjust for two-stage nested logit estimation procedure
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$
Coefficients standardized to reflect 1σ increase in value added

Figure A17: Impacts of ACT Score Value Added on College Enrollment



Coefficients standardized to reflect the effects of a 1σ increase in teacher value added.
Error bars represent 95% confidence intervals.
Coefficient estimates with standard errors reported in Appendix H.
Coefficients normalized relative to no college enrollment.
Standard errors bootstrapped with 100 replications to adjust for two-stage nested logit estimation procedure.

Table A15: Second Stage Nested Logit Coefficients, Part 1

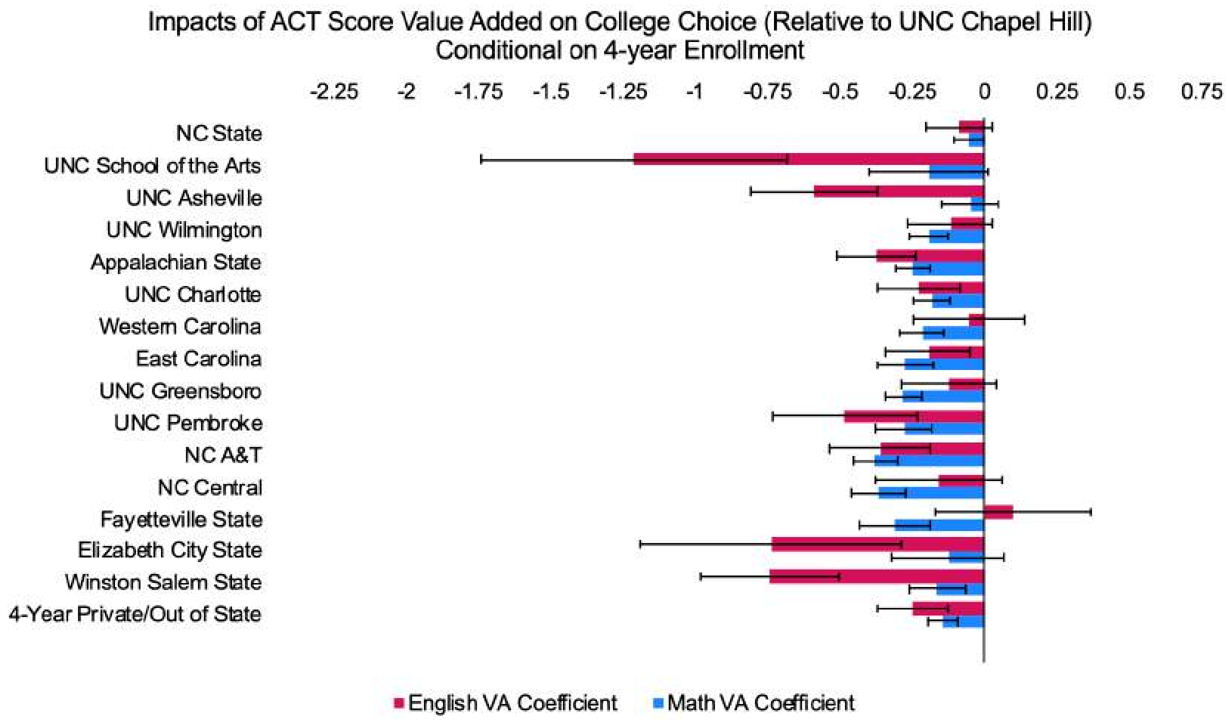
Appalachian State	
Standardized English ACT Value Added	-0.376***
	(0.135)
Standardized Math ACT Value Added	-0.251***
	(0.0612)
East Carolina	
Standardized English ACT Value Added	-0.197
	(0.146)
Standardized Math ACT Value Added	-0.277***
	(0.0618)
Elizabeth City State	
Standardized English ACT Value Added	-0.740
	(0.454)
Standardized Math ACT Value Added	-0.127
	(0.193)
Fayetteville State	
Standardized English ACT Value Added	0.101
	(0.268)
Standardized Math ACT Value Added	-0.311**
	(0.121)
NC A&T	
Standardized English ACT Value Added	-0.363**
	(0.173)
Standardized Math ACT Value Added	-0.379***
	(0.0783)
NC Central	
Standardized English ACT Value Added	-0.160
	(0.218)
Standardized Math ACT Value Added	-0.366***
	(0.0952)
UNC Asheville	
Standardized English ACT Value Added	-0.593***
	(0.218)
Standardized Math ACT Value Added	-0.0499
	(0.0981)
UNC Charlotte	
Standardized English ACT Value Added	-0.229
	(0.145)
Standardized Math ACT Value Added	-0.181***
	(0.0633)

Table A16: Second Stage Nested Logit Coefficients, Part 2

UNC Greensboro	
Standardized English ACT Value Added	-0.124
	(0.164)
Standardized Math ACT Value Added	-0.283***
	(0.0642)
UNC Pembroke	
Standardized English ACT Value Added	-0.484*
	(0.250)
Standardized Math ACT Value Added	-0.279***
	(0.0963)
UNC Wilmington	
Standardized English ACT Value Added	-0.120
	(0.145)
Standardized Math ACT Value Added	-0.194***
	(0.0651)
Western Carolina	
Standardized English ACT Value Added	-0.0544
	(0.190)
Standardized Math ACT Value Added	-0.218***
	(0.0793)
Winston Salem State	
Standardized English ACT Value Added	-0.742***
	(0.239)
Standardized Math ACT Value Added	-0.163*
	(0.0944)
NC State	
Standardized English ACT Value Added	-0.0893
	(0.113)
Standardized Math ACT Value Added	-0.0558
	(0.0498)
UNC School of the Arts	
Standardized English ACT Value Added	-1.214**
	(0.531)
Standardized Math ACT Value Added	-0.195
	(0.203)
4 Year Private/Out of State	
Standardized English ACT Value Added	-0.251**
	(0.123)
Standardized Math ACT Value Added	-0.147***
	(0.0515)
Observations	108448

Standard errors in parentheses, clustered at the high school level
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$
Coefficients standardized to reflect 1σ increase in value added
Coefficients normalized relative to more-selective UNC Chapel Hill

Figure A18: Impacts of ACT Score Value Added on College Enrollment



Coefficients standardized to reflect the effects of a 1σ increase in teacher value added.
Error bars represent 95% confidence intervals.
Coefficient estimates with standard errors reported in Appendix H.
Coefficients normalized relative to no college enrollment.
Standard errors bootstrapped with 100 replications to adjust for two-stage nested logit estimation procedure.

Table A17: College Fixed Effects from College Performance Equation

	(1) GPA	(2) STEM GPA	(3) Non-STEM GPA	(4) College Algebra	(5) Dropout	(6) Completion
Appalachian State	0.266***	0.669***	0.135**	0.132***	-0.00317	-0.0662
	(0.0584)	(0.0940)	(0.0571)	(0.0360)	(0.0234)	(0.0434)
East Carolina	0.0117	0.388***	-0.0522	0.340***	0.00709	-0.113***
	(0.0583)	(0.0838)	(0.0614)	(0.0442)	(0.0207)	(0.0366)
Elizabeth City State	0.153	0.0703	0.0651	0.267***	0.0537	-0.256**
	(0.153)	(0.306)	(0.159)	(0.0951)	(0.0711)	(0.110)
Fayetteville State	0.0731	0.578**	-0.155	0.198***	0.0462	-0.250***
	(0.149)	(0.253)	(0.147)	(0.0679)	(0.0579)	(0.0851)
NC A&T	0.0232	0.323***	0.140*	0.155***	0.0501*	-0.263***
	(0.0780)	(0.0957)	(0.0843)	(0.0419)	(0.0296)	(0.0510)
NC Central	-0.272**	0.0443	-0.310**	0.273***	0.0411	-0.277***
	(0.130)	(0.165)	(0.129)	(0.0665)	(0.0441)	(0.0741)
UNC Asheville	0.277	0.631***	0.140	0.0618	0.00233	-0.244*
	(0.186)	(0.232)	(0.206)	(0.0587)	(0.0695)	(0.125)
UNC Charlotte	0.0854	0.226**	0.165***	0.161***	0.0469**	-0.0951**
	(0.0625)	(0.0892)	(0.0591)	(0.0405)	(0.0221)	(0.0376)
UNC Greensboro	0.0981	0.244**	0.0796	-0.0285	0.0336	-0.107**
	(0.0736)	(0.114)	(0.0711)	(0.0413)	(0.0300)	(0.0467)
UNC Pembroke	-0.0223	0.478***	-0.216**	0.179***	0.0420	-0.180***
	(0.0865)	(0.102)	(0.0988)	(0.0602)	(0.0315)	(0.0579)
UNC Wilmington	0.223***	0.528***	0.110	0.731***	0.0285	-0.0374
	(0.0776)	(0.122)	(0.0738)	(0.0664)	(0.0339)	(0.0577)
Western Carolina	0.310***	0.823***	0.113	0.104**	-0.0165	-0.136**
	(0.0959)	(0.136)	(0.0952)	(0.0508)	(0.0354)	(0.0602)
Winston-Salem State	0.248**	0.631***	0.215*	0.242***	-0.0969**	-0.0302
	(0.109)	(0.146)	(0.113)	(0.0575)	(0.0467)	(0.0681)
NC State	0.211***	0.311***	0.268***	0.260***	0.00309	0.177***
	(0.0378)	(0.0586)	(0.0353)	(0.0187)	(0.0142)	(0.0235)
Observations	69661	49558	68060	73559	73559	57138
Mean	2.981	2.786	3.114	0.364	0.0863	0.707
R^2	0.262	0.243	0.256	0.274	0.0437	0.148

Standard errors in parentheses, clustered at the high school level

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

Table A18: Selection Term Coefficients from College Performance Equation

	(1) GPA	(2) STEM GPA	(3) Non-STEM GPA	(4) College Algebra	(5) Dropout	(6) Completion
Appalachian State	0.0159	-0.0416	0.0422*	-0.0348**	-0.00515	0.0286
	(0.0253)	(0.0408)	(0.0253)	(0.0170)	(0.0102)	(0.0194)
East Carolina	0.0225	0.00964	0.00759	0.00379	-0.00554	0.00668
	(0.0264)	(0.0359)	(0.0280)	(0.0191)	(0.00900)	(0.0158)
Elizabeth City State	0.0199	0.0934	0.000799	0.0278	0.00676	0.0126
	(0.0535)	(0.111)	(0.0555)	(0.0336)	(0.0257)	(0.0416)
Fayetteville State	0.0814	0.0918	0.0859	0.0865***	0.000693	-0.00490
	(0.0578)	(0.0984)	(0.0574)	(0.0266)	(0.0236)	(0.0334)
NC A&T	0.0765**	0.134***	-0.0104	0.00850	0.00620	0.0385*
	(0.0338)	(0.0408)	(0.0374)	(0.0184)	(0.0135)	(0.0221)
NC Central	0.149***	0.0970	0.175***	0.0367	-0.00303	0.0227
	(0.0554)	(0.0702)	(0.0545)	(0.0287)	(0.0188)	(0.0314)
UNC Asheville	-0.0717	-0.112	-0.0415	-0.0641***	0.0131	0.0488
	(0.0703)	(0.0885)	(0.0781)	(0.0227)	(0.0267)	(0.0492)
UNC Chapel Hill	0.0967***	0.0970***	0.0865***	0.0805***	-0.0180***	0.0479***
	(0.0174)	(0.0293)	(0.0155)	(0.0121)	(0.00660)	(0.0106)
UNC Charlotte	0.115***	0.187***	0.0588**	0.0988***	-0.0217**	0.0224
	(0.0281)	(0.0364)	(0.0279)	(0.0199)	(0.00949)	(0.0169)
UNC Greensboro	0.0272	0.0249	0.00143	0.0811***	0.00693	-0.0197
	(0.0337)	(0.0520)	(0.0323)	(0.0178)	(0.0128)	(0.0196)
UNC Pembroke	0.0387	-0.0105	0.0685*	0.0849***	0.00167	-0.0120
	(0.0335)	(0.0398)	(0.0383)	(0.0236)	(0.0127)	(0.0225)
UNC Wilmington	0.0383	-0.0311	0.0738**	-0.118***	-0.0159	0.0125
	(0.0364)	(0.0553)	(0.0344)	(0.0299)	(0.0150)	(0.0260)
Western Carolina	-0.0266	-0.0947*	0.0235	0.00778	0.0111	0.00955
	(0.0393)	(0.0535)	(0.0397)	(0.0209)	(0.0141)	(0.0248)
Winston-Salem State	0.0136	-0.0149	-0.00933	0.0256	0.0657***	-0.0706**
	(0.0472)	(0.0632)	(0.0495)	(0.0242)	(0.0212)	(0.0280)
NC State	0.0243	0.119***	-0.0213	-0.180***	-0.0153**	-0.0929***
	(0.0181)	(0.0280)	(0.0179)	(0.00811)	(0.00631)	(0.0133)
Observations	69661	49558	68060	73559	73559	57138
Mean	2.981	2.786	3.114	0.364	0.0863	0.707
R^2	0.262	0.243	0.256	0.274	0.0437	0.148
F-Statistic	4.495	4.971	4.030	56.25	2.298	7.211

Standard errors in parentheses, clustered at the high school level

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

Table A19: Selected Covariate Coefficients from College Performance Equation

	(1) GPA	(2) STEM GPA	(3) Non-STEM GPA	(4) College Algebra	(5) Dropout	(6) Completion
A. No Correction						
Math 1 EOC	0.0586***	0.0996***	0.0498***	-0.0110**	-0.00589**	0.0136***
	(0.00775)	(0.0110)	(0.00781)	(0.00456)	(0.00286)	(0.00519)
English 2 EOC	0.0934***	0.0702***	0.0958***	-0.00311	-0.00464	0.0156***
	(0.00858)	(0.0125)	(0.00880)	(0.00528)	(0.00322)	(0.00571)
Honors Math Course	0.103***	0.141***	0.103***	-0.0287***	-0.0132***	0.0317***
	(0.0102)	(0.0148)	(0.0104)	(0.00596)	(0.00381)	(0.00691)
Honors English Course	0.109***	0.0779***	0.126***	-0.000771	-0.0275***	0.0604***
	(0.0117)	(0.0164)	(0.0118)	(0.00613)	(0.00454)	(0.00730)
B. Lee Correction						
Math 1 EOC	0.0611***	0.102***	0.0513***	-0.00968**	-0.00593**	0.0140***
	(0.00775)	(0.0110)	(0.00785)	(0.00453)	(0.00287)	(0.00519)
English 2 EOC	0.0941***	0.0719***	0.0955***	-0.00657	-0.00495	0.0140**
	(0.00870)	(0.0127)	(0.00887)	(0.00532)	(0.00323)	(0.00568)
Honors Math Course	0.108***	0.146***	0.106***	-0.0284***	-0.0132***	0.0315***
	(0.0105)	(0.0153)	(0.0107)	(0.00589)	(0.00387)	(0.00694)
Honors English Course	0.119***	0.0893***	0.132***	0.00387	-0.0271***	0.0605***
	(0.0117)	(0.0164)	(0.0118)	(0.00605)	(0.00461)	(0.00723)
Observations	69661	49558	68060	73559	73559	57138
Mean	2.981	2.786	3.114	0.364	0.0863	0.707
R^2 (No Correction)	0.261	0.241	0.255	0.269	0.0432	0.146
R^2 (Lee Correction)	0.262	0.243	0.256	0.274	0.0437	0.148

Panel A: standard errors in parentheses, clustered at the high school level

Panel B: standard errors in parentheses, bootstrapped with 100 replications to adjust for two-stage selection correction procedure

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

Coefficients standardized to reflect 1σ increase in value added

Table A20: Impacts on College Performance without Correction, Probit

	(1) GPA	(2) STEM GPA	(3) Non-STEM GPA	(4) College Algebra	(5) Dropout	(6) Completion
English ACT VA	0.0221	0.00522	0.0200	0.00660	-0.00763	0.00488
	(0.0186)	(0.0281)	(0.0197)	(0.0125)	(0.00704)	(0.0124)
Math ACT VA	0.0262***	0.0276**	0.0253***	-0.0302***	-0.00571**	0.00690
	(0.00713)	(0.0107)	(0.00741)	(0.00498)	(0.00286)	(0.00503)
Observations	69661	49558	68060	73261	73240	57106
Mean	2.981	2.786	3.114	0.365	0.0866	0.707
R^2/Pseudo-R^2	0.261	0.241	0.255	0.254	0.0699	0.128

Standard errors in parentheses, clustered at the high school level

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

Columns (1)-(3): Coefficients from OLS regressions

Columns (4)-(6): Average marginal effects from probit regressions

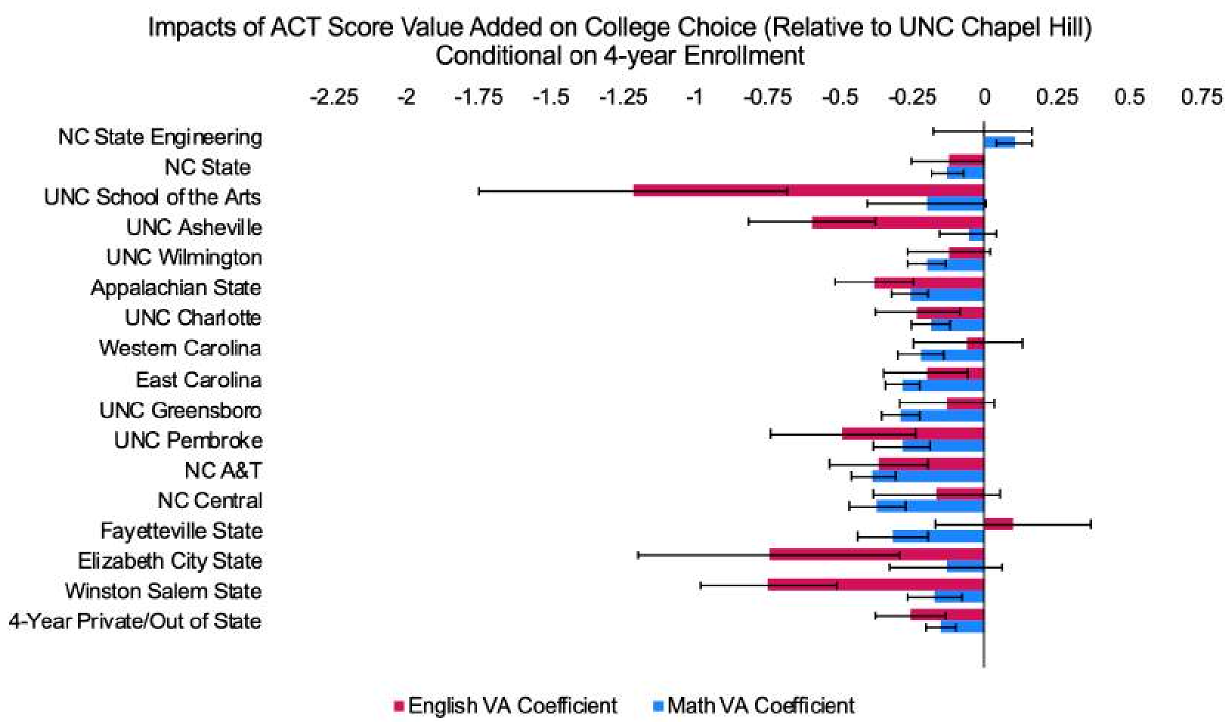
Coefficients standardized to reflect 1σ increase in value added

Table A21: Impacts on College Performance with Selection Correction, Probit

	(1) GPA	(2) STEM GPA	(3) Non-STEM GPA	(4) College Algebra	(5) Dropout	(6) Completion
English ACT VA	0.0233	0.00872	0.0206	0.00771	-0.00811	0.00458
	(0.0186)	(0.0281)	(0.0197)	(0.0125)	(0.00703)	(0.0123)
Math ACT VA	0.0272***	0.0292***	0.0261***	-0.0296***	-0.00579**	0.00585
	(0.00713)	(0.0108)	(0.00741)	(0.00495)	(0.00287)	(0.00504)
Observations	69661	49558	68060	73261	73240	57106
Mean	2.981	2.786	3.114	0.365	0.0866	0.707
R^2/Pseudo-R^2	0.262	0.243	0.256	0.256	0.0703	0.130

Standard errors in parentheses, clustered at the high school level
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$
Columns (1)-(3): Coefficients from OLS regressions
Columns (4)-(6): Average marginal effects from probit regressions
Coefficients standardized to reflect 1σ increase in value added

Figure A19: Impacts of ACT Score Value Added on College Choice, Separating Engineering



Coefficients standardized to reflect the effects of a 1σ increase in teacher value added.
Error bars represent 95% confidence intervals
Coefficients normalized relative to more-selective UNC Chapel Hill.
Standard errors clustered at the high school level.

Table A22: Impacts on STEM Major Choice without Correction

	(1) Intended STEM Major	(2) Completed STEM Major
English ACT VA	0.00591	-0.00303
	(0.0117)	(0.0166)
Math ACT VA	0.0154***	0.0223***
	(0.00523)	(0.00571)
Observations	74068	40394
Mean	0.142	0.147
R^2	0.142	0.127

Standard errors in parentheses

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

Coefficients standardized to reflect 1σ increase in value added

Completed major conditional on 5-year college completion

I Alternative Instruments

My results are robust to replacing the lagged peer enrollment instruments with a set of indicators for which college is nearest to a student's high school, conditional on the distance to the nearest college. This exclusion restriction implies that, proximity to a particular college in the UNC system impacts the student's college choice, but does not impact their college performance. By comparing students who are equidistant to the nearest college, the nearest college instruments ameliorate typical concerns with distance instruments. In particular, prior work suggests that students who live further away from colleges in rural or economically isolated areas are negatively selected on unobservable characteristics, such as ability or family income, which impact college performance (e.g. Carneiro and Heckman, 2002).

Table A23 presents F-statistics from tests of joint instrument significance in Equation (5), demonstrating that the nearest college instruments are highly predictive of enrollment at each college in the UNC system. In particular, coefficient estimates reveal that a student is significantly more likely to attend the college nearest to their high school. Table A24 demonstrates that the nearest college instruments are not significantly predictive of 12^{th} grade GPA or composite ACT score, providing evidence in support of the exclusion restriction.

Table A23: Testing Relevance of Nearest College Instruments

Outcome Equation	F-Statistic
Appalachian State University	52.70
East Carolina University	102.0
Elizabeth City State University	692.7
Fayetteville State University	659.2
NC A&T University	678.9
NC Central University	9.336
UNC Asheville	57.64
UNC Charlotte	94.91
UNC Greensboro	78.20
UNC Pembroke	98.67
UNC Wilmington	50.55
Western Carolina	111.7
Winston Salem State	650.5
NC State	23.92
UNC School of the Arts	6.218
4-Year Private/Out of State	28.68

F-Statistics from joint tests of instrument significance in multinomial logit model corresponding to equation (5).

Table A24: Exclusion Restriction

	(1) GPA	(2) ACT
Nearest Appalachian State	0.0476*	-0.661***
	(0.0278)	(0.156)
Nearest East Carolina	0.0324	-0.489***
	(0.0244)	(0.175)
Nearest Elizabeth City State	-0.00168	-0.356**
	(0.0408)	(0.161)
Nearest Fayetteville State	0.117***	-0.290*
	(0.0368)	(0.173)
Nearest NC A & T	0.0321	-0.425**
	(0.0357)	(0.177)
Nearest NC Central	0.00389	-0.321*
	(0.0349)	(0.170)
Nearest UNC Asheville	0.00729	-0.892***
	(0.0289)	(0.166)
Nearest UNC Charlotte	-0.0113	-0.843***
	(0.0211)	(0.151)
Nearest UNC Greensboro	0.00793	-0.536***
	(0.0411)	(0.183)
Nearest UNC Pembroke	0.0730**	-0.819***
	(0.0347)	(0.183)
Nearest UNC Wilmington	0.0478*	-0.557***
	(0.0276)	(0.163)
Nearest Western Carolina	0.0714*	-0.520***
	(0.0372)	(0.183)
Nearest Winston-Salem State	0.0518*	-0.341*
	(0.0286)	(0.174)
Nearest NC State	0.0455**	-0.551***
	(0.0216)	(0.153)
Nearest UNC School of the Arts	0.0338	-0.633***
	(0.0252)	(0.170)
Observations	179091	271581
F-Statistic	2.169	5.722

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

Table A25 presents selection-corrected estimates from the college performance Equation (10). Both selection-corrected and reduced-form estimates, shown in Table 7, indicate positive effects of ACT score value added on a host of college performance measures, including freshman year GPA in both STEM and non-STEM courses, enrollment in a college algebra course, dropout during or after freshman year, and college completion within 5 years of initial enrollment. Compared to reduced-form estimates, effects of math ACT score value added on freshman year GPA, college algebra course-taking, 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.

Table A25: Impacts on College Performance, Nearest College Instruments

	(1) GPA	(2) STEM GPA	(3) Non-STEM GPA	(4) College Algebra	(5) Dropout	(6) Completion
English ACT VA	0.0374**	0.0312	0.0314	0.00324	-0.00843	0.00256
	(0.0187)	(0.0287)	(0.0195)	(0.0127)	(0.00674)	(0.0125)
Math ACT VA	0.0281***	0.0406***	0.0250***	-0.0285***	-0.00536**	0.00633
	(0.00755)	(0.0109)	(0.00773)	(0.00488)	(0.00267)	(0.00488)
Observations	69661	49558	68060	73559	73559	57138
Mean	2.981	2.786	3.114	0.364	0.0863	0.707
R^2	0.245	0.223	0.240	0.257	0.0333	0.134

Standard errors in parentheses, clustered at the high school level

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

Coefficients standardized to reflect 1σ increase in value added

J Dahl Selection Correction

Results are qualitatively similar when applying the semi-parametric Dahl (2002) selection correction instead of the Lee (1983) selection correction. The main advantage of the Dahl method is a less restrictive assumption on the error structure: Unlike Lee, Dahl allows for the covariances between the outcome equation errors and the selection equation errors to have any arbitrary sign (Bourguignon et al., 2007). Using the Dahl method, the college performance equation becomes:

$$\begin{aligned} College\_Performance_{icst} = \pi_0 + \pi_{1English}\hat{\theta}_{English-t} + \pi_{1Math}\hat{\theta}_{Math-t} + \pi_2 X_{it} \\ + \gamma_s + \alpha_t + \tau_c + \mu(\{P_c\}) + u_{icst} \end{aligned} \tag{18}$$

Here $\{P_c\}$ is the set of all choice probabilities from the nested logit selection equation. Dahl's method does not require imposing Lee's index sufficiency assumption (that is, assuming only the first-best choice probability matters for selection). However, controlling for all choice probabilities becomes computationally infeasible and leads to collinearity issues as the number of choice probabilities increases. Typically, applications of the Dahl approach assume that a small number of choice probabilities can form a sufficient statistic for selection. Common choices include the first-best probability, the probability of the observed choice, and one conceptually important probability, such as the probability of staying in the same state in migration models. I use the first-best probability and the probability of choosing a 2-year college, as additional choice probabilities are either collinear or not statistically significant in the college performance equation.

The unknown function μ is typically approximated using an interacted polynomial expansion. I compare specifications with second-order and third-order polynomials and interaction terms as in Dahl (2002) and Ransom (2021). I use a quadratic polynomial without interaction effects, as cubic polynomial terms and interaction terms are either collinear or not statistically significant in the college performance equation. I allow the unknown function μ to differ across students based on their observed college choice.

Compared to reduced-form estimates (Table 7), effects of math ACT score value added on freshman year GPA and freshman year dropout are slightly smaller after applying the

Dahl correction, while they are slightly larger after applying the Lee correction (Table 7). Coefficients on college algebra course-taking are larger in magnitude and coefficients on college completion are smaller in magnitude after applying both the Dahl and Lee corrections. Differences in selection-corrected vs reduced-form coefficients are relatively small for both corrections.

Table A26: Impacts on College Performance with Dahl Selection Correction

	(1) GPA	(2) STEM GPA	(3) Non-STEM GPA	(4) College Algebra	(5) Dropout	(6) Completion
English ACT VA	0.0226	0.00772	0.0204	0.00648	-0.00782	0.00164
	(0.0186)	(0.0282)	(0.0197)	(0.0124)	(0.00680)	(0.0122)
Math ACT VA	0.0224***	0.0226**	0.0218***	-0.0287***	-0.00454	0.00244
	(0.00721)	(0.0109)	(0.00746)	(0.00484)	(0.00279)	(0.00515)
Observations	69663	49559	68062	73561	73561	57140
Mean	2.981	2.786	3.114	0.364	0.0863	0.707
R^2	0.265	0.247	0.259	0.277	0.0448	0.151

Standard errors in parentheses, bootstrapped with 100 replications to adjust for two-stage selection correction procedure

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

Coefficients standardized to reflect 1σ increase in value added

Table A27: Dahl Selection Term Coefficients from College Performance Equation

	(1) GPA	(2) STEM GPA	(3) Non-STEM GPA	(4) College Algebra	(5) Dropout	(6) Completion
Appalachian State × P(First-Best)	0.591	0.860	0.282	0.598	-0.0176	0.215
	(0.683)	(1.041)	(0.708)	(0.453)	(0.276)	(0.520)
Eastern Carolina × P(First-Best)	0.307	0.317	0.505	0.532	-0.0954	-0.0884
	(0.447)	(0.673)	(0.468)	(0.368)	(0.152)	(0.268)
Elizabeth City State × P(First-Best)	1.022	0.310	1.389	-0.123	-0.911	0.556
	(1.080)	(2.316)	(1.173)	(0.656)	(0.573)	(0.808)
Fayetteville State × P(First-Best)	-1.466	-0.588	-1.626	0.332	0.166	-0.0742
	(1.505)	(2.259)	(1.529)	(0.581)	(0.553)	(0.822)
NC A&T × P(First-Best)	-0.00743	0.165	0.867	0.189	0.198	0.126
	(0.900)	(1.112)	(1.006)	(0.471)	(0.337)	(0.581)
NC Central × P(First-Best)	-3.468*	-2.037	-3.559*	-1.357	-0.0321	-0.687
	(1.957)	(2.560)	(1.963)	(1.004)	(0.728)	(1.086)
UNC Asheville × P(First-Best)	0.737	4.550	-0.205	1.230	-0.160	-0.441
	(3.193)	(4.392)	(3.512)	(0.911)	(1.235)	(2.146)
UNC Chapel Hill × P(First-Best)	-0.761***	-0.986***	-0.653***	-0.344**	0.0395	-0.0202
	(0.180)	(0.318)	(0.173)	(0.145)	(0.0612)	(0.121)
UNC Charlotte × P(First-Best)	-1.263***	-1.868***	-0.426	-0.881***	0.262*	-0.444
	(0.408)	(0.516)	(0.423)	(0.322)	(0.150)	(0.286)
UNC Greensboro × P(First-Best)	-0.139	-0.672	0.111	-1.432***	0.0596	0.198
	(0.505)	(0.835)	(0.485)	(0.285)	(0.188)	(0.377)
UNC Pembroke × P(First-Best)	-1.241**	-1.096**	-1.490**	-1.263***	0.317**	-0.557*
	(0.556)	(0.490)	(0.622)	(0.318)	(0.146)	(0.286)
UNC Wilmington × P(First-Best)	-0.0810	-0.285	-0.102	2.572***	-0.235	-0.409
	(0.629)	(1.124)	(0.585)	(0.521)	(0.434)	(0.492)
Western Carolina × P(First-Best)	0.108	1.086	-0.631	-0.0418	0.0345	-0.716
	(0.802)	(1.076)	(0.850)	(0.486)	(0.308)	(0.546)
Winston-Salem State × P(First-Best)	1.324	1.103	2.729**	0.736	-2.093***	2.390***
	(1.348)	(2.031)	(1.310)	(0.798)	(0.719)	(0.835)
NC State × P(First-Best)	-1.009***	-1.152***	-0.609**	1.575***	0.125	0.301*
	(0.272)	(0.389)	(0.279)	(0.125)	(0.0996)	(0.175)
Appalachian State × P(2-Year)	-0.188	0.185	-0.242	-0.312**	0.0139	-0.234
	(0.230)	(0.358)	(0.237)	(0.134)	(0.0908)	(0.159)
Eastern Carolina × P(2-Year)	-1.753***	-1.642***	-1.766***	0.274**	-0.00129	-0.492***
	(0.252)	(0.329)	(0.250)	(0.133)	(0.0773)	(0.149)
Elizabeth City State × P(2-Year)	-0.784	-3.414	-0.840	0.120	-0.338	-0.144
	(0.723)	(2.135)	(0.761)	(0.555)	(0.463)	(0.572)
Fayetteville State × P(2-Year)	-1.414*	-1.162	-1.582**	0.622**	0.00215	-0.333
	(0.746)	(1.082)	(0.735)	(0.305)	(0.269)	(0.463)
NC A&T × P(2-Year)	-0.0291	0.0584	-0.667	-0.0663	0.169	-0.631**
	(0.422)	(0.516)	(0.439)	(0.232)	(0.157)	(0.259)
NC Central × P(2-Year)	-0.390	-0.670	-0.353	0.119	0.0586	-0.319
	(0.539)	(0.649)	(0.526)	(0.260)	(0.199)	(0.303)
UNC Asheville × P(2-Year)	-0.484	-1.529**	-0.309	-0.830***	0.126	-0.0352
	(0.443)	(0.721)	(0.481)	(0.159)	(0.184)	(0.382)
UNC Chapel Hill × P(2-Year)	-0.934**	-1.425**	-1.292***	0.660***	-0.335**	0.128
	(0.467)	(0.604)	(0.378)	(0.222)	(0.159)	(0.252)
UNC Charlotte × P(2-Year)	-0.130	-0.381	-0.0497	0.877***	-0.0120	-0.182
	(0.278)	(0.324)	(0.296)	(0.163)	(0.0875)	(0.156)
UNC Greensboro × P(2-Year)	-1.247***	-2.233***	-1.084***	0.229	0.215**	-0.335*
	(0.314)	(0.417)	(0.302)	(0.148)	(0.105)	(0.191)
UNC Pembroke × P(2-Year)	-0.672	-1.114*	-0.414	-0.435*	0.198	0.164
	(0.415)	(0.626)	(0.400)	(0.236)	(0.170)	(0.265)
UNC Wilmington × P(2-Year)	-0.0623	-0.679	0.205	0.744***	-0.0831	0.279
	(0.320)	(0.503)	(0.279)	(0.241)	(0.126)	(0.225)
Western Carolina × P(2-Year)	-1.466***	-1.904***	-1.229***	0.143	0.0537	-0.329
	(0.308)	(0.399)	(0.330)	(0.173)	(0.123)	(0.218)
Winston-Salem State × P(2-Year)	-1.675***	-2.608***	-1.189***	0.0622	0.278*	-0.980***
	(0.431)	(0.572)	(0.422)	(0.258)	(0.164)	(0.278)
NC State × P(2-Year)	-0.256	-0.601	-0.130	0.389***	-0.00161	0.270
	(0.265)	(0.386)	(0.267)	(0.132)	(0.102)	(0.176)
Observations	69663	49559	68062	73561	73561	57140
Mean	2.981	2.786	3.114	0.364	0.0863	0.707
R^2	0.265	0.247	0.259	0.277	0.0448	0.151
F-Statistic	6.787	7.138	5.434	28.07	2.398	5.437

Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$
F-statistic from joint test of significance of selection terms
Coefficients on quadratic terms omitted
Choice probabilities interacted with indicator for college attended

K Data Appendix

K.1 Sample Restrictions

Figures A20 and A21 depict the loss of sample size resulting from each sample restriction, leading to three final estimation samples: the English value added estimation sample, the math value added estimation sample, and the college outcomes estimation sample.

Figure A20: Value Added Estimation Sample Restrictions

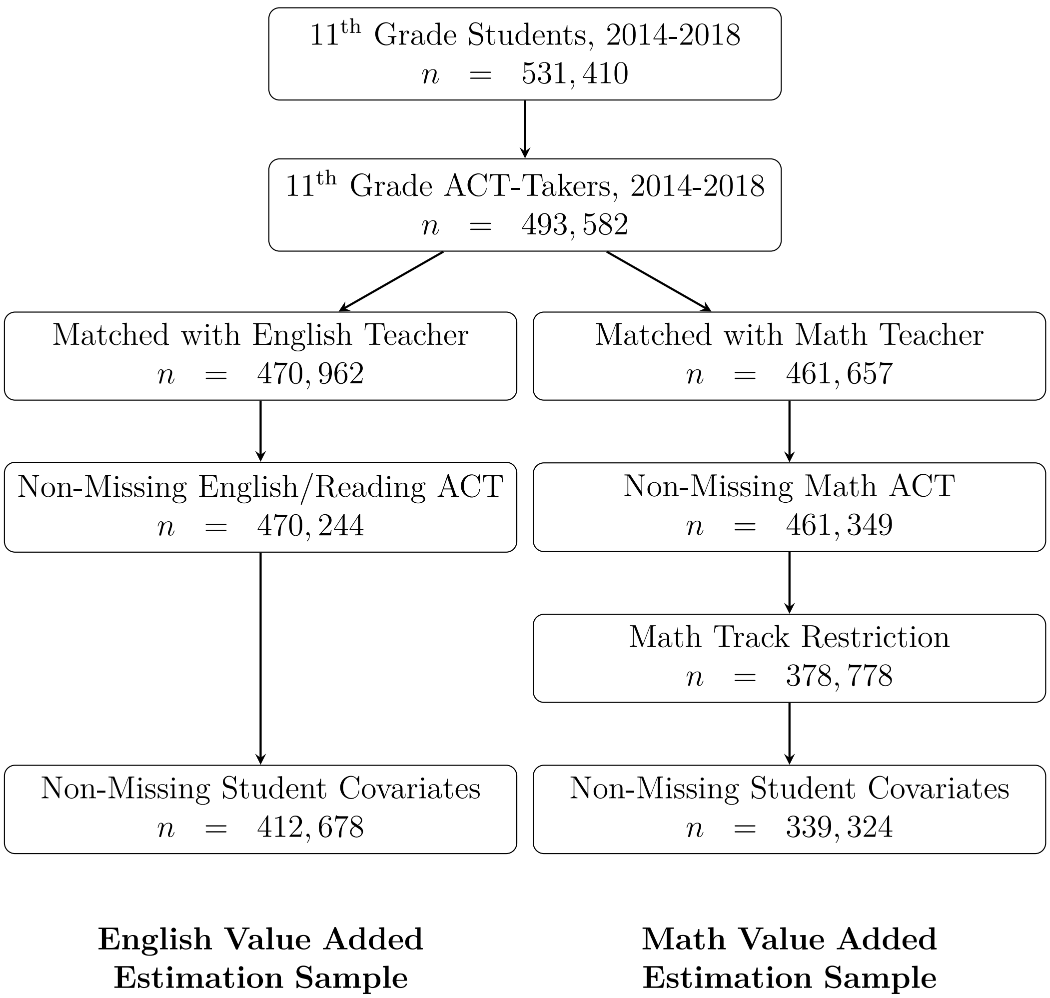


Figure A21: College Outcomes Estimation Sample Restrictions

11th Grade ACT-Takers, 2015-2018
$n = 399,389$

↓

Matched with English and
Math Teacher VA Estimate
$n = 294,894$

↓

Non-Missing Student Covariates
$n = 272,096$

College Outcomes
Estimation Sample

The sample is qualitatively similar after imposing sample restrictions. Table A28 demonstrates that the characteristics of the full sample of 11^{th} grade students are similar to the characteristics of 11^{th} grade students with non-missing ACT scores.

Table A28: Student Summary Statistics by Sample

	11^{th} Graders Mean (SD)	ACT-Takers Mean (SD)	English VA Mean (SD)	Math VA Mean (SD)	College Outcomes Mean (SD)
Economically Disadvantaged	0.400	0.386	0.390	0.386	0.367
Female	0.500	0.507	0.505	0.512	0.511
Black	0.256	0.247	0.250	0.245	0.232
Hispanic	0.127	0.125	0.123	0.122	0.122
ACT Composite	18.59	18.61	18.51	18.47	18.83
	(5.165)	(5.160)	(5.064)	(4.804)	(5.025)
ACT Math	19.01	19.03	18.97	18.86	19.18
	(4.822)	(4.820)	(4.751)	(4.478)	(4.735)
ACT English+Reading Average	18.05	18.07	17.94	17.93	18.32
	(6.001)	(5.997)	(5.876)	(5.639)	(5.839)
Math Teacher Match	0.911	0.937	1.000	1.000	1.000
English Teacher Match	0.921	0.946	1.000	1.000	1.000
Math and English Teacher Match	0.891	0.919	1.000	1.000	1.000
Intend 2-Year College	0.350	0.351	0.361	0.365	0.348
Intend 4-Year Private/Out-of-State	0.127	0.132	0.129	0.129	0.130
Enrolled in UNC On-Time	0.194	0.207	0.208	0.213	0.273
Freshman UNC GPA	2.961	2.960	2.950	2.932	2.968
	(0.807)	(0.801)	(0.802)	(0.803)	(0.805)
Freshman UNC Dropout	0.0932	0.0920	0.0911	0.0927	0.0917
Graduated from UNC within 5 Years	0.708	0.708	0.704	0.693	0.707
Observations	531410	493582	412894	339249	272096

UNC GPA, dropout, graduation conditional on UNC enrollment

K.2 Administrative Data vs Self-Reported College Enrollment

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). The high school graduation survey overreports UNC system enrollment relative to administrative data. While 34.52% of students report intending to enroll in a 4-year public in-state institution, only 72% of those students (24.92% of the full sample) are present in UNC system enrollment records during the summer or fall semester following high school graduation, as shown in Table A29 ("on-time enrollment"). Table A30 demonstrates that the high school graduation survey aligns more closely with administrative data on UNC enrollment when including delayed enrollment in addition to on-time enrollment. Table A31 demonstrates that students who report intending to enroll in a 4-year public in-state institution but are not present in UNC system enrollment records during the summer or fall semester following high school graduation are more likely to be economically disadvantaged, Black, or Hispanic, and have lower ACT scores on average compared to students who report intending to enroll in a 4-year public in-state institution and are present in UNC system enrollment records during the summer or fall semester following high school graduation.

In the nested logit model, I aggregate survey categories as follows. "4-Year Private/Out-of-State" includes "4-Year Private in North Carolina," "4-Year Public Out-of-State," and "4-Year Private Out-of-State." "2-Year" includes "2-Year Public in North Carolina,", "2-Year Private in North Carolina," "2-Year Public Out-of-State," and "2-Year Private Out-of-State." "No College" includes "Trade School in North Carolina," "Trade School Out-of-State," "Employment," "Military," and "Other" as well as students who do not graduate on time or do not report a post-graduation intention.[62] Students who enroll in the UNC System on time but report a different intention in the survey (1.88% of the full sample) are classified within the UNC System.

[62] The share of students in the college analysis sample who do not graduate high school is 4.75%, consistent with sharp declines in high school dropout in recent decades in the U.S. (McFarland et al., 2018). High school dropout is less common in my analysis sample than in the full population of North Carolina high school students because students who do not take the ACT test and students in remedial math courses are excluded from the sample.

Table A29: Alignment Between Graduate Survey and On-Time UNC System Enrollment

	Enroll in UNC System (%))		
	No	Yes	Total
4-Year Public in North Carolina	9.596	24.92	34.52
4-Year Private in North Carolina	6.732	0.589	7.321
4-Year Public Out-of-State	3.401	0.134	3.535
4-Year Private Out-of-State	2.701	0.0635	2.765
2-Year Public in North Carolina	33.55	0.765	34.31
2-Year Private in North Carolina	0.347	0.0116	0.358
2-Year Public Out-of-State	0.744	0.0121	0.757
2-Year Private Out-of-State	0.0801	0.00210	0.0822
Trade School in North Carolina	0.636	0.00840	0.644
Trade School Out-of-State	0.151	0.000788	0.151
Employment	9.739	0.0827	9.821
Military	4.153	0.0386	4.192
Other	1.466	0.0777	1.544

Table A30: Alignment Between Graduate Survey and UNC System Enrollment by Fall 2023

	Enroll in UNC System (%))		
	No	Yes	Total
4-Year Public in North Carolina	7.101	27.42	34.52
4-Year Private in North Carolina	5.633	1.688	7.321
4-Year Public Out-of-State	2.843	0.692	3.535
4-Year Private Out-of-State	2.290	0.475	2.765
2-Year Public in North Carolina	29.47	4.842	34.31
2-Year Private in North Carolina	0.297	0.0612	0.358
2-Year Public Out-of-State	0.680	0.0764	0.757
2-Year Private Out-of-State	0.0709	0.0113	0.0822
Trade School in North Carolina	0.613	0.0310	0.644
Trade School Out-of-State	0.145	0.00604	0.151
Employment	9.539	0.282	9.821
Military	3.968	0.223	4.192
Other	1.344	0.200	1.544

Table A31: Student Summary Statistics by Survey and Admin Data Alignment

	Not Aligned Mean (SD)	Aligned Mean (SD)
Economically Disadvantaged	0.386	0.211
	(0.487)	(0.408)
Female	0.533	0.583
	(0.499)	(0.493)
Black	0.329	0.229
	(0.470)	(0.420)
Hispanic	0.129	0.062
	(0.335)	(0.241)
ACT Composite	18.91	22.38
	(4.873)	(4.675)
ACT Math	19.19	22.32
	(4.645)	(4.789)
ACT English+Reading Average	18.42	22.26
	(5.687)	(5.440)
Observations	36554	94938

K.3 College Performance Measures

Freshman GPA

All GPA measures are constructed using course-level grades on a 4.0 scale with maximum value 4.33 and minimum value 0. Overall freshman GPA is the credit hour-weighted average of course-level grades across all graded courses taken during a student's first two semesters of UNC system enrollment excluding summer terms. STEM and non-STEM freshman GPA are defined analogously, restricting STEM GPA to courses with 2-digit Classification of Instruction Programs (CIP) codes 03, 11, 14, 15, 26, 27, 40, 41, and 51 and restricting non-STEM GPA to all other courses with non-missing CIP codes.[63]

[63] I classify 2-digit CIP codes, established by the National Center for Education Statistics (NCES), as STEM or non-STEM using a method similar to Altonji et al. (2016) and Ransom (2021). STEM fields include: natural resources and conservation, computer and information sciences and support services, engineering, engineering technologies/technicians, biological and biomedical sciences, mathematics and statistics, physical sciences, science technologies/technicians, and health professions and related clinical sciences.

College Algebra

The UNC System does not have a common course numbering system for undergraduate courses[64] I define a college algebra course as any 100-level course which includes the word "algebra" in the title. I measure college algebra course enrollment during any semester of enrollment in the UNC system, not restricted to freshman year.

Dropout and Completion

Freshman dropout is defined as dropout after the first or second semester of UNC system enrollment, excluding summer terms. Students are classified as dropouts if they are not present in the UNC system data after two semesters, even if they return in future semesters. Completion is defined as graduation from any institution in the UNC system within 5 years of initial enrollment in the UNC system. In my sample, only 7% of students who enroll in the UNC system on-time and graduate within 5 years transfer schools within the UNC system between initial enrollment and graduation. Thus, the 5-year completion rate from any UNC system institution (70.8%) is similar to the 5-year completion rate from the school where a student initially enrolls (65.8%). A 5-year completion rate is unavailable for the youngest cohort in my sample, decreasing sample size and statistical power for this outcome.

K.4 College Distances

I use annual high school location data (latitude and longitude) from the Common Core of Data (CCD), matching each student with the location of their high school during the year in which they took the ACT. I use 2015 college location data (latitude and longitude) from the National Historical Geographic Information System. Distances from high schools to the nearest colleges are geodetic distances in kilometers, measuring the length of the shortest curve between two points along the surface of a spherical model of the Earth.[65]

[64]While the UNC System began working toward a "Common Numbering System" in 2020, during my sample period the implementation had only been expanded to a small number of commonly taught, lower-division courses.

[65]I calculate distances using the Stata package `geonear`.

K.5 High School Courses, Tracks, and Classrooms

I define high school courses by aggregating 4-digit NC DPI course codes to account for multiple versions of the same course and changes in course codes over time. Table A32 describes the mappings from 4-digit English and math course codes to high school courses used as covariates in ACT score value added estimation. After completing Algebra 2/NC Math 3, students can choose between several math courses. During my sample period, the most common choices were Precalculus and Advanced Functions and Modeling. Advanced Functions and Modeling is a less rigorous alternative to Precalculus.

Table A32: High School Course Definitions

Course Name	Course Codes
English	
11^{th} Grade English	1023, 1033 (NC English III), 1A00 (AP Language)
Other English Course	1A01 (AP English Literature), 1I00, 1I01, 1I02, 1I03 (IB Language A), all other course codes starting with 102 or 103 (electives)
Math	
Algebra 2/NC Math 3	2024, 2034, 2053, 2300, 2301, 2309
Precalculus	2070, 2403
Advanced Functions	2025, 2403
Other Math Course	All other course codes starting with 2

I define the standard math track as taking Algebra 2 or NC Math 3 in 11^{th} grade. I defined the advanced math track as taking Algebra 2 or NC Math 3 in 10^{th} grade. I drop all students who took Algebra 2 or NC Math 3 prior to 10^{th} grade or after 11^{th} grade from my math ACT score value added estimation sample. This excludes very advanced students and remedial students.

I define course levels using the last digit of 5-digit NC DPI course codes. The three levels are honors-level (last digit 5), college-level (last digit 7, corresponding to an AP course, or 8, corresponding to an IB course), and standard-level (all other courses).

I define a high school classroom as the combination of school identifier, academic year, course code, academic term (semester, trimester, or quarter), and course section identifier.