Does Better Academic Preparation Predict Teacher Workforce Outcomes?

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Abstract

We link comprehensive student data on university applications and transcripts from three public universities in Washington to teacher workforce entry, effectiveness (measured by value added), and retention. We find that SAT scores are not strongly related to any of these outcomes, but college students with higher university GPAs are more likely to become teachers, and those who enter the workforce with higher GPAs are more effective as measured by math and English language arts (ELA) value-added. These findings are robust to sample selection adjustments and to checks for selection into different college courses, school districts, and out of the teacher workforce. The relationship between GPA and teacher effectiveness is driven largely by grades in math courses designed specifically for teachers. Performance in regular math courses does not predict effectiveness or retention. However, we find that teachers who take at least one advanced math course (400-level or higher) are more effective in both math and ELA than those who do not. Finally, teachers who expressed interest in education at the time of university application are more likely to remain in the workforce once they enter than those who did not. Together, these results suggest that information from college applications and transcripts carries meaningful signals about future teacher effectiveness and retention.

1. Introduction

Academic achievement is the principal screen through which the United States regulates entry into teaching. Teacher preparation programs commonly impose minimum grade point average (GPA) thresholds for admission (Council for the Accreditation of Educator Preparation, 2022); state licensure regimes require specified coursework and passing scores on one or more basic skills, subject matter, or pedagogical examinations (Goldhaber, 2025); and federal and state scholarship programs condition financial support on maintaining strong college grades in exchange for a commitment to teach. Each of these instruments treats college academic performance as a proxy for future classroom effectiveness. However, whether it is a valid one is largely untested.

The stakes are high, because teachers are widely considered the most important resource in schools (Goldhaber, 2016; Backes et al., 2025), meaningfully affecting both short- and long-run student outcomes on test- and non-test-based measures (e.g., Aaronson et al., 2007; Chetty et al., 2014b; Jackson, 2018; Kraft, 2019; Backes et al., 2024). Screening on an uninformative margin is costly in both directions: it deters candidates who would have been effective, and it admits candidates who will not be. Calls to raise the academic bar for entry have nonetheless proceeded largely without evidence on whether the bar measures the right thing. Some scholars and policymakers argue that the U.S. system would benefit from more selective entry and earlier identification of top academic talent (e.g., Darling-Hammond & Rothman, 2011), and the absence of rigorous selection in teacher preparation and recruitment is itself identified as a lever for improving workforce quality (Goldhaber, 2019). Whether tightening academic standards would improve the workforce remains an open question.

The evidence gap reflects a data constraint more than a lack of interest. Answering the question requires linking individual college transcripts to later employment records and student achievement. The few studies that observe any preservice measure have been limited largely to admissions test scores and credit totals (Harris & Sass, 2011). What a candidate studied, and how well, has not previously been observed at scale for a cohort that can then be followed into classrooms.

We assemble longitudinal administrative data from three large public universities in Washington and link complete undergraduate records—course-by-course grades, credits, and major—to state data on licensure, teaching employment, and student achievement. The linked panel follows 113,287 college graduates from college application through workforce entry and observes classroom productivity (value-added) for 801 (math) and 851 (ELA) teachers who teach in tested grades and subjects for cohorts entering teaching between 2009–10 and 2021–22. We examine three outcomes: entry into the Washington public school teaching workforce, in-service effectiveness measured by value added in tested grades and subjects, and year-to-year attrition from teaching.

Entry into teaching is strongly predicted by demographics. Consistent with the sparse literature that includes preservice measures, female and White graduates are significantly more likely to become teachers, as are students who expressed an interest in education at the time of college application. Academic performance also predicts entry: credit accumulation and cumulative GPA are both positively related to the probability of teaching, and the GPA relationship is strongest for grades earned in pedagogy coursework.

Turning to teacher productivity (measured by value added), we find little evidence that SAT scores or total credits earned toward the BA predict teacher effectiveness, reinforcing existing concerns about the informational content of these preparation metrics (Harris & Sass, 2011). By contrast, cumulative college GPA—a measure not previously examined in this literature—is a significant positive predictor of value added in both mathematics and ELA: a one-point increase in GPA is associated with an increase in teacher value added of 0.10 and 0.07 student standard deviations, respectively. This represents about a 0.02-0.03 increase in student achievement associated with a 1 SD increase in teacher GPA. Decomposing GPA by course type, we find the relationship is driven by performance in pedagogy courses designed specifically for prospective teachers, and by mathematics pedagogy courses in particular. GPA in general coursework carries little additional predictive content once pedagogy grades are controlled for.

The principal threat to a causal interpretation of these estimates is nonrandom selection into teaching: value added is observed only for graduates who choose to teach and are hired, and the traits that raise GPA may also govern that choice. We address this with a Heckman selection model, instrumenting entry with the number of teacher openings at an individual's student-teaching school in the year after student teaching occurred. The identifying assumption is that job availability at the placement school shifts whether a candidate enters teaching but does not affect effectiveness conditional on entry. Openings are a strong predictor of entry in the first stage, and the GPA estimates are unchanged under the selection correction.

Three further checks address nonrandom sorting of teachers into courses, across districts, and out of the profession: we standardize grades within course before constructing GPA, add district fixed effects, and restrict the sample to teachers who do not attrit. The positive relationship between college GPA and value added persists in all three, indicating that it is not an artifact of coursetaking patterns, teacher placement, or differential survival in the profession.

Preservice preparation is, with one exception, weakly related to retention. Consistent with prior research using broader academic ability measures (Nguyen et al., 2020), most preservice variables (including GPA) are not strongly linked to year-to-year retention. The exception is expressed interest in education at the time of college application. Teachers who indicated an early interest in education are 1.0 to 1.2 percentage points less likely to leave in a given year, a reduction of roughly 12 to 15 percent against a baseline annual attrition rate of about 8%.

Taken together, these results refine rather than validate the case for academic screening. The component of college performance that predicts downstream instructional quality is not general academic ability, as proxied by admissions tests or credits earned, but performance in the pedagogical coursework that preparation programs themselves deliver. This is, to our knowledge, the first large-scale evidence that how well candidates perform in teacher preparation—and in mathematics pedagogy in particular—carries information about their later effectiveness in the classroom. The policy implication is that GPA thresholds and test-score screens are blunt proxies for a signal that preparation programs already generate and are positioned to measure directly.

The remainder of the paper proceeds as follows. Section 2 situates the paper in the literature on teacher quality and selection into teaching. Section 3 describes the data and record linkage. Section 4 sets out the empirical strategy. Section 5 presents results for entry, effectiveness, and attrition. Section 6 concludes.

2. Background

This section reviews three strands of literature related to entry into the public school teaching workforce, teacher effectiveness, and teacher attrition. Evidence on the predictors of entry into teaching remains limited, largely due to data constraints. By contrast, considerably more is known about the characteristics and credentials associated with teacher effectiveness and attrition. However, most of this evidence draws on administrative data covering in-service teachers, and so tells us little about what teachers studied, how they performed academically, or where they trained.[1] A handful of other studies touch on related questions, though none does so comprehensively.

We start with teacher workforce entry, where the evidence is thinnest. Data linking job choices with detailed college records has historically been limited, so much of the evidence about the choices of individuals pursuing a teaching career comes from surveys, such as the National Survey of Recent College Graduates or the Baccalaureate and Beyond study. Most studies find negative associations between college entrance exams (i.e., the SAT or the ACT) and the likelihood of pursuing a path into teaching. College-bound high school seniors who report an interest or intention to major in education score lower on college entrance exams than their peers that do not express an interest in education (Gitomer et al., 1999; Goldhaber et al., 2025); those who enroll in colleges of education have lower scores on entrance exams (Henke et al., 2000; Henke et al., 1996); and college graduates with higher exam scores are less likely to become teachers (Bacolod, 2007; Goldhaber and Liu, 2003; Hanushek & Pace, 1995; Henke et al., 1996; Hoxby & Leigh, 2004; Lakdawalla, 2001).[2]

More recently, Bartanen et al. (2025) use Common Application data to examine differences in initial interest in teaching across time and student characteristics. They find that men, students of color, and higher-achieving students (on college entrance exams) are considerably less likely to express interest in teaching than their counterparts, and they document a gradual but meaningful decline in interest from 2014 to 2025. Notably, the Common Application data allow comparison to related professions such as nursing and social work, and they find that racial and ethnic gaps in interest are larger in teaching than in those fields.

[1] A notable exception is Harris & Sass (2011), who examine college coursework directly (we discuss their findings in more detail below).
[2] Goldhaber and Liu (2003) also find that college majors considering teaching are less likely to have higher income parents, be male, or have majored in a STEM subject.

Goldhaber et al. (2025) use data from three large public universities in Washington to track whether students who expressed interest in teaching at college application follow through by applying to a teacher education program (TEP). Female, White, and lower-SAT students are substantially more likely to express initial interest in education, but only about a third of students who enter college intending to teach actually apply to a teacher education program (TEP) within four years. Even holding initial expressed interest constant, the same demographic characteristics continue to predict TEP application, suggesting the teacher pipeline does not simply sort on initial interest, but reinforces existing demographic patterns throughout the early college years.

There is also some evidence of changes over time in the academic caliber of those who enter the teaching workforce. Corcoran, Evans, and Schwab (2004) document a decline in the academic aptitude of entering teachers over the latter half of the 20th century, attributing it largely to the expansion of labor market opportunities for women. More recent evidence, however, suggests this trend has reversed. Goldhaber and Walch (2014) find that STEM majors and higher-scoring college graduates were more likely to become teachers in 2008 than in the early 1990s, and Lankford et al. (2014) document a steady increase in the academic ability of both certified and entering teachers in New York State since 1999—gains that were widespread and substantially narrowed differences in teacher academic ability across school poverty levels and racial groups.

A much larger set of studies use administrative data to assess the extent to which different characteristics and teacher credentials predict teacher contributions to “value-added” (used interchangeably with “effectiveness” and “student achievement” or “performance”, and described in more detail below). There is broad consensus in this literature that teacher experience is strongly predictive of value-added (e.g., Papay and Kraft, 2015; Rivkin et al., 2005;

Rockoff, 2004), but far less consistent evidence about whether other teacher credentials, such as having a master's degree or a credential from the National Board for Professional Teaching Standards is linked to effectiveness (e.g., Backes et al., 2025; Goldhaber and Anthony, 2007; Harris and Sass, 2009).

A common interpretation of the research literature linking teacher characteristics to student achievement is that readily quantifiable characteristics of teachers, such as their experience, education, and other credentials, explains only a small portion of the variation in teacher effectiveness (e.g., Goldhaber, 2002; Hanushek and Rivkin, 2010; Rivkin et al., 2005). Importantly, however, a limitation of most of the literature is the reliance on state or district administrative data that tends to include only a limited amount of information about preservice teachers.[3]

A primary source of preservice information about teachers' academic performance comes from state licensure tests, which prospective teachers are required to pass to be eligible to teach in most states. A substantial body of evidence finds a positive relationship between how well prospective teachers perform on licensure exams and how effective they are at raising student test scores, particularly in math (e.g., Clotfelter et al., 2007; Cowan et al., 2023; Goldhaber, 2007; Goldhaber et al., 2017).[4] Licensure tests differ across states, and states often require prospective teachers to pass multiple tests; however, not all studies find significant relationships, even across the multiple licensure tests required within a single state.[5] Taken together, the evidence suggests that while licensure tests are a meaningful signal of future teaching quality,

[3] Typically, this information is connected to teacher pay (e.g., degree and experience levels) or characteristics that are used for public reporting.
[4] A recent review (Putnam and Walsh, 2021) finds that stronger performance on licensure exams predicts greater student test score gains in 11 out of 15 studies reviewed.
[5] Both Goldhaber et al. (2017) and Orellana and Winters (2025), for instance, find that the predictive power of licensure tests varies considerably across subjects.

their predictive power varies considerably depending on the specific test, subject area, and grade level involved.

Rockoff et al. (2011) examine whether more comprehensive background information about teachers is more predictive of teacher effectiveness. They administered an in-depth survey to new elementary and middle school math teachers in New York City and collected measures of cognitive ability and content knowledge (e.g., undergraduate major, institutional selectivity, college entrance exam scores, and licensure test scores), personality traits (the Big Five Inventory), beliefs about ability to influence student learning, and performance on a commercial teacher selection instrument (the Haberman Star Teacher PreScreener). The authors found only modest and marginally significant relationships between most of these individual predictors and student achievement; collectively, however, the covariates explained approximately 12 percent of the variation in teacher quality, a figure substantially higher than the roughly 3 percent explained in studies relying solely on the teacher characteristics and credentials available from administrative data (Goldhaber et al., 1999).

None of the aforementioned studies include detailed information about college performance, specifically how students did in their college courses. This is a notable gap, since a natural hypothesis, dating back to Shulman (1986, 1987), is that students who have more preparation in a subject, or who demonstrate greater mastery of it, should be better prepared to teach that subject.[6] We are aware of only a few studies (Boyd et al., 2009; Harris and Sass, 2011; Monk, 1994; Monk and King, 1994) that relate refined measures of teachers' college coursetaking to the later achievement of their students. These studies focus on completed coursework rather than performance in courses, however.

[6] Hill et al. (2005) find that teachers' performance on a mathematical knowledge assessment is a significant, positive predictor of student math achievement gains in 1st and 3rd grade.

Most closely related to the work we report on below is research by Harris and Sass (2011), who draw on administrative data covering all public school students in Florida. Their study examines teacher effectiveness in both math and reading across grades 3–10 for the academic years 1999–2000 through 2004–2005. For less experienced teachers who attended Florida public universities or community colleges, the authors also incorporate college transcript data. A notable strength of this study is its fine-grained treatment of college coursework: Rather than relying on broad credential categories, Harris and Sass distinguish among undergraduate courses according to whether they emphasize content knowledge, pedagogical knowledge, or classroom practices—a level of specificity that exceeds prior work in this area. Despite this granularity, the study finds little evidence that more college coursework predicts greater teacher effectiveness in math or reading at the elementary level.[7] Indeed, the study concludes, "We find almost no evidence that specific undergraduate coursework in education affects an individual's productivity as a teacher" (p. 811).

The study by Harris and Sass (2011) arguably provides the most rigorous existing evidence linking teachers' academic preparation to subsequent workforce outcomes. However, its focus on college preparation is limited in two important respects. First, as noted above, the study measures only whether teachers completed coursework in a given subject, not how well they performed in those courses. Although completing more coursework should improve teachers' content knowledge, mastery of the material—as reflected in course grades—is likely to be a more meaningful indicator of preparation.

Second, the study does not account for selection into the teaching profession. The largely null findings across grade levels may therefore be biased if academic preparation also influences

[7] The exceptions are: 1) courses on classroom management taken by high school reading teachers; and 2) statistics credits taken by middle school math teachers.

the likelihood of entering teaching. As discussed above, the average academic ability of teachers has declined substantially since the early 1970s, coinciding with the expansion of labor market opportunities for women. If individuals in the upper tail of the academic ability distribution are systematically less likely to enter teaching, then analyses based only on variation among practicing teachers will be affected by range restriction. Moreover, estimates of the relationship between academic ability and teacher effectiveness may be further attenuated if teachers with lower measured academic ability possess unobserved characteristics that both increase their likelihood of entering the profession and enhance their classroom performance.

While there is an extensive literature linking inservice teacher attributes and credentials to attrition,[8] the evidence linking teacher *preservice* preparation is less robust. Existing studies generally find that a teacher's pathway into the profession is predictive of later attrition, with teachers who are fully and traditionally credentialed (as opposed to have an alternative or emergency teaching license) tending to have lower attrition (e.g., Boyd et al., 2006; Guthery et al., 2022).[9] More closely related to our work, evidence consistently finds that individuals with better academic ability—measured by attributes such as college entrance exams, the institutional selectivity of colleges, and licensure test scores—have higher levels of teacher attrition (Murnane et al., 1991; Murnane and Olsen, 1990; Podgursky, Monroe & Watson, 2004). This finding is generally attributed to those with stronger academic credentials having higher opportunity costs in teaching given that stronger candidates have access to more lucrative alternative careers (Bacolod, 2007; Dolton et al., 1999; Flyer and Rosen, 1997; Goldhaber and Player, 2011; Stinebrickner, 1998). This is also thought to be a reason that teachers with science

[8] For a review, see Nguyen et al. (2020).
[9] In an investigation of components of teacher education, Ronfeldt and Reininger (2012) find that while the duration of student teaching is not strongly related to attrition, measures of the quality of student teaching (e.g., the instructional effectiveness of the mentor teacher) do predict attrition.

and math backgrounds have higher attrition rates (Feng, 2014; Harris and Adams, 2007; Ingersoll, 2001).

As is the case for the literature on teacher effectiveness, there is limited research directly examining whether academic performance in college coursework (e.g., grades in specific subject-area courses) predicts subsequent teacher attrition. The existing literature instead tends to rely on broader proxies for academic ability, such as licensure test scores, standardized entrance exams, or institutional selectivity, with comparatively little attention to detailed transcript-based measures of undergraduate academic performance. As we describe below, the detailed transcript data we utilize allow us to address this gap in the literature.

3. Data and Measures of Academic Preparation and Performance

This analysis uses student-level application data from three public universities in Washington, referred to here as University 1, University 2, and University 3. Collectively, these universities supply about 20% of new teachers educated in Washington (Title II, 2022). University 1 provided data on undergraduate university applicants for students beginning in 2014 (with application data going back further for students enrolled in 2014), and Universities 2 and 3 provided these data back to 2008. These universities also provided data on student teaching experiences, including the year and school in which student teaching occurred.[10] The application data capture demographic (i.e., gender and race/ethnicity) and academic (i.e., ACT and SAT scores) information. Because SAT scores are not required for transfer students at these universities, and the SAT data are not complete at all universities, about 37% of students have missing SAT scores. For students with missing SAT scores but non-missing ACT scores, we use

[10] In Washington, student teaching is required of all prospective teachers for licensure. We use the student teaching data in an instrumental variables model described below. For more information on the student teaching data and the role of student teaching in teacher preparation, see Goldhaber et al. (2020).

pre-2016 concordance tables to map ACT scores to SAT scores. For students who took the SAT after the SAT test change in 2016, we use SAT concordance tables so that all scores are interpretable as pre-2015 SAT measures. Students that still have missing SAT scores are imputed with the mean SAT score at their institution. We include indicators in all models for students whose SAT scores were converted from ACT scores, converted using the concordance tables, or who did not submit SAT or ACT scores.

Of particular interest is information collected at the time of university application regarding the applicant's academic interests or intended major. These measures are created somewhat differently at each university. At University 1, we combine information from an academic interest survey with an "intended major" field within the applications to code all academic interests and/or intended majors that fall within education. At University 2, the application includes an "academic plan" that we use to identify students interested in education. At University 3, the application includes an "intended major" field that can be used to identify education fields. Applications to University 3 allow students to select up to two intended majors. To be consistent with the two other universities, we randomly select one of these intended majors and consider a student to have an education interest if they select an education field in the randomly selected response. Overall, 7.3% of students were interested in teacher education at the time of university application, ranging from about 3% at University 2 to over 12% at University 1.[11]

We focus on individuals who obtained degrees from the three universities by 2020-21 (whether they become teachers or not) and link graduates to two other datasets crucial to our

[11] The proportion expressing interest in education is roughly equivalent to the proportion graduating with an education degree (Goldhaber et al., 2025) from these universities. It is also roughly in line with national evidence on the share of university enrollment and degree production nationally (NCES, 2024).

analyses: data on teachers and students provided by Washington's Office of Superintendent of Public Instruction (OSPI) and the Education Research and Data Center (ERDC).[12] OSPI provided information on students and teachers necessary to estimate teacher value-added (described below),[13] and ERDC linked the data and provided college transcript records for all students.

The OSPI data include information on all K-12 teachers between 2009–10 and 2021–22, allowing us to observe hiring and retention outcomes; the data also include teachers' subject endorsement areas, which we include as controls in all models. For a subset of teachers who can be linked to student test scores, we calculate value-added measures of teacher effectiveness (described in more detail below). The OSPI data include annual student test scores (for Grades 3–8) in math and English Language Arts (ELA) as well as student demographic and program participation data for all K–12 students in the state. The state's CEDARS data system allows students to be linked to their classroom teachers through unique course IDs.[14]

We estimate value-added models in math and ELA, which require student-teacher links and both current- and prior-year test scores. Because Washington suspended regular standardized testing during the 2019–20 and 2020–21 school years, we lack the prior-year scores needed to estimate value-added in 2020–21 or 2021–22, and our value-added sample is correspondingly limited to teachers who taught self-contained classes in Grades 4–5 or math/ELA in Grades 6–8 between 2009–10 and 2018–19. Our analysis of teacher hiring includes all teachers hired through

[12] ERDC maintains the state's P–20 longitudinal data warehouse that includes statewide longitudinal de-identified data about people's preschool, educational, and workforce experiences.
[13] Note that Washington does not collect teacher observation ratings (referred to as in Washington as TPEP ratings) at the individual teacher level, so it is not possible to use these as a measure of inservice teacher performance.
[14] CEDARS data include fields designed to link students to their individual teachers, based on reported schedules. However, limitations of reporting standards and practices across the state may result in ambiguities or inaccuracies around these links.

2021–22, while our analysis of teacher retention includes all teachers hired through 2020–21 (using 2021–22 to assess retention).

We use college transcript data to create measures of college preparation and performance. The college transcripts include information on coursetaking and grades in courses throughout college, along with six-digit Classification of Instructional Programs (CIP) codes, a standardized taxonomic system used to categorize and track fields of study and instructional programs offered at postsecondary institutions.[15]

We use CIP codes to organize courses into ten different categories. The categories most relevant to our analysis are math courses for teachers (defined as any math course offered in an education school and any course in a math department specifically identified as being "for teachers" in the course title), regular math courses (i.e., all other courses offered by math departments), equivalent sets of courses for science, and education pedagogy courses (i.e., all other courses offered in colleges of education). We then follow Goldhaber et al. (2025) and categorize all other courses into five areas following the Survey of Earned Doctorates: Other STEM, Business, Psychology/Social Sciences, Humanities, and Other Courses. For each student we calculate the number of credits the student earned within each of these areas and their GPA in these courses.[16]

We use Bachelors (BA) and Masters (MA) graduation years to identify courses that were taken as part of each student's BA and MA coursework and create separate coursetaking measures for each of the ten coursework categories. Thus, teachers who enter the workforce with

[15] For more on CIP codes, see: https://nces.ed.gov/ipeds/cipcode/Default.aspx?y=56.
[16] The transcripts also list the level of the courses that students take: 100-level courses tend to be introductory courses that do not require prerequisites; 200-level courses tend to be intermediate in terms of skill requirements and often do have prerequisites; and 300+-level courses are focused topics that generally cater to majors in a discipline. We use these measures in supplementary analyses.

only a BA degree have only BA coursetaking data, while teachers who enter the workforce with both a BA and MA degree have both types of coursework. Importantly, we ignore courses taken *after* entering the teacher workforce because teachers that choose to take additional coursework as a teacher may differ systematically from teachers that do not.[17] As shown in **Figure 1**, the median student takes the required 180 credits to get a BA degree, but the distribution of credits has some spread below this median (likely students transferring credits from institutions not submitting transcript records to ERDC) and above this median (students who took more credits than required for graduation), and the upper end of the distribution is higher when we consider all students including those who took MA coursework.

A final data issue is that, because the coursetaking data only go back to 2005-06, some students in the earliest years of data may have left-censored coursetaking data (e.g., if they took courses at a community college prior to entering one of these universities in years before we have coursetaking data). We account for this by including application year and graduation year effects in all models so that students are only compared to students who both applied and graduated from these universities in the same year.

For the analysis of teacher workforce entry, we observe 113,287 students at these universities who have university application data and university coursetaking data, and who graduated by the 2020–21 school year. Of these, 3,559 are observed as teachers (3.1% of all students); this group forms the sample used for the workforce attrition analysis. For the value-added analysis, we have 1,958 individual-year observations (801 individuals) in math and 2,054 individual-year observations (851 individuals) in English language arts.

[17] There are also potentially selection issues associated with including teachers' masters courses from before they entered the workforce, but we also experiment with models omitting these courses and results are largely the same.

We only observe individuals who become teachers within the time span of our data, so there is also right censoring: some graduates who will eventually teach have not yet entered the workforce by the time we observe them. However, as we have shown in prior work (e.g., Goldhaber et al., 2014, 2022), over 90% of college graduates who we observe as teachers are seen in the workforce within three years of receiving their degree.

In **Table 1** we report the mean values across individuals for selected college preparation and performance measures for the full sample (column 1), individuals who are never observed in the teacher workforce, "nonteachers" (column 2), individuals that we observe as teachers in at least one school year, 2009–10 to 2021–22 (column 3), and teachers for whom we are able to estimate value-added in math (column 4) and value-added in ELA (column 5).[18] Stars identify whether a particular mean is significantly different from the mean for non-teachers.

Not surprisingly, college graduates who go on to become teachers (hired teachers) differ substantially from non-teachers. They are, for instance, far more likely to have indicated an interest in education upon entering college (nearly 60%) than those we never observe as teachers (6%). Consistent with national evidence (NCES, 2023), graduates we observe as teachers are also far more likely to be female (81%) and White (79%) than non-teachers (55% female and 69% White). Teachers in general tend to have lower SAT scores than non-teachers (among those reporting SAT scores), by about 23 points, though SAT scores for teachers in the value-added samples (columns 4 and 5) are comparable to those of non-teachers. Teachers are also more likely to complete a master's program; however, only about 15% of teachers in our sample entered teaching with an MA, while the rest entered the workforce with only a BA.

[18] In each subject, we can calculate value-added for about 22 percent of those individuals we observe in the workforce.

There are also significant differences in the coursetaking patterns for individuals who are observed in the teacher workforce versus those who are never observed as teachers (we aggregate courses for display purposes). Not surprisingly, teachers complete more education-focused courses—about 3 times as many credits as non-teachers. But we also see interesting variation in content area coursetaking. For instance, the total number of math credits for teachers, 26.3, is higher than the total math credits for non-teachers, 25.1, though there may be significant differences in the content of those courses as nonteachers take more math credits in the math department that are *not* geared toward teachers compared to teachers (15.0 vs. 13.1). The general pattern of divergence in terms of where content courses are taken holds for science and other content courses as well.[19]

Teachers have notably higher average BA level GPAs than non-teachers—3.55 versus 3.29 on the 4.0 scale. This represents a difference of about 0.65 SDs. However, this difference is greatly reduced, to about 0.10 SDs, when we compare the normalized (within institution, course, and year) GPAs of teachers and non-teachers. This suggests that most of the difference in GPAs between teachers and non-teachers is driven by the fact that teachers enroll in courses that, on average, give higher grades. This is not surprising given that GPA reflects both student performance and the grading standards of the courses in which students enroll, and there is substantial evidence that grading standards vary significantly across college departments (Hernandez-Julian and Looney, 2016; Koedel, 2011; Sabot, 1991). But it is notable that teachers have higher grades in math courses, on average, even after normalization.

Figure 2 further illustrates why accounting for differences in grade distributions across subjects may be important. The box-and-whisker plots display grade distributions for three

[19] The differences between those individuals we observe as teachers and the subset of those for whom we can estimate value-added are generally not statistically significant.

course categories—education pedagogy, math for teachers, regular math—as well as overall GPA pooled across years and all three universities. Education-focused courses show both higher average grades and more compressed distributions than their general-curriculum counterparts (we show the distributions of all other subject courses for teachers and non-teachers in **Figure 3**). These patterns motivate our decision to normalize grades within courses before calculating GPAs in some robustness checks. Below we describe this normalization procedure, along with our value-added measures.

Specifically, we create alternative GPA measures that are calculated from grades that are standardized by course, year, and university, "zGPAs". These measures can be interpreted as each student's GPA relative to other students who took the same courses in the same year at the same university. This measure accounts for differences in the mean and spread of grades across courses (i.e., the distributional differences shown in Figure 2).

Finally, a key outcome measure in this analysis is teacher value-added (VA). VA models are designed to quantify the contribution of individual teachers to student test-score gains. There is an extensive literature about whether VA represents an unbiased estimate of the effects of individual teachers (Bacher-Hicks et al., 2014; Chetty et al., 2014a; Jackson, 2014; Kane & Staiger, 2008; Kane et al., 2013; Rothstein, 2010, 2014). Evidence on the unbiasedness of value-added estimates is generally stronger for math than for ELA/reading. Quasi-experimental validation using teacher switching as a source of identifying variation finds little evidence of bias in either subject (Chetty, Friedman, & Rockoff, 2014a). Math VA estimates tend to be more stable across years and specifications and are more strongly correlated with observational measures of teaching quality.[20]

[20] This likely reflects the more classroom-bound nature of math skill production relative to reading, which may be more influenced by out-of-school factors.

Due to the structure of our data sharing agreements, we estimated teacher value-added for every teacher in the state in tested grades and subjects in each school year *prior to* sending the data to ERDC for matching with the student coursetaking data. So the value-added data are at the teacher-year level and calculated from the following estimating equation predicting student achievement on Washington's standardized math and reading exams as a function of lagged student achievement, as well as other student covariates that are correlated with student test performance:

$$Y_{ijst} = \alpha_0 + \alpha_1 Y_{i(t-1)} + \alpha_2 X_{it} + VA_{jst} + \varepsilon_{ijst} \quad (1)$$

In Equation 1, Y_{ijst} is the state test score for each student i with teacher j in subject s (math or reading) and year t, normalized within grade and year; $Y_{i(t-1)}$ is a vector of the student's scores the previous year in both math and reading, also normalized within grade and year; and X_{it} is a vector of student and classroom attributes in year t (gender, race, eligibility for free or reduced-price lunch, English learner status, disability type, migrant status, and homeless status, as well as the means of these variables at the classroom level). The VA estimates, $\widehat{VA}_{jst}$, represent the contribution to student learning gains of teacher j in subject s and year t. We have validated this specification in prior work (e.g., Goldhaber et al., 2017) using tests developed by Chetty et al. (2014a).

4. Analytic Methods

The analysis estimates three sets of regression models predicting, respectively, (1) whether each student entered the K-12 teacher workforce, (2) teacher value-added in math and ELA, among those who were hired and for whom value-added estimates are available, and (3) year-to-year teacher attrition for college graduates that entered the teacher workforce. Each set of models uses a common specification, with additional covariates and extensions described below.

All primary analyses use OLS (linear probability models for binary outcomes), though the Heckman models described later use a probit in the first stage.[21] Standard errors in the teacher-outcome models are clustered at the teacher level to account for the panel structure of the data.

Workforce Entry: The workforce entry model is estimated at the college student level (one observation per student in the data). The outcome $Teach_i$ is an indicator equal to 1 if the student was subsequently employed as a K-12 teacher. The estimating equation is:

$$\text{Teach}_i = \alpha + \beta_1 \text{ EduInterest}_i + \beta_2 \text{ X}_i + \beta_3 \text{ Credits}_i + \beta_4 \text{ GPA}_i + \gamma^{inst} + \delta^{yr} + \varepsilon_i \qquad (2)$$

where EduInterest indicates whether the student was interested in education at the time of university application; as noted earlier, this variable represents intended major in some universities and academic plan in other. The vector X_i contains all remaining control variables: gender and race/ethnicity indicators (reference categories: male, White); SAT score scaled to 100-point units, with separate indicators for students whose scores were imputed from ACT concordance tables and for students who took the post-2016 SAT (scaled to pre-2015 equivalents); indicators identifying if a student enrolled in their university as a transfer student, whether the student entered the workforce with a master's degree, whether the student is currently enrolled in an MA program at the time of teaching, and endorsement subject area controls. Credits is total earned credits per 10 (by subject-area category in broader specifications); GPA is the student's overall GPA (or the normalized, "zGPA," measure in extensions). Institution fixed effects (γ^{inst}) and application year and graduation year fixed effects (δ^{yr}) are included in all specifications.

Equation (2) shows the most complete specification. Three nested specifications are estimated sequentially: (1) demographics only (education interest, gender, race/ethnicity,

[21] Results for the LPM and probit models are qualitatively similar.

institution and graduation year FEs); (2) adding SAT score and transfer status; and (3) further adding total credits and overall GPA. A fourth specification replaces the overall credits and GPA summary measures with parallel credits and GPA terms for each of ten subject-area categories (Regular Math, Math for Teachers, Ed Pedagogy, Regular Science, Science for Teachers, Other STEM, Business, Psychology/Social Science, Humanities, and Other), with GPA imputed to the full-sample category mean for students with zero credits in that category. Two additional specifications further restrict the sample to students with student teaching placement data and by adding controls for the "stay ratio" (Ronfeldt, 2012) of the student teaching school and for the number of available teaching openings at the student teaching school in the following year; this latter variable becomes the instrument for the Heckman models described below.

Teacher Value-added: The value-added models are estimated on the panel of teacher-year observations for which value-added estimates are available. Separate models are estimated for math value-added (VA^{math}) and ELA value-added (VA^{ELA}). The estimating equation is:

$$VA_{it} = \alpha + \beta_1 \text{ EduInterest}_i + \beta_2 X_i + \beta_3 \text{ Credits}_i + \beta_4 \text{ GPA}_i + \beta_5 \lambda_i + \gamma^{exp} + \gamma^{inst} + \delta^{yr} + \delta^{sy} + \varepsilon_{it} \quad (3)$$

The subscript *it* indexes teacher *i* in school year *t*. EduInterest, X, Credits, and GPA are defined as in equation (2), with Credits and GPA reflecting coursetaking completed before entering the teacher workforce.[22] λ_i is the inverse Mills ratio from the Heckman selection correction (described below); it is set to zero in base specifications. Experience fixed effects (γ^{exp}) are a set of five dummies for years of teaching experience (less than 1 year is the reference category; dummies for 1 to <2, 2 to <3, 3 to <4, 4 to <5, and 5 or more years). Institution (γ^{inst}) and graduation year (δ^{yr}) fixed effects are included in all specifications. School year fixed effects

[22] One concern about the course-taking measures is that they may include many lower-level courses. In extensions, we include indicators for whether students took a course at the 400 level or above in each subject area.

(δ^{sy}) are included in value-added and attrition models to account for statewide trends in student achievement and teacher workforce conditions across years.[23]

Teacher Attrition: The attrition model is estimated on the broader teacher-year panel (i.e., not limited to teachers with observed VA), excluding the final panel year (school year 2022), for which forward-looking attrition cannot be defined. The outcome $Attrit_{it}$ is a binary indicator equal to 1 if teacher *i* is not observed in the Washington public school staffing data in school year *t*+1. The estimating equation is:

$$\text{Attrit}_{it} = \alpha + \beta_1 \text{EduInterest}_i + \beta_2 X_i + \beta_3 \text{Credits}_i + \beta_4 \text{GPA}_i + \beta_5 \lambda_i + \gamma^{exp} + \gamma^{inst} + \delta^{yr} + \delta^{sy} + \varepsilon_{it} \quad (4)$$

The structure of equation (4) is identical to equation (3). All variables are defined as before. As with the value-added models, three nested specifications are estimated: without GPA, with GPA, and with a Heckman correction using the same first-stage probit structure described above (with the selection equation now predicting having a non-missing attrition observation rather than a non-missing value-added estimate).

Heckman Selection Correction: As described above, value-added estimates and attrition outcomes are observed only for teachers who enter the workforce, raising the possibility of sample selection bias if the characteristics that predict workforce entry are also correlated with underlying teacher effectiveness or attrition. To address this, the third specification includes a Heckman selection correction. The first stage is a probit model predicting workforce entry (or entry with an observed value-added estimate) as a function of education interest, the preservice

[23] We also experiment with weighting these regressions by the inverse of the standard error of the value added estimate (i.e., so teachers with more precisely-estimated value added receive more weight) and results are extremely similar, so we present this unweighted specification for simplicity.

preparation variables defined above, the stay ratio of the student teaching school,[24] the number of available teaching openings at the student teaching school in the year *following* student teaching (our excluded instrument)[25], and experience, institution, and graduation-year fixed effects.

The identifying assumption is that, conditional on the stay ratio and the other covariates predicting workforce entry, the number of teaching openings affects value-added and attrition only through its effect on workforce entry—that is, it is otherwise unrelated to these outcomes. We test this by examining whether the number of teaching openings is correlated with pre-employment characteristics of student teachers (e.g., SAT scores) and the schools in which student teaching is occurring (e.g., free- or reduced-price lunch percentage of students), after conditioning on the stay ratio and other covariates in the selection equation. We find limited evidence of such relationships, consistent with openings affecting workforce entry without independently predicting teacher effectiveness or reflecting differences in school context.[26]

Additional Robustness Checks: In addition to sample selection bias, we are concerned with three additional sources of bias due to non-random sorting across college courses, non-random sorting across hiring districts, and non-random selection out of the teacher workforce (attrition). Three sets of robustness checks are reported in appendix tables that are designed to address each of these concerns. First, **Tables A1** and **A2** replace the raw overall GPA with a within-institution, within-course, within-year standardized GPA (zGPA), which adjusts for cross-institutional and cross-cohort differences in grading standards. These normalized GPA measures

[24] As shown in Ronfeldt (2012), the school stay ratio also proxies for otherwise unobservable characteristics of the student teaching school, such as teachers' perceptions of working conditions.

[25] Only 6 percent of student teachers are at a school with no openings the following year, but there is reasonable spread with the median being 4 openings and the quartiles of the distribution as 2 and 6, respectively.

[26] Specifically, while a small number of coefficients were statistically significant (e.g., male candidates and candidates in a MA program were more likely to student teach in a school with more openings), only 10-15% of coefficients were statistically significant in this specification, suggesting that school openings did not vary systematically across different candidates along observed dimensions.

are designed to address concerns about differences in grading standards across college courses. Second, **Tables A3** and **A4** add district fixed effects to all three specifications, providing a within-district comparison that absorbs any time-invariant differences across the districts where teachers are employed and address concerns about non-random sorting across hiring districts. Finally, **Tables A5** and **A6** restrict the estimation sample to each teacher's first observed school year, thus addressing concerns with non-random attrition from the workforce because every teacher is observed exactly once in these specifications.

5. Results

We begin with models (**Table 2**) predicting whether college graduates enter the teacher labor market by the end of the observed time panel.[27] An important caveat is that we observe only teachers who are employed when individual and school district preferences align (Boyd et al., 2013); we cannot determine whether the college graduates we do not observe as teachers chose not to pursue teaching, or instead sought a public school teaching position but were not hired in Washington.

We then present findings for the subgroup of individuals for whom we have student teaching records, which we draw on in models addressing sample selection concerns in our analyses of the relationship between college preparation and both teacher value-added (**Table 3**) and attrition (**Table 4**). We conclude the section with robustness checks and supplementary analyses.

Teacher Workforce Entry

Table 2 reports marginal effect estimates from linear probability models predicting public school teacher workforce entry. Column 1 presents a sparse specification including individual

[27] We estimate linear probability models throughout; logit specifications yield substantively similar results.

demographic characteristics, SAT scores (and an indicator for whether these scores were imputed from the ACT/new SAT or missing), and applicants' expressed interest in an education career at the time of college application. All models in the table also include indicators for whether individuals transferred from community colleges into the university sample ("transfer"), as well as cohort, year, and university fixed effects.

White (the omitted comparison category) and female graduates are significantly more likely to enter the public school teacher labor market, consistent with patterns in both teacher credential attainment and the broader teacher workforce (Goldhaber et al., 2025). The magnitudes of these differentials are large. For example, females are about 1.8 percentage points more likely to be observed as teachers, which is nearly 70% over the 3.1% baseline rate of college graduates in our sample observed in the teacher labor market.

As expected, expressing an interest in education at the time of college application is strongly predictive of subsequent teacher labor market entry, increasing the probability by over 20 percentage points.[28] Perhaps more surprising—given the widespread perception that teachers are disproportionately drawn from the lower end of the SAT distribution (Auguste et al., 2010)—is that an individual's SAT score is only weakly predictive of workforce entry across all students (a 100-point increase only decreases the probability of becoming a teacher by 0.1 percentage points), and is not a statistically significant predictor of teacher labor market entry once we control for coursetaking (in column 3) or limit to students who at least completed student teaching (in columns 5 and 6).

When we add overall measures of college credits and GPA to the model in column 2, students who take more credits and students with higher GPAs are more likely to become

[28] We also experiment with specifications that exclude the reported interest in education variable. The coefficients from these models are qualitatively similar.

teachers. When we further add controls for credits and GPA by subject area (column 3), the coefficient on the initial interest variable diminishes substantially, and many of the individual demographic indicators are no longer significant. This is not surprising: students with more interest in teaching take substantially different courses than those without it. Indeed, coursework focused on teaching, both pedagogical courses and content courses designated for future teachers, is highly predictive of teacher workforce entry.

In column 4 we limit the sample to individuals observed as completing student teaching. Among these students, almost none of the demographic measures (with the notable exception of Asian students, who are less likely to become teachers) are significant, suggesting that much of the sorting by gender and race/ethnicity occurs before the point of student teaching.

Finally, we add the number of teacher openings in an individual's student teaching school the school year after student teaching occurred (the instrument we use in the Heckman model) in column 5. The coefficient represents the estimated effect of one more opening on the likelihood of observing an individual as a teacher in math or in ELA. The significant estimate suggests that each additional job opening in the student teaching school increases the likelihood of student teachers being observed as teachers by about .5 percentage points. This is approximately a 1 percent increase in the baseline value (65%) of observing a student teacher employed as a public school teacher in Washington in our sample period, consistent with prior work (Goldhaber et al., 2017).[29]

Value-added Estimates

[29] The specification in column 5 of Table 2, estimated as a probit, is the first-stage of the Heckman selection models used to predict teacher attrition in Table 4. The first stage of the Heckman selection models predicting teacher value added predicts selection into the teacher value-added sample; the coefficient on teacher openings in these specifications is similar to the overall sample (beta = .003) but not statistically significant.

Table 3 reports teacher value-added results for math (columns 1–3) and ELA (columns 4–6); coefficients represent estimated effects of teacher characteristics and preparation on value-added, measured in student-level standard deviations. We proceed in steps. Columns 1 and 4 replicate sparse models from the existing literature linking teacher experience (not reported in the table) and coursetaking to student achievement. Columns 2 and 5 add novel information on college performance. Columns 3 and 6 present specifications that correct for sample selection.[30]

Consistent with Harris and Sass (2011), we find no statistically significant evidence that teacher effectiveness is associated with SAT scores. We can rule out effects as large as 1.2% of a student-level SD of test performance associated with a 100-point increase in SAT scores.[31] Nor do we find evidence that value-added is positively associated with the number of credits completed in any content area. Indeed, total credits completed has a negative relationship with math value-added, perhaps reflecting that students who take longer to complete college are less effective teachers on average.[32] Interestingly, we also do not find evidence that interest in education at the time of university application is a significant predictor of value-added. Finally, consistent with a large literature on the value of a teacher's master's degree (Backes, 2025), we find no evidence that holding an MA is positively predictive of teacher effectiveness. We include separate indicators for teachers who enter the profession with an MA and those who obtain one

[30] While not reported in Table 3, we find consistent evidence across specifications that teacher experience matters. In math, students assigned to teachers with 1–2 years of experience, relative to those assigned to novice teachers, have achievement that is 0.05 to 0.06 student-level SDs higher; ELA findings are similar, with student achievement 0.04–0.06 SDs higher. These estimates are quite similar to those of Harris and Sass (2011), who find returns to experience of 0.03 to 0.06 SDs for the first few years of teaching.
[31] The coefficient on an indicator for whether students submitted an SAT score to college was also not statistically significant (not reported).
[32] Recall from Table 1 and Figure 1 that there is substantial variation in credits; the SD across the whole sample is nearly 50.

after entry.[33] Regardless, teachers with an MA are not more effective than those holding a BA only.

When we add novel information about college GPA, we find consistent evidence that GPA is a statistically significant positive predictor of teacher effectiveness in both math and ELA (columns 2 and 5). A 1.0 scale-score increase in overall college GPA is associated with a 0.10 standard deviation (SD) increase in math value-added ($p < 0.01$) and a 0.07 SD increase in ELA value-added ($p < 0.01$). Given the standard deviations shown in Table 1, these equate to .02-.03 increases in value added associated with a 1 SD increase in GPA. These findings are similar when using the normalized GPA measures in place of raw GPA (see Appendix Tables A1 and A2), suggesting that the result is not an artifact of cross-course variation in grading standards.[34]

Finally, in Heckman sample selection correction models for math (column 3) and ELA (column 6), there is little change in magnitudes of the coefficients. This is not surprising given that the inverse Mills ratio is statistically insignificant in both models, suggesting that selection into the analytic sample is uncorrelated with unobserved determinants of value added and that sample selection bias is unlikely to affect the primary estimates.

Teacher Attrition

Table 4 reports marginal effect estimates from attrition models. The specifications parallel those in Table 3 for value-added. We find that few preservice preparation variables predict year-to-year teacher attrition. The notable exception is expressed interest in education at

[33] Relative to BA-only holders, the effectiveness of teachers who enter with an MA is given by the sum of the "entered with an MA" and "obtained an MA" coefficients; the effectiveness of teachers who obtain an MA after workforce entry is given by the "obtained an MA" coefficient alone.

[34] This coefficient is not significantly different for elementary and middle school teachers or for teachers that entered the workforce with a BA or an MA.

the time of college application. Teachers who indicated an interest in education when applying to college are 1.0 to 1.2 percentage points less likely to leave the teaching workforce in a given year, a meaningful reduction given typical annual attrition rates (about 8% per year). The direction of this finding is consistent with prior research linking early career commitment signals to longer teaching careers (Nguyen et al., 2020). By contrast, neither college GPA nor total credits completed are significantly related to attrition, suggesting (perhaps surprisingly) that changes in the measures of academic preparation that predict teacher effectiveness do not translate into greater retention. SAT scores and entry degree are also not significant predictors of attrition across specifications.

Robustness and Heterogeneity Checks

We further explore the positive findings on GPA by disaggregating GPA across different subject areas, focusing on four areas most plausibly related to teaching effectiveness and attrition: regular math, math for teachers, educational pedagogy, and humanities. We plot the relationship between GPAs in each subject and math value added (Figure 4), ELA value-added (Figure 5), and attrition (Figure 6) following the procedure described in Section 4.

For value-added, GPA in math for teachers courses is positively related with value-added in both math *and*, surprisingly, ELA (see also the linear specification in Appendix Table A7).[35] For retention, GPA in educational pedagogy—despite having a relatively limited range of observed GPAs as shown in Figure 2—is a significant predictor of lower attrition rates.

As noted above, selection into the teacher workforce is a primary concern when estimating the relationship between preservice teacher variables and teacher value-added, something we address through the Heckman models. Three additional sources of bias, however,

[35] These results are robust to specifications that control for student GPA in all ten subject areas defined in Section 3.

warrant attention. The first is nonrandom sorting of students into courses, which we address by replacing GPA measures with the standard normalized GPA measures described previously (Appendix Tables A1-A2). As noted earlier, the mainline findings are unchanged when we use the standardized GPA measure, suggesting that student sorting across courses is not biasing our findings.

The second potential source of bias is nonrandom sorting of teachers into jobs, whereby unobserved attributes of colleagues (e.g., Jackson and Bruegmann, 2009) or students may be misattributed to the value-added of teachers (Appendix Tables A3-A4). In these specifications, value added is identified from within-district variation in teacher effectiveness, and any time-invariant attributes of school districts are absorbed by the district fixed effects.[36] As reported in Appendix Tables A3 (for value-added) and A4 (for attrition), while there is some attenuation of the estimates, the primary findings remain statistically significant and positive.

The final concern is selection bias from nonrandom attrition from the teacher workforce (e.g., Goldhaber et al., 2020). We address this by limiting to first-year teachers in Appendix Tables A5 and A6. If anything, the estimated relationships between preservice variables and value-added, the GPA measures in particular, are even more predictive of value-added when we focus on first-year teacher effectiveness and retention.

Finally, we report several supplementary analyses described in Section 4 in Appendix Table A7. As suggested by Figures 3 and 4, GPA in math for teachers courses is significantly and positively predictive of value-added in both math and ELA. But while the number of regular math credits is weakly negatively predictive of math value-added (perhaps as a result of teachers who took more remedial math courses being less effective), and the GPA in these courses is not

[36] Unfortunately, our samples are too thin to enable estimation with school fixed effects.

predictive of math value-added, the indicator for whether the teacher took at least one math course at a 400 level or above is significantly predictive of value-added in both subjects. This relationship is driven by the difference between students who took a 400-level course or higher relative to students who only took 100-level courses. This suggests that the types of courses taken are important in addition to performance in these courses.

6. Discussion and Conclusions

This paper links undergraduate transcript records for graduates of three large public universities in Washington to their subsequent careers in the state's public schools. We confirm prior findings that returns to teaching experience are concentrated in the first few years and flatten quickly thereafter, and that conventional preparation metrics—SAT scores and total credits completed—have little predictive power for value-added. Our central result is that cumulative college GPA predicts value-added in both math and ELA, by .02-.03 student standard deviations per standard deviation increase in GPA, or roughly half the return to the first year of teaching experience in Washington. This relationship survives corrections for selection into the teaching workforce, nonrandom sorting across districts, and nonrandom attrition from the profession.

What GPA measures is less clear than what it predicts. One interpretation is that it serves as a proxy for teachers' general academic ability: students who are stronger academically both earn higher grades and teach more effectively, whether because grades reveal capacity that was already there (selection), or because the coursework builds it (treatment). On this reading, GPA outperforms total credits because credits index time spent in coursework rather than mastery of it. Two features of our results sit awkwardly with a purely general-ability account. First, GPA predicts effectiveness while SAT scores—a more direct measure of general academic skill—do not. This points toward the attributes grades capture and that admissions tests may not capture, such as effort, conscientiousness, self-regulation, and persistence over an extended period (a semester, a degree)—the so-called "soft skills" captured by GPA (Borghans et al., 2008; Duckworth et al., 2008). Second, our results are driven by grades in math-for-teachers courses rather than in general mathematics coursework. That is what one would expect if what preparation programs convey and grade is a specialized pedagogical content knowledge known as mathematical knowledge for teaching (MKT), which concerns not only knowledge of mathematical content but also how to represent concepts and interpret student solution methods and errors (Ball, 1990; Hill et al., 2005; Ball, Thames, & Phelps, 2008). We cannot separate these channels with the data at hand, but the joint pattern—a GPA effect, an SAT null, and concentration in math-for-teachers coursework—fits domain-specific skill and non-cognitive attributes better than general academic ability alone.

The same pattern in ELA is harder to interpret. The value-added literature has generally found smaller and less consistent teacher effects in ELA, so a robust preparation signal here is itself a new result. But no construct analogous to MKT has been developed and validated for ELA instruction, which leaves open whether GPA captures subject-specific pedagogical knowledge here or the more general capacities set aside above. Selection remains a live alternative: if students who would have been effective teachers in any subject also earn higher grades in preparation coursework, we would observe what we observe.

Several limitations bound these conclusions. Our estimates are associations, not the causal effect of raising a given candidate's GPA. The selection correction addresses entry into teaching, but grades remain a choice variable correlated with characteristics we do not observe. Effectiveness is measured only in tested grades and subjects, and only for graduates of three universities in one state, whose preparation programs may not resemble those elsewhere. And because grades are assigned at instructor discretion, variation in grading standards across programs and over time will attenuate the signal we recover.

For policy and practice, the starting point is that the literature has struggled to identify teacher preparation inputs with detectable effects on student outcomes, and that undergraduate coursework, in particular, has appeared unrelated to effectiveness (Harris & Sass, 2011). That record underpins calls for pathways into teaching that do not require formalized teacher education and for reductions in pedagogical instruction (e.g., Walsh, 2001; U.S. Department of Education, 2002; Aldeman, 2024). Our results complicate that case: a specific, already-measured feature of teacher preparation—performance in pedagogical coursework—has a robust relationship with classroom effectiveness. Our findings do not settle the debate, however, because entry requirements affect teacher supply as well as teacher quality, and the net effect on the workforce depends on both margins.

The more immediate implication is for screening. Admissions and completion standards for teacher preparation programs often incorporate academic performance thresholds (see Slavit et al., 2025), but licensure and hiring decisions make little systematic use of transcripts that districts and programs already hold. Because the GPA-value-added relationship is concentrated in math courses designed specifically for teachers, the informative screen is narrower than overall GPA. That grades carry this information at all implies that instructors observe something about teaching potential, which may be worth extracting for in-service training as much as for selection. Two cautions attach to any such use. Grades are only useful if they represent students' knowledge and skills, and there is increasing concern about grade inflation (Rojstaczer & Healy, 2012). Indeed, we show that grades in courses for future teachers are compressed toward the top of the distribution relative to other college coursework. Formalizing grades into accountability or hiring systems would place pressure on precisely the instructors whose discretion generates the signal, and a screen resting on a handful of courses concentrates that pressure further. Whether the signal survives being made a target is an open question, and one that bears directly on the design of grading standards across disciplines (Gans & Kominers, 2026).

Two questions follow directly. The first is whether the relationship we document is causal or reflects unobserved teacher characteristics that grades happen to proxy; variation in grading standards across instructors or cohorts may offer a route to identification. The second is whether building performance in math-for-teachers coursework into preparation program accountability or hiring screens improves workforce quality at scale—a question for policy experimentation rather than for more observational data.

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Tables and Figures

Table 1. Summary Statistics

Variable	Full	Non-Teachers	Hired Teachers	Math VA	ELA VA
% Education interest	7.4	5.7	58.6*	59.9*	56.1*
% Female	55.9	55.1	81.3*	81.2*	80.4*
% White	69.4	69.1	79.5*	79.5*	78.9*
% Black	2.2	2.3	0.9*	1.4	1.4
% Hispanic	9.4	9.4	8.1*	7.8	7.8
% Asian	6.0	6.1	3.0*	2.9*	3.8*
% Other race	12.9	13.1	8.5*	8.5*	8.1*
SAT score	1088	1089	1066*	1082	1079
	(150.3)	(150.6)	(138.5)	(133.5)	(140.9)
% Transfer	33.7	33.5	39.7*	44.1*	42.0*
% MA degree	4.8	4.5	14.5*	11.2*	17.3*
Credits					
BA	173.4	173.3	177.6*	172.9	170.9
	(54.8)	(54.7)	(56.7)	(58.2)	(57.4)
Regular Math	14.9	15.0	13.1*	14.9	10.0*
	(14.2)	(14.2)	(16.0)	(16.5)	(8.1)
Math for Teachers	11.3	10.1	13.2*	14.2*	13.3*
	(6.9)	(6.8)	(6.6)	(7.0)	(5.9)
Ed Pedagogy	22.2	16.3	68.1*	71.2*	69.6*
	(30.8)	(25.8)	(28.1)	(26.4)	(26.1)
GPA					
Cumulative (BA-level)	3.30	3.29	3.55*	3.58*	3.56*
	(0.40)	(0.40)	(0.29)	(0.30)	(0.30)
Regular Math	2.89	2.88	3.01*	3.06*	2.99*
	(0.74)	(0.74)	(0.74)	(0.71)	(0.75)
Math for Teachers	3.55	3.51	3.60*	3.63*	3.61*
	(0.52)	(0.56)	(0.43)	(0.42)	(0.43)
Ed Pedagogy	3.68	3.66	3.81*	3.83*	3.83*
	(0.47)	(0.50)	(0.19)	(0.18)	(0.18)
N (unique students)	**113262**	**109702**	**3560**	**800**	**848**

*Note: Columns 3-5 report * for means significantly different from Non-Teachers (column 2) at p < 0.05 (two-sided t-test). Standard deviations for continuous variables are in parentheses. SAT imputed from ACT score (pre-2016 verbal/math concordances, ACT 11-36) or from new SAT (Iowa Board of Regents concordance table) for students with missing original SAT. BA and MA credits and GPA are restricted to students with a non-missing value for that degree. GPA means for subject-area categories restricted to students with non-zero credits in the relevant category. Credits include all coursetaking (including zero for students without credits in a category).*

Table 2. Teacher Workforce Entry

	(1)	(2)	(3)	(4)	(5)
Education interest	0.225***	0.219***	0.017***	0.020	0.019
	(0.002)	(0.002)	(0.002)	(0.015)	(0.015)
Female	0.018***	0.014***	-0.002*	0.004	0.006
	(0.001)	(0.001)	(0.001)	(0.016)	(0.016)
Black	-0.014***	-0.006*	-0.004	-0.073	-0.064
	(0.003)	(0.003)	(0.003)	(0.063)	(0.063)
Hispanic	-0.005***	-0.003*	-0.005***	0.023	0.023
	(0.002)	(0.002)	(0.001)	(0.023)	(0.023)
Asian	-0.011***	-0.010***	-0.005***	-0.092***	-0.077**
	(0.002)	(0.002)	(0.002)	(0.034)	(0.034)
Other race	-0.010***	-0.008***	-0.004***	-0.040*	-0.036*
	(0.001)	(0.001)	(0.001)	(0.021)	(0.021)
MA degree	0.052***	0.043***	0.013***	0.098***	0.094***
	(0.002)	(0.002)	(0.002)	(0.020)	(0.020)
SAT score (per 100 pts)	-0.001***	-0.005***	-0.000	-0.007	-0.008
	(0.000)	(0.000)	(0.000)	(0.006)	(0.006)
BA transfer	0.007***	0.004***	0.002	0.048***	0.041**
	(0.001)	(0.001)	(0.001)	(0.017)	(0.017)
Credits at entry degree (per 10)		0.002***			
		(0.000)			
GPA at entry degree		0.045***			
		(0.001)			
Regular Math: 10 credits			0.002***	0.018***	0.017***
			(0.000)	(0.005)	(0.005)
Regular Math: GPA			-0.001*	-0.022**	-0.024**
			(0.001)	(0.011)	(0.011)
Math for Teachers: 10 credits			0.064***	0.030**	0.027**
			(0.002)	(0.012)	(0.011)
Math for Teachers: GPA			0.036***	0.028	0.023
			(0.003)	(0.019)	(0.019)
Ed Pedagogy: 10 credits			0.041***	0.013***	0.014***
			(0.000)	(0.003)	(0.003)
Ed Pedagogy: GPA			0.020***	0.141***	0.130***
			(0.002)	(0.038)	(0.038)
Humanities: 10 credits			0.001***	0.006**	0.005
			(0.000)	(0.003)	(0.003)
Humanities: GPA			0.001	-0.004	-0.008
			(0.001)	(0.018)	(0.018)
Student teaching school stay				-0.013*	-0.009
ratio				(0.007)	(0.007)
Teaching openings					0.005**
					(0.002)
N	113,281	113,281	113,281	4,811	4,811
R-Squared	0.146	0.157	0.374	0.116	0.118

*Note: Linear probability models. Outcome = employed as a K-12 teacher with positive FTE. Models (1)-(3): full student sample. Models (4)-(5): restricted to students with student teaching data. All models include institution, application year, graduation year, and endorsement area fixed effects. Reference categories: male, white, no MA degree. SAT coefficient = expected change in hiring probability per 100-point increase. SAT imputation indicators (SAT missing, imputed from ACT, imputed from new SAT) included in all models but not shown. Entry-degree GPA/credits use cumulative BA values, or cumulative MA values for students who entered with an MA. GPA/credits imputed to full-sample mean for students with a missing value. Credits and GPA for remaining subject categories (Regular Science, Science for Teachers, Other STEM, Business, Psychology/Social Sciences, Other Courses) included but not shown. * p<0.10 ** p<0.05 *** p<0.01*

Table 3. Math and ELA Teacher Value Added

	Math Value Added			ELA Value Added		
	(1)	(2)	(3)	(4)	(5)	(6)
Education interest	-0.000	-0.008	-0.008	-0.007	-0.011	-0.015
	(0.016)	(0.016)	(0.017)	(0.014)	(0.014)	(0.014)
Entered with MA	-0.071*	-0.088**	-0.078	-0.042	-0.054*	-0.053*
	(0.039)	(0.038)	(0.061)	(0.029)	(0.029)	(0.029)
Credits at entry degree (per 10)	-0.005***	-0.003*	-0.003*	-0.002	-0.001	-0.001
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
SAT score (per 100 pts)	0.004	-0.002	-0.002	0.001	-0.003	-0.001
	(0.006)	(0.006)	(0.007)	(0.006)	(0.006)	(0.006)
BA Transfer	0.028	0.024	0.022	0.012	0.010	0.018
	(0.017)	(0.017)	(0.020)	(0.015)	(0.015)	(0.016)
Currently MA degree	0.016	0.020	0.023	0.010	0.014	0.019
	(0.019)	(0.019)	(0.019)	(0.014)	(0.015)	(0.015)
GPA at entry degree		0.097***	0.092***		0.064***	0.064***
		(0.025)	(0.032)		(0.023)	(0.023)
Inverse Mills ratio			-0.031			0.072
			(0.117)			(0.084)
N	1,958	1,958	1,946	2,054	2,054	2,044
R-Squared	0.093	0.104	0.104	0.058	0.064	0.065

*Note: OLS regression. Columns 1-3: math teacher value added. Columns 4-6: ELA teacher value added. All models include experience dummies, institution, application year, endorsement area, and entry-degree graduation year fixed effects. Standard errors clustered at teacher level. Gender (female) and race/ethnicity (Black, Hispanic, Asian, other race) are included as controls but not reported; reference categories: male, white. SAT imputation indicators (SAT missing, imputed from ACT, imputed from new SAT) are included as controls but not shown. Heckman models (columns 3 and 6) include an inverse Mills ratio from a first-stage probit predicting having outcome data. * p<0.10 ** p<0.05 *** p<0.01.*

Table 4. Teacher Attrition

	(1)	(2)	(3)
Education interest	-0.008**	-0.008*	-0.007*
	(0.004)	(0.004)	(0.004)
Entered with MA	-0.009	-0.008	-0.005
	(0.008)	(0.008)	(0.008)
Credits at entry degree (per 10)	0.001	0.000	0.000
	(0.001)	(0.001)	(0.001)
SAT score (per 100 pts)	-0.000	0.000	0.001
	(0.002)	(0.002)	(0.002)
BA Transfer	-0.001	-0.001	-0.001
	(0.005)	(0.005)	(0.005)
Currently MA degree	-0.004	-0.004	-0.004
	(0.005)	(0.005)	(0.005)
GPA at entry degree		-0.006	-0.006
		(0.007)	(0.007)
Inverse Mills ratio			0.012
			(0.021)
N	18,467	18,467	18,278
R-Squared	0.017	0.017	0.017

*Note: Linear probability models. Outcome: teacher attrition (excludes syear = 2022). All models include experience dummies, institution, application year, and entry-degree graduation year fixed effects, and an indicator for having attained a master's or doctoral degree. Standard errors clustered at teacher level. Gender (female) and race/ethnicity (Black, Hispanic, Asian, other race) are included as controls but not reported; reference categories: male, white. SAT imputation indicators (SAT missing, imputed from ACT, imputed from new SAT) are included as controls but not shown. Heckman model (column 3) includes an inverse Mills ratio from a first-stage probit predicting having outcome data. Reference category: experience < 1 year. * p<0.10 ** p<0.05 *** p<0.01*

Figure 1. Distribution of Credits Earned

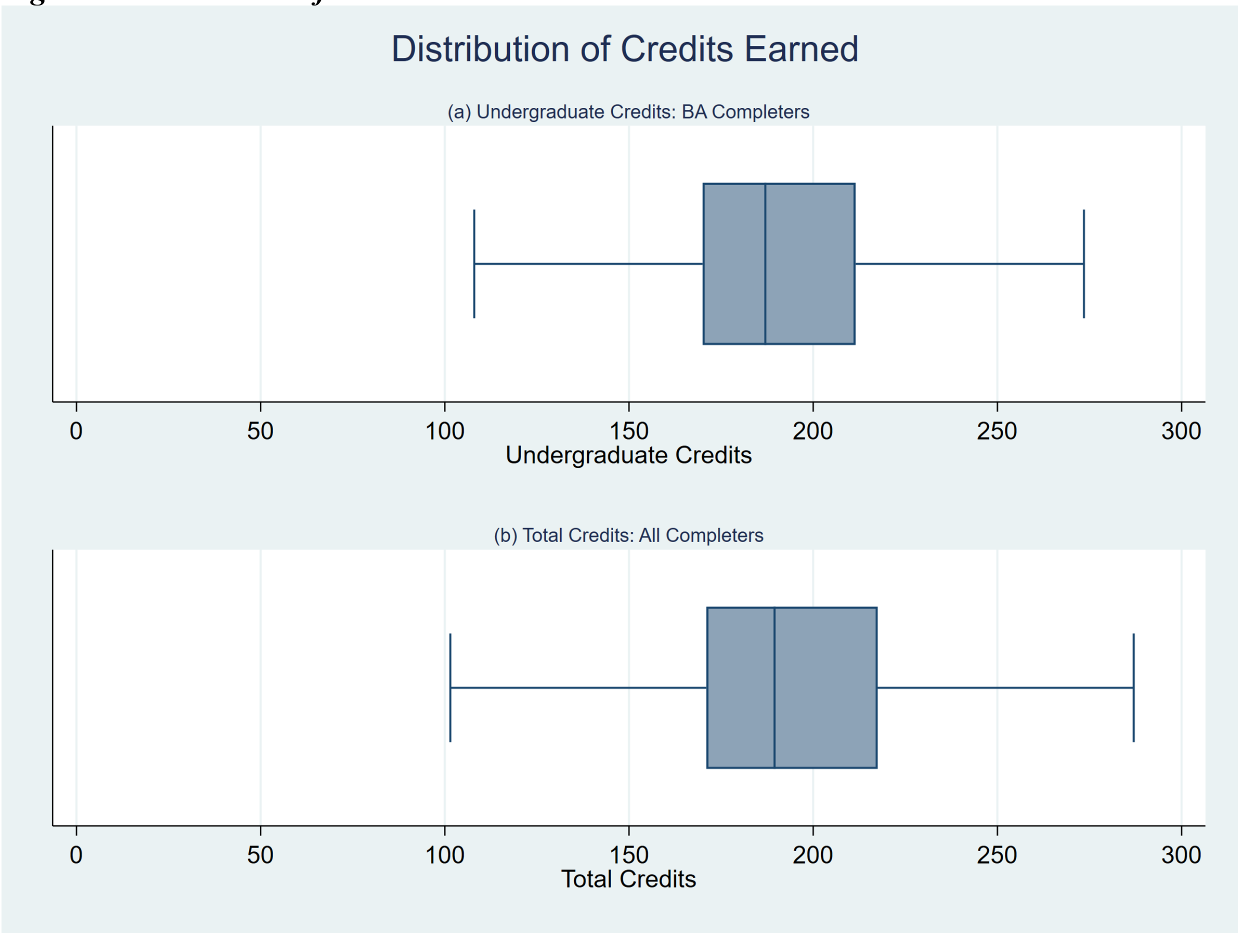
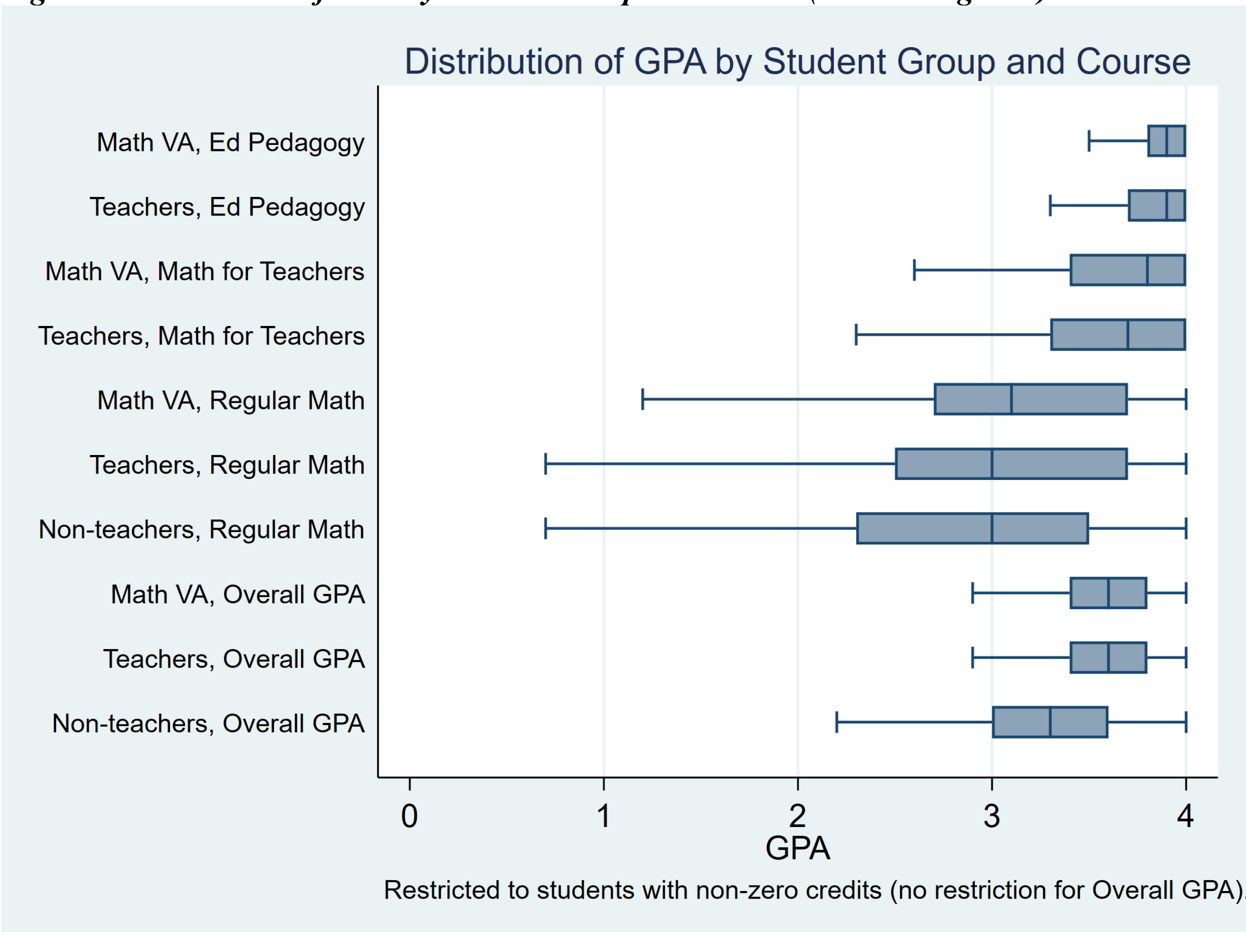
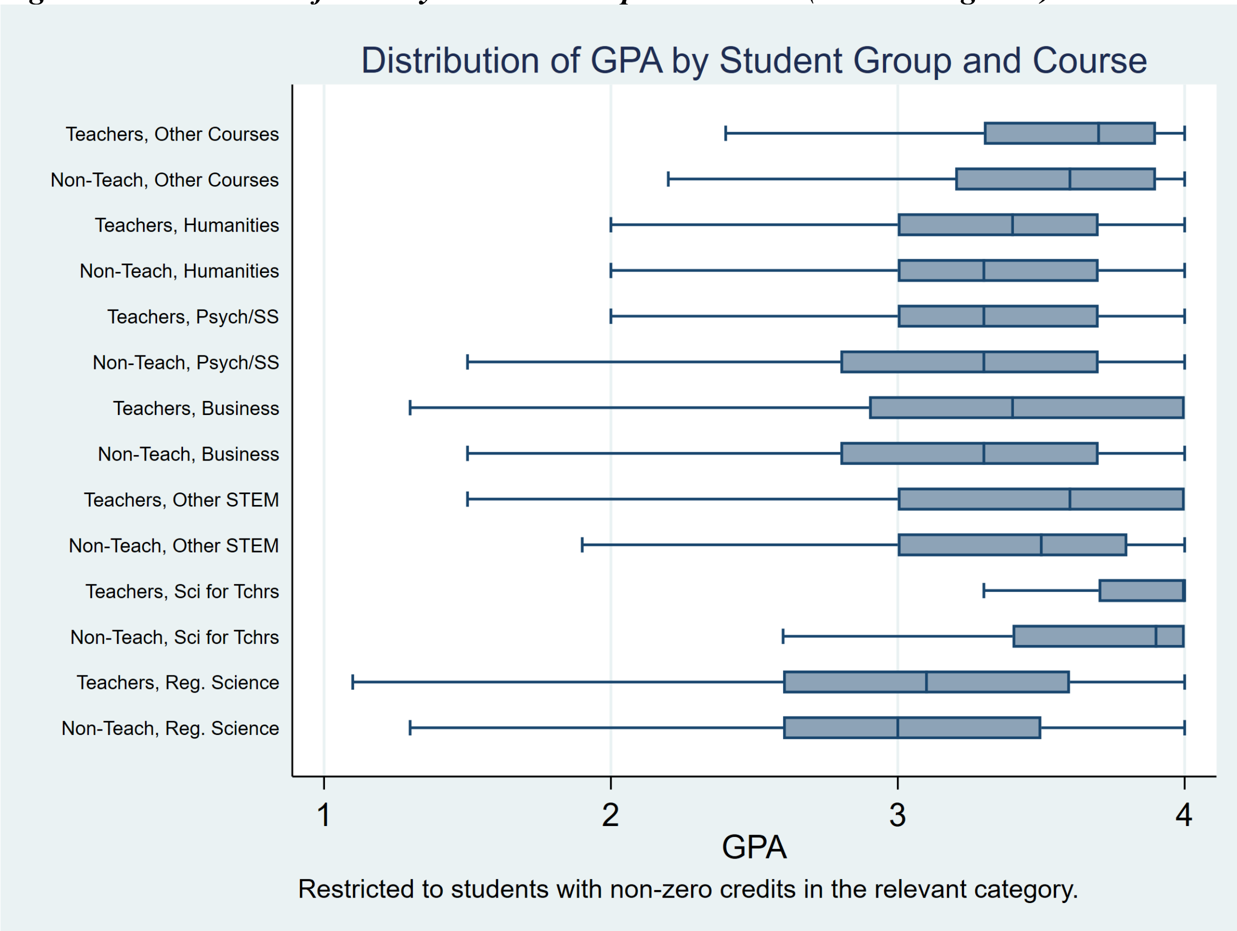


Figure 2. Distribution of GPA by Student Group and Course (Math Categories)



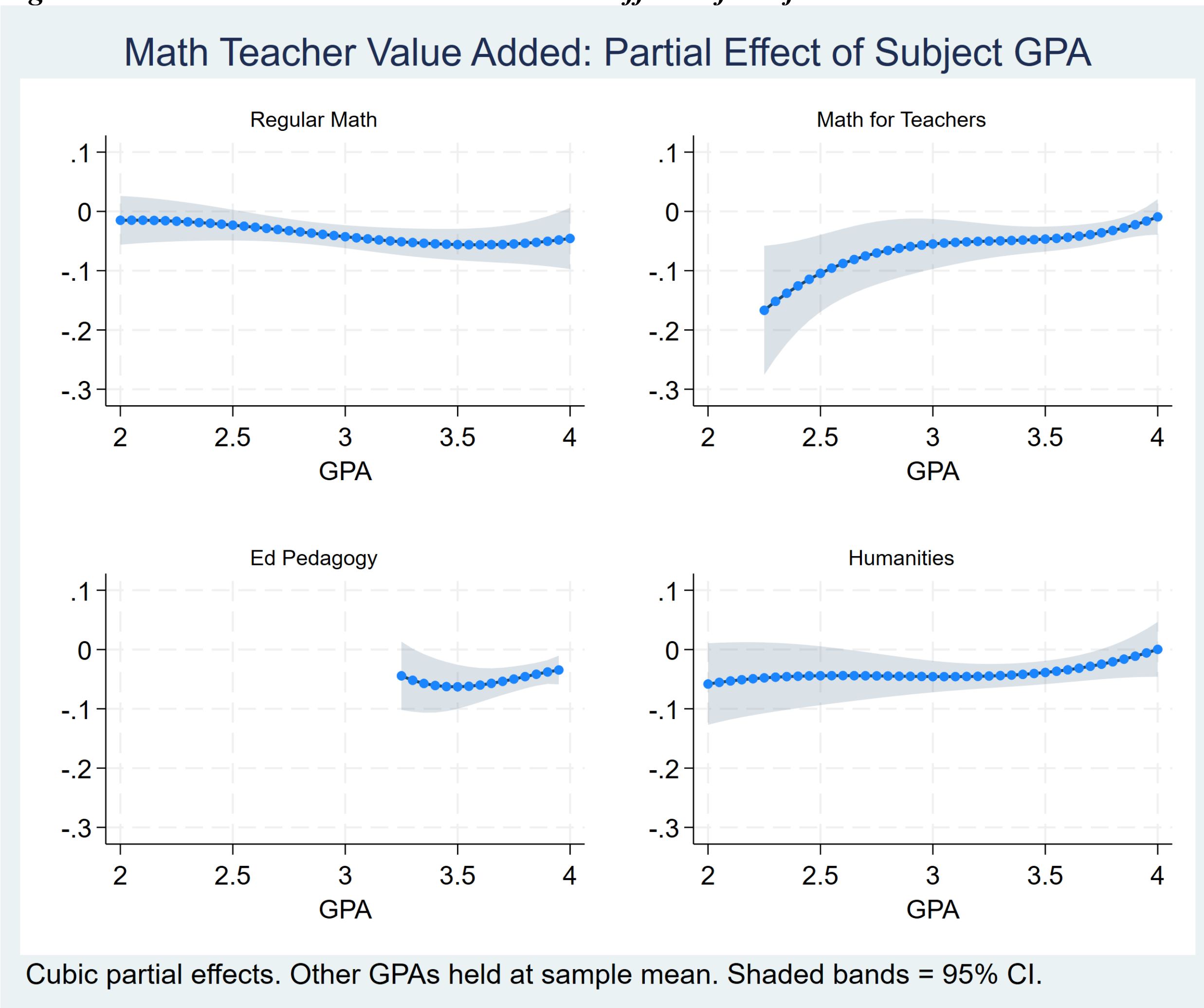
Note: Horizontal box plots. Whiskers extend to data minimum and maximum. Restricted to students with non-zero credits in the relevant subject category (no restriction for Overall GPA). VA = Value Added.

Figure 3. Distribution of GPA by Student Group and Course (Other Categories)



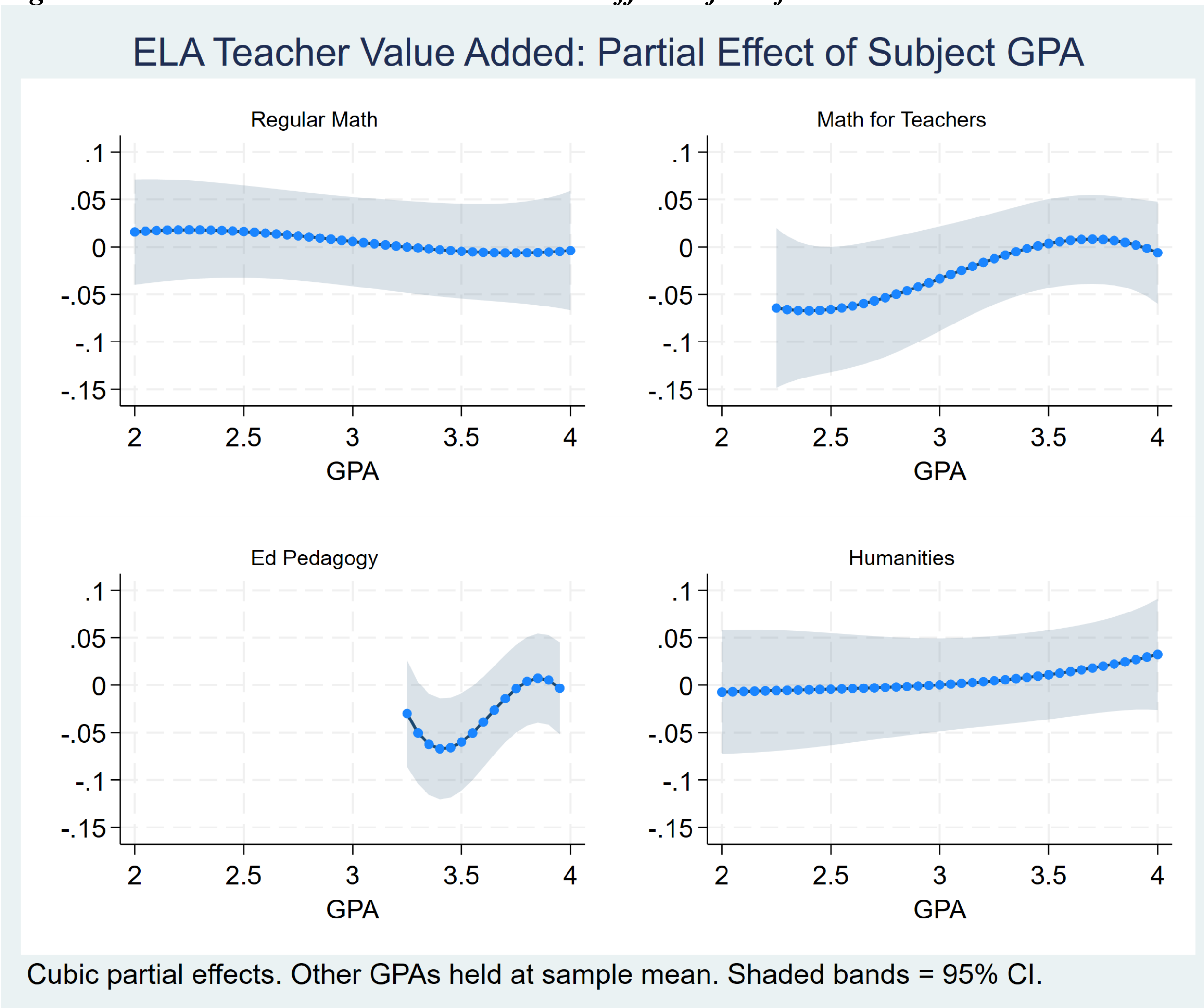
Note: Horizontal box plots. Whiskers extend to data minimum and maximum. Restricted to students with non-zero credits in the relevant subject category.

Figure 4. Math Teacher Value Added - Partial Effects of Subject-Area GPA



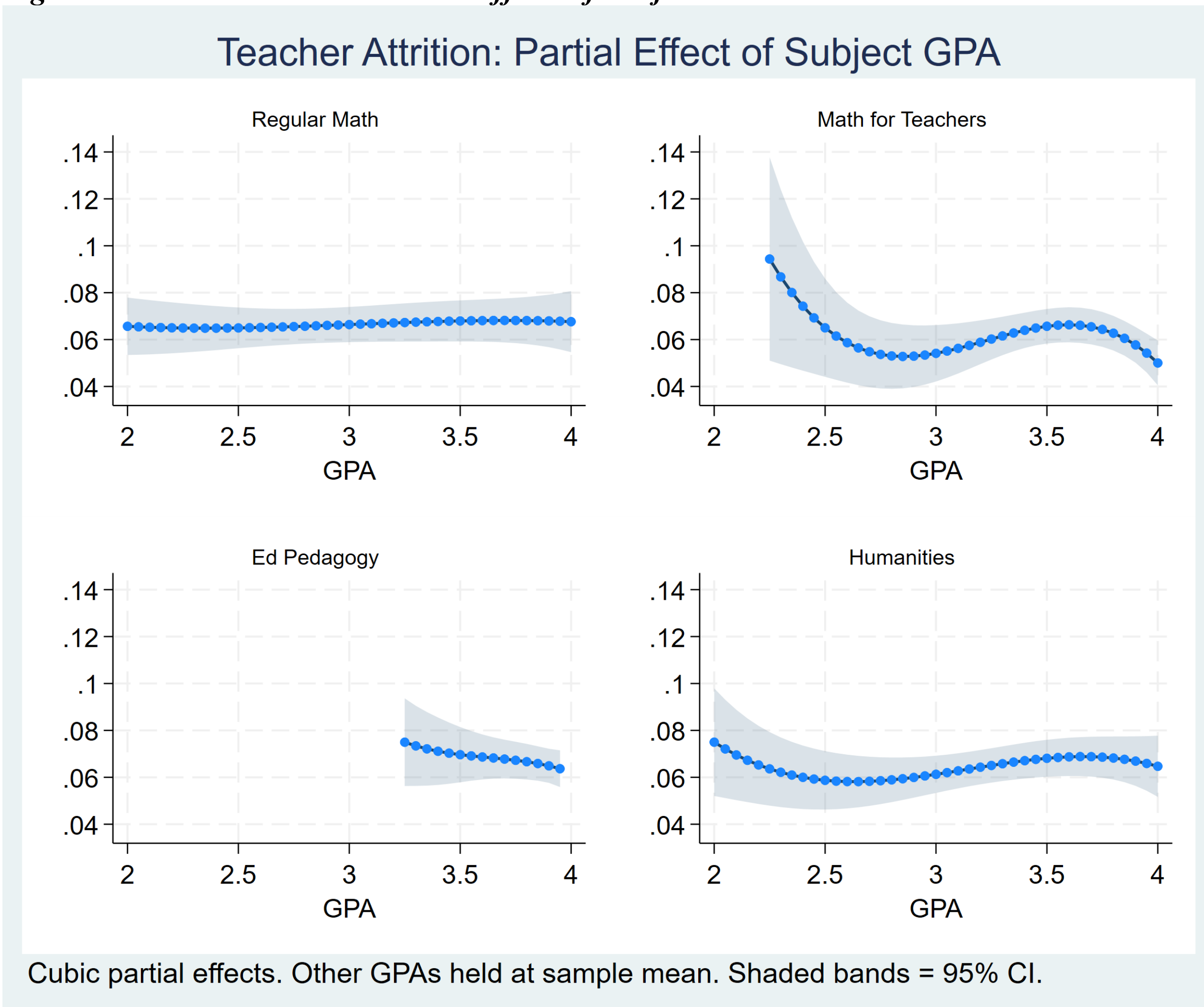
Note: Each panel shows the partial effect of that subject area's GPA on Math Teacher Value Added, from a single regression including all four subject-area GPAs as cubics simultaneously (Regular Math, Math for Teachers, Ed Pedagogy, Humanities). Controls include education interest, credits (per 10) for each focal subject area, and experience, institution, and graduation year fixed effects. All other subject-area GPAs held at sample mean. Shaded bands show 95% confidence intervals. Y-axis scale is common across all four panels. Predictions only plotted for observed range of student GPA in each subject.

Figure 5. ELA Teacher Value Added - Partial Effects of Subject-Area GPA



Note: Each panel shows the partial effect of that subject area's GPA on ELA Teacher Value Added, from a single regression including all four subject-area GPAs as cubics simultaneously (Regular Math, Math for Teachers, Ed Pedagogy, Humanities). Controls include education interest, credits (per 10) for each focal subject area, and experience, institution, and graduation year fixed effects. All other subject-area GPAs held at sample mean. Shaded bands show 95% confidence intervals. Y-axis scale is common across all four panels. Predictions only plotted for observed range of student GPA in each subject.

Figure 6. Teacher Attrition - Partial Effects of Subject-Area GPA



Note: Each panel shows the partial effect of that subject area's GPA on Teacher Attrition, from a single regression including all four subject-area GPAs as cubics simultaneously (Regular Math, Math for Teachers, Ed Pedagogy, Humanities). Controls include education interest, credits (per 10) for each focal subject area, and experience, institution, and graduation year fixed effects. All other subject-area GPAs held at sample mean. Shaded bands show 95% confidence intervals. Y-axis scale is common across all four panels. Predictions only plotted for observed range of student GPA in each subject.

Appendix Tables

Table A1. Math and ELA Teacher Value Added (Normalized GPA specification)

	Math Value Added			ELA Value Added		
	(1)	(2)	(3)	(4)	(5)	(6)
Education interest	-0.000	-0.003	-0.004	-0.007	-0.009	-0.013
	(0.016)	(0.016)	(0.017)	(0.014)	(0.014)	(0.014)
Entered with MA	-0.071*	-0.078**	-0.070	-0.042	-0.046	-0.045
	(0.039)	(0.038)	(0.059)	(0.029)	(0.029)	(0.029)
Credits at entry degree (per 10)	-0.005***	-0.004**	-0.004**	-0.002	-0.002	-0.002
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
SAT score (per 100 pts)	0.004	-0.000	-0.001	0.001	-0.002	-0.000
	(0.006)	(0.006)	(0.007)	(0.006)	(0.006)	(0.006)
BA Transfer	0.028	0.027	0.025	0.012	0.013	0.022
	(0.017)	(0.017)	(0.020)	(0.015)	(0.015)	(0.016)
Currently MA degree	0.016	0.015	0.018	0.010	0.009	0.015
	(0.019)	(0.019)	(0.019)	(0.014)	(0.014)	(0.014)
Normalized GPA at entry stage		0.064***	0.061**		0.041**	0.043**
		(0.022)	(0.025)		(0.019)	(0.019)
Inverse Mills ratio			-0.028			0.086
			(0.111)			(0.084)
N	1,958	1,958	1,946	2,054	2,054	2,044
R-Squared	0.093	0.100	0.100	0.058	0.062	0.063

*Note: Same as Table 3 but using entry-degree cumulative normalized GPA (standardized within institution, course, and year) in place of GPA. Heckman first stage also uses normalized GPA. * p<0.10 ** p<0.05 *** p<0.01*

Table A2. Teacher Attrition

	(1)	(2)	(3)
Education interest	-0.008**	-0.008*	-0.007*
	(0.004)	(0.004)	(0.004)
Entered with MA	-0.009	-0.008	-0.005
	(0.008)	(0.008)	(0.008)
Credits at entry degree (per 10)	0.001	0.000	0.000
	(0.001)	(0.001)	(0.001)
SAT score (per 100 pts)	-0.000	0.000	0.001
	(0.002)	(0.002)	(0.002)
BA Transfer	-0.001	-0.001	-0.001
	(0.005)	(0.005)	(0.005)
Currently MA degree	-0.004	-0.003	-0.004
	(0.005)	(0.005)	(0.005)
Normalized GPA at entry stage		-0.007	-0.007
		(0.006)	(0.006)
Inverse Mills ratio			0.012
			(0.021)
N	18,467	18,467	18,278
R-Squared	0.017	0.017	0.017

*Note: Same as Table 4 but using entry-degree cumulative normalized GPA (standardized within institution, course, and year) in place of GPA. Heckman first stage uses normalized GPA imp_entry. SAT imputation indicators (SAT missing, imputed from ACT, imputed from new SAT) are included as controls but not shown. * p<0.10 ** p<0.05 *** p<0.01*

Table A3. Math and ELA Teacher Value Added (District Fixed Effects Specifications)

	Math Value Added			ELA Value Added		
	(1)	(2)	(3)	(4)	(5)	(6)
Education interest	0.013	0.008	0.006	-0.003	-0.007	-0.010
	(0.017)	(0.017)	(0.017)	(0.014)	(0.014)	(0.014)
Entered with MA	-0.060	-0.078*	-0.065	-0.039	-0.051*	-0.053*
	(0.041)	(0.041)	(0.067)	(0.029)	(0.030)	(0.030)
Credits at entry degree (per 10)	-0.005**	-0.003	-0.003	-0.001	-0.000	-0.000
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
SAT score (per 100 pts)	0.007	0.001	-0.000	0.002	-0.002	-0.001
	(0.007)	(0.007)	(0.008)	(0.006)	(0.006)	(0.006)
BA Transfer	0.048***	0.045**	0.042**	0.018	0.017	0.020
	(0.018)	(0.018)	(0.021)	(0.015)	(0.015)	(0.017)
Currently MA degree	0.004	0.008	0.012	0.004	0.008	0.009
Education interest	(0.018)	(0.018)	(0.017)	(0.014)	(0.015)	(0.015)
GPA at entry degree		0.094***	0.088**		0.058**	0.058**
		(0.027)	(0.037)		(0.024)	(0.024)
Inverse Mills ratio			-0.038			0.012
			(0.122)			(0.085)
District fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
N	1,958	1,958	1,946	2,054	2,054	2,044
R-Squared	0.246	0.254	0.256	0.208	0.212	0.214

*Note: Same as Table 3 but district fixed effects are added to all specifications (columns 1-6). Heckman models (columns 3 and 6) additionally include an inverse Mills ratio. * p<0.10 ** p<0.05 *** p<0.01*

Table A4. Teacher Attrition (District Fixed Effects Specifications)

	Attrition (1)	Attrition (2)	Attrition (3)
Education interest	-0.009**	-0.008*	-0.007*
	(0.004)	(0.004)	(0.004)
Entered with MA	-0.007	-0.006	-0.003
	(0.008)	(0.009)	(0.009)
Credits at entry degree (per 10)	0.000	0.000	0.000
	(0.001)	(0.001)	(0.001)
SAT score (per 100 pts)	-0.001	-0.000	0.000
	(0.002)	(0.002)	(0.002)
BA Transfer	0.000	0.001	0.001
	(0.005)	(0.005)	(0.005)
Currently MA degree	-0.003	-0.003	-0.004
	(0.005)	(0.005)	(0.005)
GPA at entry degree		-0.010	-0.010
		(0.007)	(0.008)
Inverse Mills ratio			0.015
			(0.021)
District fixed effects	Yes	Yes	Yes
N	18,467	18,467	18,278
R-Squared	0.038	0.038	0.039

*Note: Same as Table 4 but district fixed effects are added to all specifications (columns 1-3). Heckman model (column 3) additionally includes an inverse Mills ratio. * p<0.10 ** p<0.05 *** p<0.01*

Table A5. Math and ELA Teacher Value Added (First-Year Teachers Only)

	Math Value Added			ELA Value Added		
	(1)	(2)	(3)	(4)	(5)	(6)
Education interest	0.030	0.025	0.025	-0.014	-0.019	-0.015
	(0.028)	(0.028)	(0.028)	(0.023)	(0.024)	(0.023)
Entered with MA	0.056	0.025	0.048	0.028	0.014	-0.009
	(0.094)	(0.091)	(0.122)	(0.055)	(0.055)	(0.054)
Credits at entry degree (per 10)	-0.006*	-0.004	-0.003	0.002	0.004	0.005*
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
SAT score (per 100 pts)	0.009	0.002	-0.001	0.000	-0.003	-0.005
	(0.011)	(0.011)	(0.013)	(0.008)	(0.008)	(0.009)
BA Transfer	0.047	0.045	0.038	0.009	0.011	0.005
	(0.032)	(0.031)	(0.034)	(0.033)	(0.033)	(0.032)
Currently MA degree	-0.011	0.007	0.029	-0.033	-0.030	-0.022
	(0.074)	(0.071)	(0.075)	(0.039)	(0.039)	(0.038)
GPA at entry degree		0.120***	0.103*		0.072*	0.074*
		(0.041)	(0.054)		(0.041)	(0.041)
Inverse Mills ratio			-0.110			-0.145
			(0.192)			(0.138)
N	524	524	521	571	571	568
R-Squared	0.142	0.157	0.160	0.095	0.102	0.101

*Note: Same as Table 3 but restricted to each teacher's first observed school year in the teacher workforce. * p<0.10 ** p<0.05 *** p<0.01*

Table A6. Teacher Attrition (First-Year Teachers Only)

	(1)	(2)	(3)
Education interest	-0.023**	-0.022**	-0.027**
	(0.011)	(0.011)	(0.011)
Entered with MA	-0.017	-0.015	-0.011
	(0.033)	(0.033)	(0.033)
Credits at entry degree (per 10)	-0.000	-0.001	-0.000
	(0.001)	(0.002)	(0.002)
SAT score (per 100 pts)	0.005	0.006	0.008
	(0.005)	(0.005)	(0.005)
BA Transfer	0.005	0.005	0.008
	(0.013)	(0.013)	(0.013)
Currently MA degree	-0.010	-0.011	-0.028
	(0.027)	(0.027)	(0.027)
GPA at entry degree		-0.015	-0.019
		(0.018)	(0.018)
Inverse Mills ratio			-0.188**
			(0.095)
N	3,583	3,583	3,548
R-Squared	0.040	0.040	0.043

*Note: Same as Table 4 but restricted to each teacher's first observed school year in the teacher workforce. * p<0.10 ** p<0.05 *** p<0.01*

Table A7. Teacher Outcomes - Linear Subject GPA and 400-Level Course Indicator

	Math VA	ELA VA	Attrition
Education interest	-0.014	-0.017	-0.008**
	(0.016)	(0.014)	(0.004)
Regular Math: credits (per 10)	-0.015*	-0.006	-0.000
	(0.008)	(0.010)	(0.002)
Regular Math: GPA	-0.012	-0.003	0.000
	(0.014)	(0.011)	(0.003)
Regular Math: 400-level indicator	0.079**	0.119**	-0.013
	(0.039)	(0.056)	(0.014)
Math for Teachers: credits (per 10)	-0.002	0.010	0.009**
	(0.014)	(0.014)	(0.004)
Math for Teachers: GPA	0.053**	0.035*	-0.004
	(0.021)	(0.018)	(0.006)
Math for Teachers: 400-level indicator	0.026	-0.029	0.004
	(0.023)	(0.020)	(0.006)
Ed Pedagogy: credits (per 10)	0.002	0.004	-0.002**
	(0.004)	(0.003)	(0.001)
Ed Pedagogy: GPA	0.020	0.020	-0.021*
	(0.040)	(0.032)	(0.012)
Ed Pedagogy: 400-level indicator	-0.004	0.003	-0.018
	(0.087)	(0.048)	(0.020)
Humanities: credits (per 10)	-0.005	0.000	-0.000
	(0.005)	(0.004)	(0.001)
Humanities: GPA	0.038**	0.023	0.001
	(0.018)	(0.015)	(0.005)
Humanities: 400-level indicator	-0.042	-0.014	0.013*
	(0.028)	(0.024)	(0.007)
Entered with MA	-0.060	-0.045	-0.008
	(0.041)	(0.032)	(0.008)
Currently MA degree	0.014	0.011	-0.002
	(0.019)	(0.015)	(0.005)
N	1,958	2,054	18,467
R-Squared	0.106	0.071	0.018

*Note: Each column is a separate OLS regression including only the four focal subject areas (Regular Math, Math for Teachers, Ed Pedagogy, Humanities). Each subject is represented by credits (per 10), a linear GPA term, and a 400/500-level course indicator (coded 1 if the highest course taken in that subject area was at the 400 or 500 level). Controls include education interest, an indicator for having a master's or doctoral degree, experience, institution, and graduation year fixed effects. Standard errors clustered at teacher level. Column 3 excludes school year 2022. * p<0.10 ** p<0.05 *** p<0.01*