The Return to University Courses*

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Abstract

We use transcript-level administrative data from four-year college students in Texas linked to their K-12 education records and quarterly earnings to examine the effect of the courses students take on future earnings. Most of our variation comes from non-major coursework. We first estimate course value-added, which represents the residual variance across classes with respect to how affect post-collegiate earnings. A one standard deviation increase in course value-added increases earnings by $575 per quarter, which is 15% of a standard deviation of earnings. The standard deviation of course value-added varies across subjects, ranging from $346 (social science) to $992 (biology and health), but value-added does not vary much by student demographic or academic background. We then estimate the average return to courses by subject relative to liberal arts, with estimates ranging from -$114 (interdisciplinary studies) to $443 (computer science). We also document important differences in course returns across subjects based on a student's major. Finally, we show evidence that course grades, the level of the course, and whether the course is part of the core curriculum influence future earnings. Together, our results show that courses vary in their quality and that post-college earnings are strongly influenced by the courses students take outside of their major.

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1 Introduction

Persistently high returns to skill in the labor market have supported high average returns to postsecondary education investments in the US. This average, however, masks important heterogeneity along a number of dimensions, including institution type, institution quality, and course of study (Lovenheim and Smith, 2023). A growing body of research examines each of these aspects of heterogeneous returns to higher education. The literature on the returns to different courses of study is comparatively sparse and mostly has focused on the returns to college major. However, the courses one takes to complete a major represent a minority of courses taken in college; courses are roughly equally split between within-major, general education, and non-major elective courses (Paulson, 2015). Are the returns to college major the dominant way through which courses translate into labor market returns, or are there returns more broadly to different courses students take in college, conditional on major choice? Currently, little is known about the return to college coursework, especially outside of one's major. This is an important oversight, because much human capital is likely to be transferred through these courses, and the high cost of college makes these non-major courses expensive. It thus is critical to know the value they bring to students and how they impact student higher education investments.

In this paper, we conduct the most comprehensive analysis to date on the return to college coursework, using administrative data from the State of Texas that combines K-12 education records with higher education records for all in-state students and quarterly earnings records for covered workers from the unemployment insurance system. Our data are unique in containing full college transcripts for every postsecondary student, including every course taken, major choices, and the grade received in each class. Prior research using individual-level administrative data has not had access to college transcripts combined with pre-collegiate academic records, and prior college transcript studies employ much smaller samples.[1] Our analytic sample uses students who attended a public high school in Texas

[1]Most college transcript studies use the college transcripts from the NCES longitudinal datasets, which have much smaller samples than the Texas administrative data we use.

between 2012 and 2019 and who go on to complete a four-year postsecondary degree in Texas.

Aligned with the analyses in Andrews et al. (2024) and Imberman et al. (2025), we focus on the following 14 subject areas: agriculture, architecture, communications, computer science, vocational, education, engineering, biology and health, interdisciplinary studies, physical sciences and math, social science, economics, business, and liberal arts. Critically, we control for each student's major because major choice has a mechanical effect on the courses one takes and impacts subsequent earnings (Arcidiacono, 2004; Kirkeboen et al., 2016; Bleemer and Mehta, 2022; Andrews et al., 2024). Hence, we are comparing outcomes of students in the same university and who majored in the same area but who took courses in different subjects both within and outside of their major. The major fixed effects capture much of the variation in coursetaking within a major, which allows us to focus predominantly on coursetaking variation from outside of the major.

We estimate selection-on-observable models that control for rich pre-collegiate academic achievement and background characteristics as well as high school, college, and major fixed effects to examine how taking courses in one of 14 broad field of study areas affects post-collegiate earnings. In addition to student-level observables, we follow the insights from Altonji and Mansfield (2018) and control for course-level means of observables to address selection. We additionally show that conditional on the fixed effects in our models, the student and course-level academic achievement and background controls have little effect on our estimates. This finding suggests that the fixed effects are sufficient to control for selection of higher potential earning students into specific classes.

We first estimate value-added models that show the residual variance across classes with respect to how they lead to future earnings. We adapt the shrinkage estimator from Chetty et al. (2014) to account for the fact that some courses are larger than others. This analysis leads to value-added estimates overall and by field, which allows us to assess whether there is variation in the "quality" of college courses, as defined by their ability to raise labor market earnings. Our estimates show how expected earnings increase when one moves up the college

course quality distribution. We estimate course value-added overall, by subject area, and by demographics: gender, race/ethnicity, and SES. Second, we estimate how taking classes in a given subject area affects future earnings, on average. We also allow the effects of course-taking to vary by one's major field, which provides insight into the value of breadth. Finally, we estimate how the returns to courses vary by the level of the course and the grade one receives.

Our results point to a large amount of variation in course quality, as measured by the variation in their value-added for future earnings. The standard deviation of value-added across all courses is \$575 per quarter, which is 15% of a standard deviation of earnings. Hence, courses differ substantially in how they affect future earnings. The range of value-added across classes in a given field varies across subject areas. The field with the widest variation is biology and health, where one standard deviation in value-added is \$992. This implies that the 95^{th} percentile course in the field gives an average quarterly return that is \$1,631 larger than the 5^{th} percentile course. Other fields with large variation in value-added include computer science (\$734), engineering (\$712), interdisciplinary studies (\$622), business (\$607), and vocational (\$612), while agriculture (\$444), architecture (\$428), liberal arts (\$410), economics (\$381), communications (\$368), and social science (\$346) exhibit lower variation in value-added. We find little systematic difference in course value-added by gender, race, or SES, although course quality variation is higher for courses designated as "Junior" or "Senior" (relative to "Freshman" and "Sophomore").[2]

Value-added measures the variance in earnings returns across courses, rather than the average return to taking courses in an area. Interpreting value-added thus rests on whether courses in different subject areas have high or low average returns. We estimate the effect of taking courses in each of 13 subject areas, with courses in liberal arts as the excluded category. This is similar to how prior research uses these data to estimate the returns to college major (Andrews et al., 2024; Imberman et al., 2025). Relative to taking a course in liberal arts, taking a course in computer science increases earnings by \$443, business by \$374, education

[2]These course designations measure the expected academic level of the course rather than the grade of those who take the course. Course levels are assigned by the Texas Higher Education Coordinating Board.

by $311, engineering by $298, vocational by $195, biology and health by $118, economics by $96, and social science by $39. Taking a course in physical sciences & math (-$49) and interdisciplinary studies (-$114) has negative average returns relative to taking a liberal arts course. These estimates are robust to controlling more flexibly for student major, dropping within-major courses, controlling for whether a student is a transfer student, controlling for instructor value-added, and to including non-completers in the sample. Our results suggest that the courses one takes matters, both in terms of which fields those courses are in as well as which courses one takes within a field. Since these estimates are conditional on major, the returns we estimate are predominantly for courses outside of the major, suggesting that non-major courses do matter for future labor market outcomes.

Finally, we examine the relationship between course grades, course level, and future earnings. We estimate how the grade received in each course correlates with future earnings by including indicators for the grade students earned in the course (A through F), with B grades as the excluded category. The grade one receives is potentially endogenous because those who obtain higher grades are likely to have other, unobserved attributes that lead to higher earnings. Nonetheless, there is little evidence on the link between postsecondary performance and earnings, so these results are informative. This is especially the case because of concerns that grade inflation reduces the information content of grades. We find consistent evidence that obtaining a higher grade is associated with higher earnings, overall and in most subject areas. Students who receive As in almost every subject area earn more, while those who receive Cs, Ds, and Fs earn much less. When we examine this relationship by quintile of average grades in the class, we find that obtaining higher grades is even more important when the average grade in the class is higher. We conduct a similar analysis examining the level of the course (Freshman-Senior). Returns are highest to more advanced courses that are designated as "Junior" and "Senior." Last, we examine whether returns vary by whether courses are designed as part of the core curriculum. Courses in the core curriculum have lower returns at every level, which could reflect that students learn less when forced to take a class. Together, these results suggest that both course level and course performance are

important for shaping post-college earnings.

This paper provides some of the first and the most comprehensive evidence to date on the labor market returns to college course-taking. Most of the prior research on the returns to what students study in college has focused on college major choice, with an array of papers showing that the field of study has important implications for future earnings (e.g., Arcidiacono (2004), Hamermesh and Donald (2008), Kirkeboen et al. (2016), Bleemer and Mehta (2022), Andrews et al. (2024)).[3] Our paper extends and complements this body of work by examining the returns to college courses that are outside of the major. Since most courses are taken outside of the major, our results allow us to paint a more complete picture of the heterogeneity in postsecondary returns as a function of what one studies. Furthemore, we show a wide range of earnings impacts of courses even within the same broad subject. The specific course students take, not just the field, are important in determining post-collegiate labor market outcomes.

A small set of studies has examined the returns to specific aspects of college courses. Silos and Smith (2015) use data on 2,130 transcripts from the HS&B survey to group courses into three categories: quantitative and scientific, humanities, and social science. They find that diversification across course types benefits those who switch occupations, while more specialization benefits those who do not. Our paper examines a broader set of courses using a much larger sample that allows us to examine the returns to course-taking in a more comprehensive manner. They also are unable to separately control for major choice in their analysis. Light and Schreiner (2019) use data from the NLSY97 and show that conditioning on the proportion of courses taken in different areas reduces the estimated returns to major, which suggests that coursework is both correlated with major choice and is linked to future earnings. Their paper does not present estimates of the returns to coursework, however. Neither of these papers estimates course value-added, which we newly bring to this literature.

Several recent papers also examine the returns to college courses through the lens of the specific skills being taught in those courses. Biasi and Ma (2022) use course syllabi to identify

[3]See Lovenheim and Smith (2023) for a recent review of this literature.

courses that are closer to the frontier of knowledge and show that courses that are closer to this frontier generate higher earnings, using data from the College Scorecard. Chau et al. (2023) similarly categorize skills using course syllabi and show using College Scorecard data that these course-specific skills explain a substantial amount of early-career post-college earnings variation. However, they do not present estimates of the returns to these skills.

Most closely related is the work of Light and Wertz (2022), who characterize courses based on occupational specificity[4] and show that taking more occupation-specific courses outside the major is strongly positively associated with future earnings. None of these papers is able to control for pre-collegiate academic achievement as we do in our analysis. While characterizing courses in terms of specific skills they impart is of value, the results will vary based on the specific skills examined. Our paper provides a more comprehensive assessment of the returns to college courses that does not rely on the parameterization or measurement of different skills, estimating overall and by-field value-added as well as the return to coursework in each field of study. We show that college coursework does matter for future earnings and that there is substantial variation both across and within fields of study that affect labor market outcomes of students.

2 Data

2.1 Construction of the Analysis Variables and Sample

We use administrative data from Texas, combining K-12 information from all students who graduate from a public high school in Texas with higher education records from all students who attend an in-state institution and quarterly earnings from all unemployment insurance (UI)-covered workers in Texas. The data structure and construction process is similar to those in Andrews et al. (2024) and Imberman et al. (2025). Relative to these prior analyses, we employ newly-added transcript-level data that contain information on every course students in Texas higher education institutions take as well as the grades they

[4]They define occupational specificity as the likelihood that a student majoring in a given field will work in an occupation that requires the skills learned in that field.

receive. The transcript data are available beginning in 2012. Our analytic sample includes students who graduate from a Texas high school, first enroll in a four-year institution in Texas between 2012 and 2019, and who obtain a BA during our observation period. We focus on college completers in order to avoid complications stemming from large differences in number of course credits from those who drop out.

The K-12 data contain a wealth of information about pre-collegiate academic achievement that we use to account for selection. These variables and the associated descriptive statistics are listed in Table 1. We include demographic characteristics – gender, race/ethnicity, whether the student was enrolled in a gifted and talented program, whether they are classified as at risk of dropout, and whether they are economically disadvantaged. We also account for two types of pre-collegiate achievement measures. The first is 8^{th} grade math and reading exam scores as well as whether they are in the top 10 percent and the top 70^{th}-90^{th} percentiles in their high school on each exam. These within-school rankings help us to account for variation in college choice stemming from the Texas Top 10 Percent Plan (Andrews et al., 2020). During the years we study, Texas high school exams were not taken by all students and were heavily selected. Hence, we focus on the 8^{th} grade exams that were taken by all students. In order to measure academic achievement and interests in different subjects prior to college, the second type of controls we include are the number of courses taken in English language arts (ELA), math & technology, science, social studies, foreign language, fine arts, and CTE & business as well as an "other" category from grades 6-12. We additionally control for the number of advanced placement (AP) classes students take in each of these categories (outside of CTE & Business and Other).

We observe all workers in covered UI employment in Texas through 2023. Because course-level data only begin in 2012, we observe earnings up to around age 29. Our results thus reflect early-career returns to coursework.[5] Earnings only are recorded if an individual works under covered employment in the state; missing observations may be due to not working or because a worker has left the state. We follow Andrews et al. (2024) and

[5]Recent research shows that the return to college major varies as students age (Andrews et al., 2024). We are unable to examine how estimated returns change with potential experience and leave this for future work.

Imberman et al. (2025) in defining an in-state employment window: any time between when a student first begins working in the state after college graduation and when we last observe earnings for them in the data. Excluding any quarters in which students are enrolled in an educational institution in state (e.g., graduate school), we assign zero earnings to workers if they are not observed within their in-state employment window.

The raw earnings data are at the quarterly level. We follow Andrews et al. (2020) as well as Andrews et al. (2016) in creating a single residualized earnings measure for each person. To do this, we use the raw quarterly earnings data and regress quarterly earnings on quarter-by-year and high school graduation cohort indicators. We then take the average residual from this regression for each person in the sample and winsorize by dropping the top 1% of residualized earnings to mitigate the influence of outliers. This is our measure of $\overline{Wage_Resid}$ used in the empirical analyses below. The mean and standard deviation of earnings and $\overline{Wage_Resid}$ are shown in Table 1.

Our analysis is conducted at the level of the student-course combination. Texas uses a unified course numbering system to identify courses, which are unique to each university. We employ this numbering system to measure unique course-university combinations, which we call "courses" for ease of exposition. We are unable to map courses to the specific departments offering them, but we are able to match them to academic fields using their CIP codes. We categorize courses into one of 14 field groups (Andrews et al., 2024; Imberman et al., 2025): agriculture, architecture, communications, computer science, vocational, education, engineering, biology & health, interdisciplinary studies, physical sciences & math, social science, economics, business, and liberal arts. Students can enroll in courses multiple times. We use the observation of the first time that a student enrolls in a course and drop subsequent enrollments (3.24% of the sample). We also drop courses with enrollments of under 5, which is the bottom 1% of the enrollment distribution. This excludes 3.65% of the sample. Finally, we drop the small number of courses that change field (CIP-2) designation over the course of study, which represent 1.59% of the sample. Our final sample includes 6.7 million student-course records for 225,366 unique students and about thirty-nine thousand

individual courses.

2.2 Descriptive Evidence

Table 1 presents descriptive statistics of our analysis variables. The analysis sample is 41% male and is 45% white. Texas is a racially and ethnically diverse state, which is reflected in our college sample that is 33% Hispanic, 10% Black, and 9% Asian. Four-year college graduates are academically positive selected, with math and reading exam scores of 0.82 and 0.62 standard deviations, respectively. They also are drawn disproportionately from the top 10% of their high school classes in terms of their test scores. These students take a diversity of courses that demonstrate their breadth of training prior to college, and on average they take at least one AP course in each of math, ELA, science and social studies while in high school.

These high-achieving students have substantial breadth of training prior to college. How specialized is their college course-taking? Figure 1 shows descriptive evidence on the distribution of number of course fields taken by students in our analysis sample. Panel (a) shows the overall distribution. Most students take courses in between 4 to 7 of the 14 fields we consider. Few students take courses in fewer than 4 fields or in more than 8. Panel (b) shows the distribution of course fields by students' final major. There is little variation across major fields in the breadth of areas in which students take courses. Liberal arts, biology & health, and architecture students exhibit the least breadth in terms number of courses taken in different fields, while interdisciplinary studies students exhibit the most cross-field breadth.[6] However, the variation across majors is small, suggesting that most students take courses in a number of different fields outside of their major during college.

Figure 2 shows further descriptive evidence on the distribution of courses taken by field. In Panel (a), we show the raw distribution of courses taken by field for our analysis sample.[7] Liberal arts, biology & health, physical sciences & math, social science, and business are

[6]This result for liberal arts students could partially reflect the fact that this is a relatively broad category that includes many different types of specific majors.

[7]Note that Figure 2 shows the distribution of courses, not course credits. Each course receives equal weight regardless of the number of credits received.

the most prevalent subjects taken by students. What fields students take courses in is likely to be heavily influenced by their major. In Panel (b), we show the same distribution by students' final major. It is clear that students take many courses in their major but that in each major there is substantial cross-field course-taking. Architecture, engineering, liberal arts, physical science & math, and business students show the least diversity in terms of the fields in which they take courses outside of their major. For example, the majority of courses taken by engineering students are in engineering and physical sciences & math. Economics, biology & health, computer science, and communications students, in contrast, take courses in a range of different fields. This descriptive evidence shows that one's major correlates with the types of courses one takes outside the major and the diversity of types of fields to which one is exposed. However, the descriptive evidence underscores that most students experience a range of fields during college. The remainder of this paper explores how these courses shape post-collegiate earnings.

3 Empirical Strategy

We employ two approaches to estimate the labor market returns to college courses. First, we estimate course-level value-added models. Second, we estimate the average return to taking courses in a given subject area, relative to the reference subject of liberal arts. We discuss each of these approaches in turn below.

In the spirit of the teacher value-added literature, we estimate the value-added of each course on students' earnings. Central to this exercise is identifying the causal role of each course in generating future earnings. Accounting for selection into different courses thus is of paramount importance, since students who select courses associated with higher earnings are likely to have attributes that make them otherwise more productive in the labor market. The teacher value-added literature handles this selection predominantly by using lagged test scores. We do not have lagged earnings (our dependent variable) since most of our sample does not have sufficient earnings prior to college. Instead, we take a selection on observables

approach and control for a rich set of demographic characteristics, pre-collegiate academic achievement measures, high school, and college fixed effects. This model is akin to the approaches taken in recent papers examining the returns to college major (Andrews et al., 2024; Imberman et al., 2025).

As described above, we first construct individual post-collegiate earnings that are residual to quarter-year and high school cohort fixed effects: $\overline{Wage_Resid}$. Our course value-added models take the following form:

$$\overline{Wage_Resid}_{ichumjt} = \alpha + \beta_1 X_i + \beta_2 \bar{X}_j + \beta_3 \bar{X}_{ut} + \phi_j + \delta_m + \gamma_{ch} + \theta_{cu} + \epsilon_{ichumjt}, \quad (1)$$

where $\overline{Wage_Resid}_{ichumjt}$ is the average residualized earnings from student i in high school cohort c from high school h and university u with major m enrolled in course j in semester t. The vector X_i contains our set of individual controls listed in Table 1 and discussed in Section 2. Equation (1) also controls for course ($\bar{X}_j$) and school-semester ($\bar{X}_{ut}$) jackknifed means of all control variables included in X. These controls are akin to the class-level means that are important for identifying teacher value-added models (Chetty et al., 2014) and have been shown to be important controls for addressing selection on unobservables in the returns to neighborhood and school quality literature (Altonji and Mansfield, 2018). Finally, we control for college major (δ_m), high school by cohort (δ_{ch}), and university by cohort (δ_{cu}) fixed effects. Standard errors are clustered at the cohort-by-university level.

The variation in course value-added is calculated by taking the standard deviation of ϕ_j, which represents the earnings return to moving up one standard deviation in the course quality distribution. Although we exclude courses with less than 5 students, courses vary considerably in the number of students enrolled. The raw standard deviation of ϕ_j can be biased by the existence of small classes. This issue is even more pronounced in our setting than in the teacher value-added literature, as some college courses have under 10 students while others have hundreds in a given semester. To address this issue, we shrink the raw course value-added estimates towards the mean using the empirical Bayes shrinkage method that minimizes mean squared error, following Chetty et al. (2014). By assigning a smaller

weight to courses with a smaller enrollment, we reduce the amount of variation stemming from noise in the earnings variable. The shrunk course VA effect, $\hat{\mu}_j$, is calculated as:

$$\hat{\mu}_j = \bar{A}_j \frac{\sigma_\mu^2}{\sigma_\mu^2 + (\sigma_\theta^2 + \sigma_\varepsilon^2/n)/(t-1)}, \tag{2}$$

where $\bar{A}_j$ is the average ϵ_{ijt} obtained from equation (1) without course fixed effects, σ_ε is the within-course variance, σ_μ^2 is the within-course cross-semester covariance, and σ_θ^2 is the remainder of the total variance of ϵ_{ijt} not accounted for by the other components of equation (2). We compute these variances following equations (2)-(4) in Kane and Staiger (2008). The variable n is the enrollment in each course and t is the total number of semesters each course is open. Note that this method assumes course quality is fixed over time and that the student- and class-level errors are i.i.d.

In addition to estimating course value-added, we estimate the average effect of taking courses in a given field, relative to liberal arts. The course VA estimates show the existence and magnitude of course quality, while this part of the analysis shows the average return to taking courses in a given area. We estimate models of the following form:

$$\overline{Wage_Resid}_{ichumjt} = \alpha + \beta_1 X_i + \beta_2 \bar{X}_j + \beta_3 \bar{X}_{ut} + \beta_4 cl_j + \delta_m + \gamma_{ch} + \theta_{cu} + \sum_{k=2}^{k=14} \omega_k \times \mathbb{1}_k + \epsilon_{ichumjt}, \tag{3}$$

where $\mathbb{1}_k$ is an indicator equal to 1 if the class is in field k and cl is a set of indicator variables for the course level ($cl_i \in \{freshman, sophomore, junior, senior\}$. We include course level indicators because the returns vary by level and the distribution of course levels students take differs considerably across fields. All other variables in equation (3) are as previously defined. Liberal arts ($k = 1$) is the excluded category.

The identification assumption in equation (3) and for our value-added estimation is that the observed demographics, pre-collegiate achievement measures, and fixed effects are sufficient to account for selection of students into courses as a function of potential earnings. There are few alternative approaches one can take to identify the returns to college courses in the US. Students can choose their major and conditional on their major can make decisions

about which courses to take. While most universities have distributional requirements, they are minor relative to the total number of courses students take. We are unaware of any policies or practices that could be used to generate exogenous variation in student course-taking,[8] which is why we employ selection on observables. We note that we have little understanding of the returns to college coursework outside of majors and that prior research either has not been able to control even for pre-collegiate achievement (e.g., Biasi and Ma (2022); Light and Wertz (2022); Chau et al. (2023)) or controls for prior achievement but cannot include the range of fixed effects in our models (e.g., Silos and Smith (2015)).[9] That we are able to include both postsecondary institution and major fixed effects means that we are comparing students within each university who take different courses, conditional on their majors. Our models thus predominantly identify the returns to non-major coursework.

Despite the potentially strong assumptions embedded in our selection on observables approach, we argue that the large set of pre-collegiate achievement controls and the range of fixed effects we include produce credible estimates of the causal effect of coursework on earnings. First, both Chetty et al. (2014) and Altonji and Mansfield (2018) show that treatment-level means are powerful controls for selection on unobservables when estimating the return to teacher, school, or neighborhood quality. Altonji and Mansfield (2018) formalize this claim by showing that jacknifed means at the school or neighborhood level are sufficient to account for selection on unobservables because these group-level means are correlated with how people value (and thus sort on) amenities. We rely on a similar logic, where sorting on class-level amenities such as difficulty, course content, assignment types, and peer composition are likely to be both important for students when selecting classes and related to class-level means. Indeed, Altonji and Mansfield (2018) argue that controlling for these group-level means leads to a lower bound on the treatment effect because it absorbs effects coming through peer effects, which is the case in our setting as well.

Second, following the logic of Oster (2019), we examine the stability of our estimates to

[8]Note that this extends to supply-side instruments coming from variation in course offerings. Variation in courses offered will not allow us to identify the return to specific courses, which is the focus of our analysis.

[9]We also highlight that this selection on observables assumption is prominent is recent US-based analyses of the return to college major (Andrews et al., 2024; Imberman et al., 2025).

excluding different sets of observables from our estimates, both with and without fixed effects. We systematically exclude each set of fixed effects shown in Table 1 (student characteristics, student achievement, pre-college courses and APs in different subjects) as well as the class-level means. Each set of controls is independently correlated both with earnings and with course selection, so examining how estimates vary when we exclude them is instructive. If there is substantial sorting on unobservables, our results should be sensitive to the exclusion of these controls. This is particularly true for the class-level means, which are designed to address selection on unobservables. We show below that the estimates are sensitive to these controls when we exclude the fixed effects, however conditional on the fixed effects our estimates change little when we exclude any set of observables or all observables. This evidence suggests that the postsecondary institution, high school, and major fixed effects are sufficient to address sorting into different college courses.

4 Results

4.1 Course Value-Added

Figure 3 presents the distribution of value-added estimates and demonstrates that there is a wide distribution of both raw and shrunk course value-added. Courses differ substantially in how they affect future earnings. Table 2 presents the estimates of the raw standard deviation of the course fixed effects from equation (1) and the shrunk standard deviation from equation (2), which are our measures of course value-added. We find consistent evidence of substantial variation in "course quality," or the effect of courses on future earnings. Moving one standard deviation up in course quality increases earnings by between \$1,006 (raw) and \$575 (shrunk). These estimates represent a 20.0% and 11.5% increase relative to mean earnings and a 26.1% and 14.9% increase of a standard deviation in earnings. Prior research has estimated teacher value-added of around 0.1 standard deviations (e.g., Chetty et al. (2014); Kane and Staiger (2008); Rivkin et al. (2005); Rockoff (2004)), so our estimates imply that college course quality effects on earnings are slightly larger than estimates of teacher quality effects on test

scores. Similarly, Chetty et al. (2014) show that a standard deviation higher teacher VA in grade school leads to about 1.5% higher earnings at age 28, which is considerably smaller than the course quality effect we estimate. This is sensible, as the college courses we examine are much more proximate to labor market outcomes than are the teachers in Chetty et al. (2014).

Table 2 also shows the standard deviation of value-added estimates by field of study. The variance in course quality effects varies considerably across fields, with biology and health ($992), computer science ($734), engineering ($712), interdisciplinary studies ($622), business ($607), and vocational ($612) at the high end of value-added estimates and education ($467), physical science & math ($460), agriculture ($444), architecture ($428), liberal arts ($410), communications ($368), economics ($381), and social science ($346) exhibiting lower variability in value-added. Hence, in some fields, the specific courses students take matter a lot in terms of future earnings, while in other fields course decisions are less consequential. These results also demonstrate that much of the variation in course value-added is within field of study.

The remaining results in Table 2 show how course value-added varies by level of the course and the demographic characteristics of students. Course value-added increases with the level of the class, such that the variation in quality is highest for junior- and senior-level classes relative to freshman- and sophomore-level classes. This result indicates that more advanced courses vary more in terms of quality than introductory-level classes taken in the first two years of college. Table 2 also shows estimates of value-added by whether a class is designated as part of the Texas Core Curriculum (TCC). TCC classes count towards distributional requirements, which induces many students to take them who otherwise would not do so. Value-added of TCC courses ($372) is much lower than for non-TCC courses ($591). The quality range of required courses is smaller than non-required courses. Combined with the fact that variation in VA is lower for lower-level courses this can explain why some fields like economics exhibit a smaller distribution of value-added: most economics enrollments outside the major are for lower level TCC classes (such an introductory microeconomics).

We next examine whether students with certain backgrounds experience larger or smaller returns to course quality. To do so, we calculate the standard deviation of value-added separately among each group using the overall value-added estimates from equations (1) and (2). Differences in the variation of course value-added by gender, race/ethnicity, and student SES are minor relative to the mean. The largest difference is for Asian students, who experience higher variation in value-added on average relative to students from other racial/ethnic backgrounds.

Table A4 provides a more detailed analysis of how course value-added varies with student demographic characteristics. We estimate models with course-semester value-added as the dependent variable and student characteristics listed in Table 1 as independent variables. The results tell a consistent story, regardless of which fixed effects are included or whether we exclude those whose race is "other:" Black, Hispanic, and Asian students all experience lower value-added than White students, although the differences are small in magnitude. Even small differences could add up across all courses to meaningful amounts for workers, however. The higher value-added in Table 2 for Asian students is driven by confounding factors that we control for in Table A4. There are small differences by high school achievement, with value-added increasing with reading scores and decreasing with math test scores, but the variation is small relative to the mean value-added. Taken together, the estimates in Table A4 suggest at most small differences in value-added by student SES and pre-collegiate achievement levels.

As discussed in Section 3, our estimates necessarily rely on selection on observables assumptions. If there is substantial selection residual to our fixed effects and controls, our estimates would be biased. We examine this question in Table 3, where we show correlations between value-added estimates that alter the control set. In Panel A, we include the high school, college, and major fixed effects, while in Panel B we do not. Column (1) shows how the baseline estimates from Table 2 correlate with value-added estimates that exclude, in turn, student characteristics, student achievement, pre-collegiate course taking, and all observable controls. Each set of estimates other than the "All Controls" results excludes

only the set of controls listed and includes all of the others. The estimates change negligibly when any one set of controls is excluded. Even excluding all controls other than the fixed effects has only a minor impact on the estimates: there is a 0.95 correlation between the estimates with and without all of the observables included in equation (1). The robustness of our results is exhibited in each pairwise comparison, as shown in the other columns of the table. Of particular importance is the insensitivity of our estimates to the exclusion of the class-level means, which have been shown to be important controls in other settings (Altonji and Mansfield, 2018; Chetty et al., 2014).

Panel B of Table 3 presents the same analysis without fixed effects. The estimates now are more sensitive to excluding the class level means and particularly to excluding all controls. The correlation between the baseline estimates and the estimates with no controls is 0.78, which is far lower than the correlation of 0.95 in Panel A. Interestingly, the other observables largely reinforce one another, such that one needs only the student observed characteristics or the fixed effects we use but not both. Following the arguments from Oster (2019), the insensitivity of our results to the set of controls we include, especially conditional on the fixed effects, indicates there is little scope for residual selection on unobservables.

4.2 The Average Return to Course Fields

Course value-added is a measure of the variance across classes in their effects on future earnings. In order to more fully understand how course-taking affects earnings, these results need to be paired with mean earnings effects. It could be the case that some low-value-added fields have high mean returns (or vice versa). Table 4 presents estimates of the average effect of taking a course in a given field on earnings from equation (3). Column (1) presents our baseline estimates that includes controls for observables, cohort-HS, cohort-university, course level, and major fixed effects.

The baseline results in column (1) show that outside of physical sciences and math and interdisciplinary studies, the effects of taking courses in a given field (relative to liberal arts) are positive and outside of agriculture are statistically significant at the 5% level

or higher. The average returns vary widely across field. The relative return to taking a course in a field ranges from -$114 (interdisciplinary studies), -$49 (physical science and math), $36 (agriculture), $77 (communications), and $97 (economics) at the low end to $235 (architecture), $298 (engineering), $311 (education), $374 (business), and $443 (computer science) at the high end.[10]

The results in column(1) of Table 4 show estimated returns by field of study that control for major, but there could be heterogeneous returns by major. In Table A1, we show estimates of equations (3) by major. The first column repeats the estimates from column (1) of Table 2 for reference. Each subsequent column presents results from a separate regression, where courses in the student's own major are the reference category. The estimates therefore show, for each major, what the returns are to taking a course in each field relative to a course in the student's own major.[11] For liberal arts majors (column 8), there are positive returns to taking courses in most other fields, with the highest returns for courses in education, engineering, business, economics, and communications. For engineering students (column 7), there are positive returns to taking business and computer science courses and negative returns to taking vocational, science & math, and biology & health classes. Economics students (column 13) experience negative effects on earnings from taking engineering, science & math, biology & health, computer science, and non-economics social science classes. Only business courses lead to statistically significant higher earnings for economics majors. Taken together, the estimates from Table 4 and Table A1 demonstrate that there are large differences in the returns to taking courses in different fields, on average, and that these returns also vary by field of study. An important implication of these findings is that the earnings-maximizing distribution of non-major coursework is heavily dependent on one's major.

Table 4 show robustness of our estimates to variations in the estimating sample and control set. Column (2) controls more flexibly for major by including 4-digit CIP code

[10]These estimates broadly align with the returns to college major (see Andrews et al. (2024)), with the exception of economics that has one of the highest returns to major but has more modest returns to non-major course-taking. As well, we find large returns to taking education courses, while prior research has found smaller returns to majoring in education (Hamermesh and Donald, 2008; Arcidiacono, 2004).

[11]There is no education major in four-year colleges in Texas, but there are education courses.

fixed effects. The estimates change negligibly. Column (3) allows for the effect of major group to vary by cohort. There are some changes to the results, notably for agriculture, architecture, interdisciplinary studies, and physical sciences & math, but on the whole the effects do not change substantively. One concern with our approach is that some students may intend to major in a subject upon entry and then switch, which would appear as non-major course-taking in our model. In column (4), we additionally control for initial major and in column (5) we control for the major that is declared at the time the course is taken. Neither additional major control has a noticeable impact on our results.

Because we include major fixed effects, our estimates predominantly reflect out of major course-taking. But there is some variation coming from differences across students in the courses they take within a given major. In column (6), we exclude any courses in the same field as one's major. Both agriculture and biology & health estimates become negative and statistically significant, suggesting that the positive effects of course-taking in these areas come from those within the major. Returns in other fields remain similar, with the estimates for engineering and architecture becoming somewhat larger. In column (7) we include an indicator for whether a student is a double major, and we add an indicator for whether a student transferred in column (8). Neither control has much of an effect on the estimates. Column (9) shows results when we include non-completers. The estimate remain stable. In column (10), we interact whether the course is part of the Texas Core Curriculum with the level of the course. If TCC courses have different returns, they could bias our estimates because they are not evenly distributed by level: more TCC courses are at the freshman and sophomore level. The results are very similar to baseline.

One key question in our analysis is whether higher-returns courses are reflective of the content of the course or the instructor. Our estimates may be picking up having higher value-added instructors rather than the return to courses students take. Light et al. (2025) use administrative Texas data to estimate instructor value-added and find that a one standard deviation increase in instructor quality raises next-semester GPA by 0.13 and earnings by 17%. We use the same method as Light et al. (2025) to calculate instructor

value-added with respect to GPA and include it as an additional control in column (11). The estimates change little with respect to our main findings, suggesting that we are measuring the return to college course-taking rather than the return to better instructors. Taken together, the results from columns (2)-(11) of Table 4 show that our estimates are robust to numerous additional controls and changes to the analysis sample.

4.3 The Role of Grades, Course Level, and Core Course Designation

No prior research of which we are aware estimates how the returns to course-taking decisions varies by the grades received in the course. We acknowledge that these results are descriptive, since we do not have plausibly exogenous variation in grades. However, these descriptive results are novel and important in understanding the linkage between course performance and future earnings. One interpretation of low grades is as an indicator that the student did not actually engage with the material and thus would not be expected to benefit. Panel A of Figure 4 shows how earnings vary with grades received. We estimate a version of equation (3) in which we include indicators for grade received (with B as the excluded category). On average, obtaining a higher grade is associated with higher earnings.

Figure A1 expands on these results by showing estimates of how the earnings returns to course-taking differ by the grade received in each field. These results come from estimation of a version of equation (3), where we interact each field with the grade received (A-F); B remains the excluded category. The interpretation of each coefficient is the average return to taking a course in each field when receiving the given grade.

The pattern of estimates is remarkably similar across fields: the return to taking a course for those who obtain an "A" is the highest and the returns decline as the grade declines. For the most part, the returns decline linearly with grade, indicating that grade performance is strongly linked to future earnings. These estimates are not necessarily causal – those earning a higher grade could have other attributes that generate higher earnings. Still, we argue that these estimates are informative for two reasons. First, they suggest that course performance does translate to earnings, which has not been shown in prior work. Second, there is much

concern over grade inflation in higher education, with many arguing that grades have become less relevant metrics of success. Our results provide direct evidence that grades continue to have informative content about human capital.

To further explore the implications of our results for grade inflation, in Figure A3 we estimate the same model by quintile of the average grade in the class. Particularly for the highest two quintiles, the benefits of an A and the penalty associated with a C (relative to a B in the same quintile) increase. This result likely is driven by the fact that when the average grade is high, it is worse to receive a grade below an A. There are important implications of this finding for grade inflation. Grade inflation does not appear to reduce returns conditional on getting a good grade, but it does penalize those who do not. The distributional consequences of grade inflation thus may be high.

In Panel B of Figure 4, we show results from a model similar to the one used for Panel A but replacing grade indicators with course level indicators (with Freshman as the excluded category). On average, earnings are much higher for Junior and Senior courses, which are more advanced. Figure A2 shows estimates by field. Across all fields other than interdisciplary studies, the return to Junior and Senior level classes is higher. As well, in most fields the returns increase linearly with the level of the course. Finally, in Figure A4, we show estimates by level and TCC designation. The return to non-TCC courses is higher at every level, which aligns with the results in Table 2 that shows low value-added for TCC courses. These results have two important implications. First, the returns to inducing students to take specific distributional courses appears low relative to the courses they take by choice. Second, some of the low returns shown in Table 4, such as economics, biology & health, and physical sciences & math, are likely driven in part by the fact that most of the enrollments are for required, lower-level courses. Taken together, the results in this section indicate that taking more advanced courses and doing well in them is strongly associated with higher earnings after college.

5 Conclusion

We use transcript-level administrative data from Texas that contains information on every course taken by four-year college graduates and their course performance from 2012 to 2019 linked to their K-12 education records and their quarterly earnings from the unemployment insurance system. These data provide a breadth and scope to study course-taking that previously has not been available to researchers. We estimate selection-on-observable models that control for pre-collegiate academic achievement and background characteristics as well as high school, college, and major fixed effects in order to examine how taking courses in one of 14 topical areas affects post-collegiate earnings.

First, we estimate course value-added, which shows the (residual) variance across classes in how they contribute to future earnings of students. Our findings indicate that a one standard deviation increase in course VA increases earnings by $575 per quarter, or 15% of a standard deviation. Variation in course value-added varies little by student demographics or prior academic achievement levels, but it does vary considerably across subject areas. High variation value-added subjects include biology & health ($992), computer science ($734), engineering ($712), interdisciplinary studies ($622), business ($607), and vocational ($612), while low value-added subjects include agriculture ($444), architecture ($428), liberal arts ($410), economics ($381), communications ($368), and social science ($346).

Second, we estimate the average returns to courses in each subject relative to liberal arts. As with value-added, there is much variation across subjects in the return to courses. The courses that have the highest returns relative to liberal arts are in computer science by ($443), business ($374), and education ($311), while courses with the lowest relative returns are in physical sciences & math (-$98), interdisciplinary studies (-$69), and social science ($39). We also show that these average returns vary by one's major. Finally, we present evidence that the returns to courses overall and within each field increase with the grade received and with the difficulty of the course, suggesting that grades and course level have meaningful content in them.

Our results show that courses taken outside of one's major are important for shaping post-collegiate labor market earnings. There are substantial average differences in returns across fields of study as well as considerable variation across classes within fields in terms of their value-added for future earnings. These findings raise the important question of why returns vary so much even within disciplines. Factors like instructor quality, peer composition, and the focus on specific skills may help explain this variation. Future work examining what makes courses higher value for students and what the earnings-maximizing mix of course-taking might be for students in different majors would be of much value.

References

Altonji, Joseph G and Richard K Mansfield, "Estimating group effects using averages of observables to control for sorting on unobservables: School and neighborhood effects," *American Economic Review*, 2018, *108* (10), 2902–2946.

Andrews, Rodney J, Jing Li, and Michael F Lovenheim, "Quantile treatment effects of college quality on earnings," *Journal of Human Resources*, 2016, *51* (1), 200–238.

_ , Scott A Imberman, and Michael F Lovenheim, "Recruiting and supporting low-income, high-achieving students at flagship universities," *Economics of Education Review*, 2020, *74*, 101923.

_ , _ , _ , and Kevin Stange, "The returns to college major choice: Average and distributional effects, career trajectories, and earnings variability," *Review of Economics and Statistics*, 2024, pp. 1–45.

Arcidiacono, Peter, "Ability sorting and the returns to college major," *Journal of econometrics*, 2004, *121* (1-2), 343–375.

Biasi, Barbara and Song Ma, "The education-innovation gap," Technical Report, National Bureau of Economic Research 2022.

Bleemer, Zachary and Aashish Mehta, "Will studying economics make you rich? A regression discontinuity analysis of the returns to college major," *American Economic Journal: Applied Economics*, 2022, *14* (2), 1–22.

Chau, Hung, Sarah H Bana, Baptiste Bouvier, and Morgan R Frank, "Connecting higher education to workplace activities and earnings," *Plos one*, 2023, *18* (3), e0282323.

Chetty, Raj, John N Friedman, and Jonah E Rockoff, "Measuring the impacts of teachers I: Evaluating bias in teacher value-added estimates," *American economic review*, 2014, *104* (9), 2593–2632.

Hamermesh, Daniel S and Stephen G Donald, "The effect of college curriculum on earnings: An affinity identifier for non-ignorable non-response bias," *Journal of Econometrics*, 2008, *144* (2), 479–491.

Imberman, Scott A, Michael F Lovenheim, Patrick L Massey, Kevin Stange, and Rodney J Andrews, "The Contribution of College Majors to Gender and Racial Earnings Differences," 2025. Working Paper.

Kane, Thomas J and Douglas O Staiger, "Estimating teacher impacts on student achievement: An experimental evaluation," 2008. NBER Working Paper No. 14607.

Kirkeboen, Lars J, Edwin Leuven, and Magne Mogstad, "Field of study, earnings, and self-selection," *The quarterly journal of economics*, 2016, *131* (3), 1057–1111.

Light, Audrey and Sydney Schreiner, "College major, college coursework, and post-college wages," *Economics of Education Review*, 2019, *73*, 101935.

_ and Sydney Schreiner Wertz, "Should English majors take computer science courses? Labor market benefits of the occupational specificity of major and nonmajor college credits," *Economics of Education Review*, 2022, *88*, 102263.

Light, Jacob, Merrill Warnock, and Anthony Yim, "Instructor Value-Added in Post-Secondary Education," 2025. Working Paper.

Lovenheim, Michael and Jonathan Smith, "Returns to different postsecondary investments: Institution type, academic programs, and credentials," in "Handbook of the Economics of Education," Vol. 6, Elsevier, 2023, pp. 187–318.

Oster, Emily, "Unobservable selection and coefficient stability: Theory and evidence," *Journal of Business & Economic Statistics*, 2019, *737* (2), 187–204.

Paulson, Annaliese, "Three Essays on General Education and Student Success. Doctoral Dissertation." PhD dissertation, University of Michigan 2015.

Rivkin, Steven G, Eric A Hanushek, and John F Kain, "Teachers, schools, and academic achievement," *econometrica*, 2005, *73* (2), 417–458.

Rockoff, Jonah E, "The impact of individual teachers on student achievement: Evidence from panel data," *American economic review*, 2004, *94* (2), 247–252.

Silos, Pedro and Eric Smith, "Human capital portfolios," *Review of Economic Dynamics*, 2015, *18* (3), 635–652.

Tables and Figures

Table 1: Summary Statistics

	Mean	SD		Mean	SD
Student Characteristics			*Number of Courses, Grades 6-12*		
Male	0.414	0.493	English Language Arts	9.242	1.977
White	0.453	0.498	Math + Technology Applications	8.549	1.890
Black	0.103	0.304	Science	7.461	1.604
Hispanic	0.332	0.471	Social Studies	8.372	1.435
Asian	0.089	0.284	Foreign Language	4.741	1.679
Gifted	0.245	0.430	Fine Arts	5.030	4.212
At Risk	0.110	0.313	CTE + Business Education	7.062	4.508
Economically Disadvantaged	0.282	0.450	Others	5.372	3.163
Student Achievement					
Math Exam Score	0.821	0.622	AP: English Language Arts	1.689	1.757
Reading Exam Score	0.619	0.421	AP: Math + Technology Applications	0.975	1.393
Top Ten Percent Math	0.366	0.482	AP: Science	1.129	1.600
70th-90th Percentile Math	0.322	0.467	AP: Social Studies	2.433	2.526
Top Ten Percent Reading	0.419	0.493	AP: Foreign Language	0.229	0.715
70th-90th Percentile Reading	0.244	0.429	AP: Fine Arts	0.149	0.598
Earning Outcomes					
Residualized Earnings	-371.900	3,235.746			
Mean Earnings	5,010.825	3,853.043			

Notes: The table reports summary statistics (mean and standard deviation) of controls and earning outcomes used in the course value-added equation (3) at the student-course-year level (N = 6,711,738). Students' characteristics include indicators for gender, race, whether a student is in a talented program, whether a student is at-risk, and whether a student is from a disadvantaged family. Students' pre-collegiate academic abilities include standardized 8th-grade math and reading test scores, indicators for whether a student is in the top decile of each exam distribution within their school, and indicators for whether a student is in the top 10-30 percent of the within-school exam distribution. The number of high school courses includes the number of general and Advanced Placement (AP) high school courses in different fields. "Others" include self-contained, physical education & health, special education, and other courses.

Table 2: Estimated Course Value-Added

	SD	Shrunk SD		SD	Shrunk SD
Full Sample	1006.487	575.296	*By Course Level*		
			Freshman	694.929	412.091
By Course Field			Sophomore	827.945	495.326
Agriculture	824.902	443.832	Junior	1008.792	580.149
Architecture	794.187	428.217	Senior	1147.904	635.570
Communications	714.358	368.143			
Computer Science	1349.307	733.514	*By Gender*		
Vocational	1070.009	612.063	Female	1100.499	631.152
Education	813.433	467.209	Male	1207.555	584.352
Engineering	1173.841	711.972			
Liberal Arts	898.731	409.534	*By Race*		
Biology + Health	1428.635	992.238	White	1113.608	598.357
Interdisciplinary Studies	1056.598	621.993	Black	1115.917	551.879
Physical Sciences + Math	897.657	460.315	Hispanic	1148.221	605.129
Social Science	728.456	345.811	Asian	1423.332	729.300
Economics	710.180	380.983			
Business	976.992	607.092	*By SES*		
			Economic Disadvantaged	1062.617	585.007
			Non Economic Disadvantaged	1135.716	593.086
			By Core Curriculum		
			TCC Course	585.208	371.570
			Non-TCC Course	1040.835	591.383

Notes: The table reports raw and shrunk standard deviations of estimated course value-added at the course level (N = 38,941). The full sample is further separated by course field and level. For standard deviations by students' gender, race, and socioeconomic status (SES), we divide the course-student observation by the demographics and calculate the standard deviations of estimated course value-added within each student group. The raw standard deviation are estimated from the course valued-added equation (3), and the shrunk standard deviation is obtained using the empirical Bayes shrinkage equation (2). Course levels are designated by the THECB and do not necessarily reflect the grade of the students enrolled.

Table 3: Correlations between VAs Estimated with Different Specifications

	Baseline (1)	Student Characteristics (2)	Student Achievement (3)	HS Course Taking (4)	Class Level Means (5)	All Controls (6)
Panel A. With Fixed-Effects						
Baseline	1.0000					
Student Characteristics	0.9992	1.0000				
Student Achievement	0.9997	0.9987	1.0000			
HS Course Taking	0.9978	0.9972	0.9974	1.0000		
Class Level Means	0.9663	0.9699	0.9653	0.9662	1.0000	
All Controls	0.9487	0.9545	0.9484	0.9531	0.9947	1.0000
Panel B. Without Fixed-Effects						
Baseline	1.0000					
Student Characteristics	0.9992	1.0000				
Student Achievement	0.9996	0.9985	1.0000			
HS Course Taking	0.9947	0.9940	0.9941	1.0000		
Class Level Means	0.9163	0.9212	0.9178	0.9131	1.0000	
All Controls	0.7742	0.7824	0.7767	0.7808	0.9447	1.0000

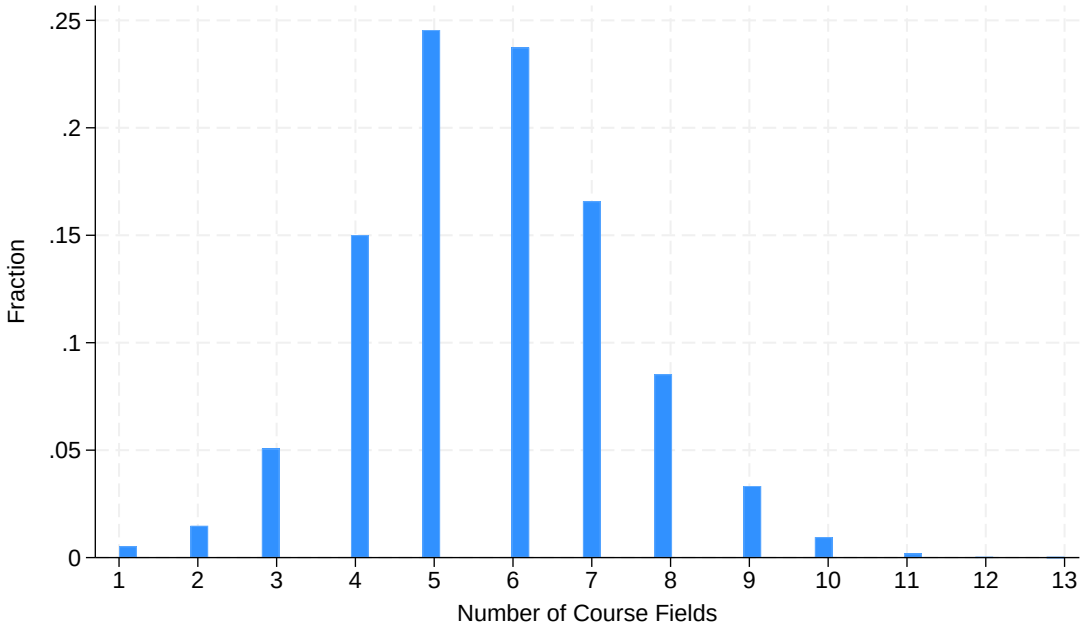
Notes: The table reports correlations between course value-added estimated with different specifications. 'Baseline' in column (1) uses base specification, while the following specifications in columns (2)-(6) remove student characteristics, student achievement, high-school course taking, class level means, and all these controls, respectively. The fixed effects (i.e., cohort-by-high school, cohort-by-university, and major fixed effects) are included in specifications in Panel A and not in Panel B.

Table 4: The Return to College Courses by Field

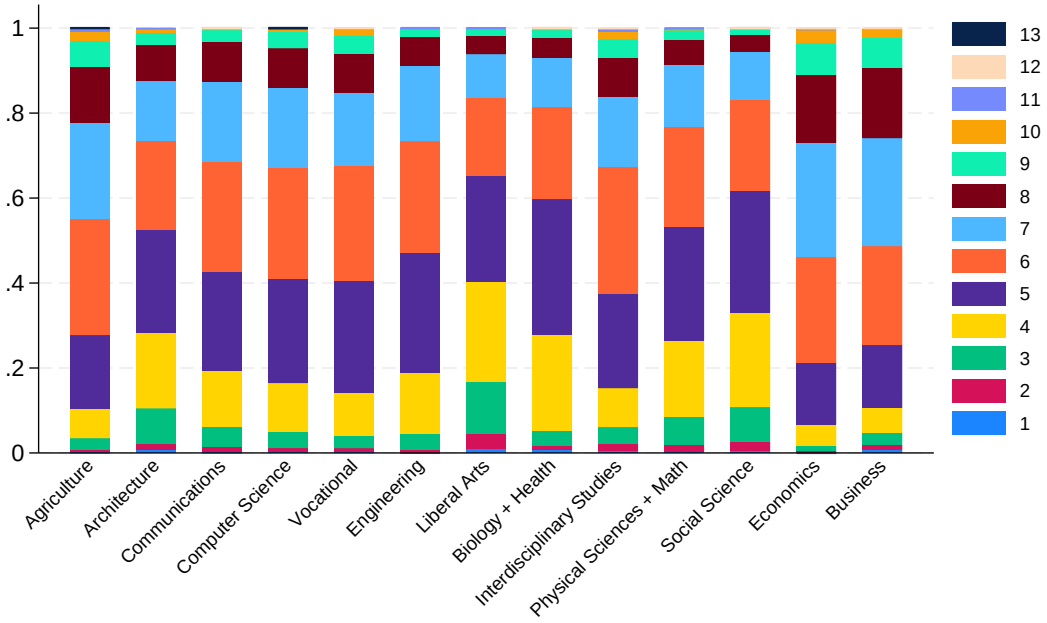
	Residualized Earnings										
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
Agriculture	35.645	33.938	109.653***	37.733	47.110**	-104.692***	38.166	37.152	-22.476	41.936	69.892***
	(24.342)	(24.020)	(16.488)	(23.247)	(22.986)	(32.451)	(24.227)	(24.131)	(21.830)	(25.567)	(23.416)
Architecture	235.463***	230.471***	47.522	241.439***	285.242***	439.838***	245.735***	240.870***	207.108***	253.879***	211.573**
	(82.272)	(82.158)	(55.669)	(74.980)	(71.069)	(104.450)	(81.106)	(83.136)	(74.515)	(81.499)	(89.658)
Communications	77.097***	81.889***	73.267***	78.565***	83.943***	72.284***	75.930***	78.668***	85.128***	86.674***	80.679***
	(18.594)	(18.608)	(11.743)	(18.778)	(20.732)	(21.724)	(18.779)	(18.618)	(15.737)	(17.716)	(19.280)
Computer Science	443.172***	438.111***	298.299***	442.309***	425.552***	345.819***	439.947***	444.110***	522.230***	465.838***	434.352***
	(26.564)	(26.325)	(21.939)	(26.308)	(27.694)	(33.160)	(26.600)	(26.483)	(24.236)	(28.075)	(25.589)
Vocational	195.300***	194.455***	150.758***	194.920***	195.320***	82.597***	195.367***	195.213***	197.745***	221.279***	201.760***
	(19.148)	(19.406)	(11.790)	(18.356)	(19.607)	(18.465)	(19.142)	(19.170)	(17.104)	(19.291)	(17.823)
Education	310.797***	316.899***	429.687***	279.595***	266.256***	378.637***	305.702***	313.008***	304.673***	318.572***	263.801***
	(33.940)	(33.774)	(26.842)	(32.834)	(32.384)	(28.632)	(33.777)	(34.014)	(31.938)	(33.714)	(33.998)
Engineering	297.929***	281.203***	263.311***	287.907***	311.591***	631.210***	295.963***	297.700***	480.264***	303.519***	325.627***
	(22.978)	(22.039)	(21.382)	(24.289)	(26.135)	(86.430)	(23.152)	(22.799)	(23.601)	(22.320)	(24.593)
Biology + Health	117.626***	119.773***	38.610***	131.303***	146.575***	-219.498***	120.516***	119.418***	108.338***	118.838***	136.619***
	(25.862)	(25.331)	(11.868)	(24.412)	(24.938)	(17.760)	(25.791)	(26.007)	(24.962)	(26.009)	(21.547)
Interdisciplinary Studies	-113.981***	-113.798***	4.219	-116.584***	-119.607***	-20.285	-118.353***	-111.781**	-20.051*	-88.034*	-146.352***
	(43.980)	(43.518)	(29.857)	(43.918)	(44.067)	(52.752)	(44.097)	(44.152)	(11.547)	(44.957)	(41.425)
Physical Sciences + Math	-49.313***	-49.854***	39.676***	-47.096***	-41.737***	-31.521**	-47.077***	-46.697***	28.593***	-63.201***	-1.583
	(13.900)	(13.927)	(10.117)	(13.380)	(13.704)	(12.572)	(13.783)	(13.914)	(10.443)	(13.172)	(14.291)
Social Science	38.847***	40.781***	16.839*	39.270***	36.606***	48.495***	38.356***	40.307***	478.138***	47.880***	62.232***
	(11.380)	(11.128)	(9.009)	(11.177)	(11.179)	(9.986)	(11.211)	(11.355)	(26.222)	(10.100)	(12.406)
Economics	96.726***	99.098***	74.831***	74.163***	45.943**	125.503***	89.131***	97.721***	-6.638	119.887***	141.145***
	(22.095)	(21.274)	(18.731)	(20.636)	(19.671)	(20.233)	(21.465)	(22.117)	(29.858)	(21.131)	(21.253)
Business	374.403***	359.745***	344.682***	355.736***	332.048***	525.570***	362.295***	375.186***	151.762***	392.181***	375.779***
	(26.143)	(23.645)	(22.154)	(24.845)	(23.896)	(33.609)	(23.978)	(26.048)	(22.604)	(26.590)	(29.079)
Controls	X	X	X	X	X	X	X	X	X	X	X
Cohort-HS & Cohort-Univ FE	X	X	X	X	X	X	X	X	X	X	X
Major FE	X			X	X	X	X	X	X	X	X
Major FE (4-digit CIP Codes)		X									
Cohort-Major FE			X								
Initial Major FE				X							
Pre-Course Major FE					X						
Dropping Within-Major Courses						X					
Double Major Controls							X				
Transfer Student Indicator								X			
Including Non-Completers									X		
Course Level*TCC Indicators										X	
Instructor Characteristics & GPA VA											X
Observations	6,711,738	6,711,738	6,711,738	6,711,664	6,702,588	3,960,744	6,711,738	6,711,664	8,261,220	6,711,738	6,141,862
Adjusted R-squared	0.204	0.206	0.268	0.205	0.205	0.194	0.205	0.205	0.177	0.204	0.205

Notes: The dependent variable is the residualized earnings for each individual as described in Section 3. The estimates are obtained using equation (3). "Controls" are listed in Table 1. All estimates include cohort-by-high school and cohort-by-university fixed effects. We include major fixed effects in column (1), while using 4-digit CIP codes in column (2) and cohort-by-major fixed effects in column (3). Columns (4) and (5) add initial major and pre-course major fixed effects, respectively. Column (6) drops within-major courses, while column (7) controls for double major variation. Column (8) includes a dummy indicating whether a student was transferring from other post-secondary institutions. Column (9) uses the baseline specification but includes undergraduate students who have not yet received a degree (non-completers). Column (10) includes the interaction term between course level and TCC (Texas Core Curriculum) indicators, while Column (10) controls for instructor's characteristics (i.e., age, gender, ethnicity, tenure rank) and GPA value-added. All estimated returns to course fields are relative to liberal arts (the excluded category). Standard errors clustered at the cohort-university level are in parentheses.

Figure 1: Breadth of Course Fields by Major



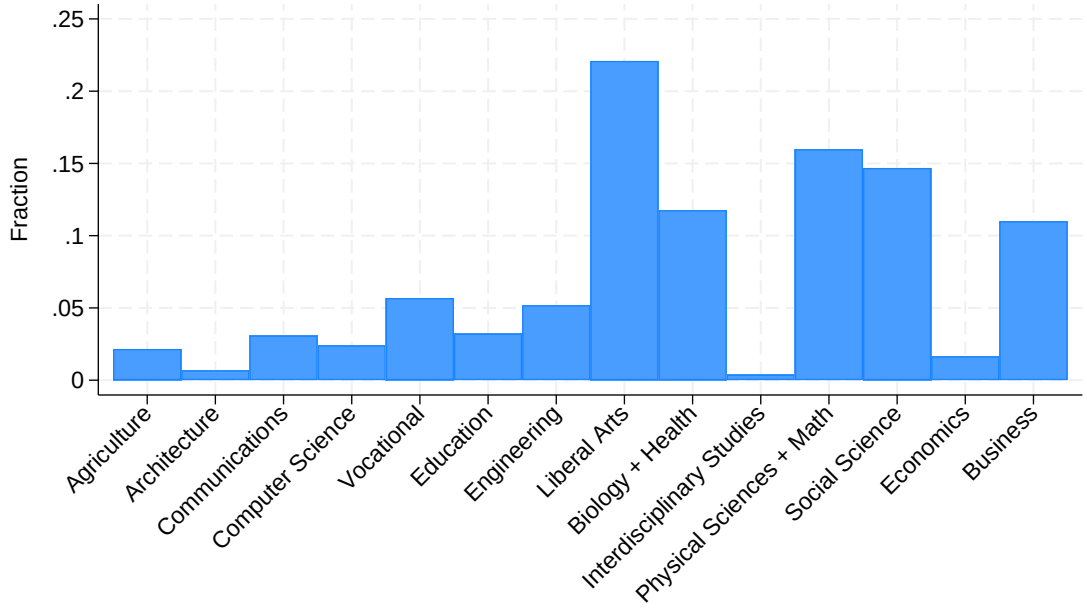
(a) Breadth of Course Fields



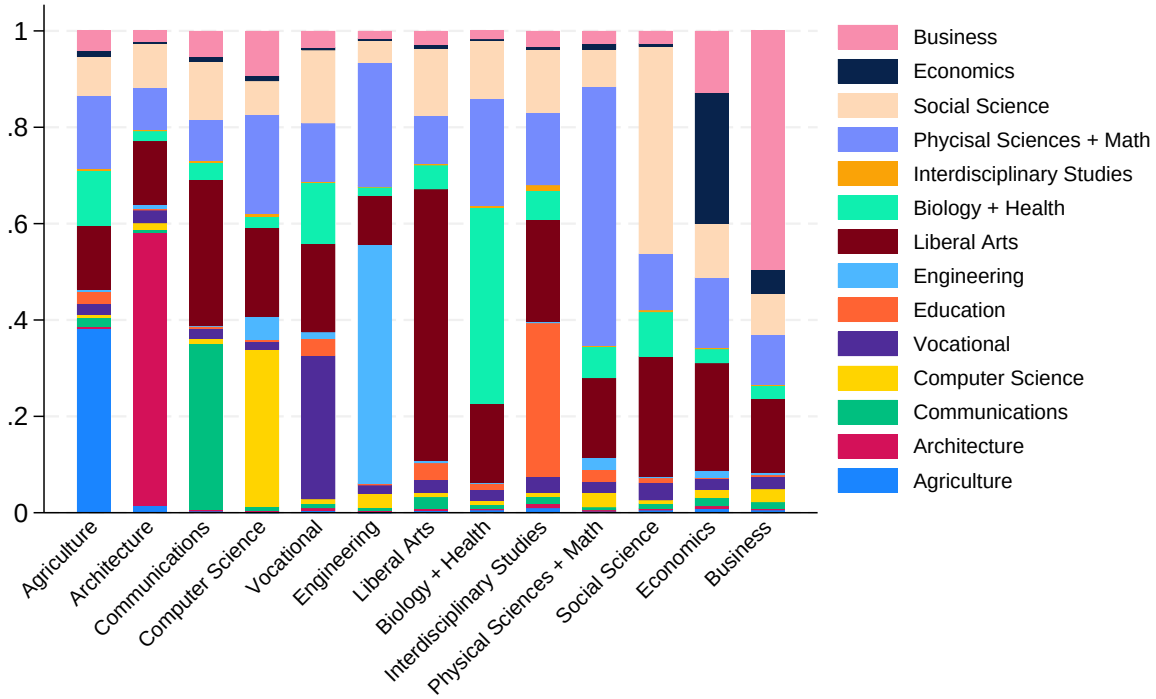
(b) Breadth of Course Fields by Major

Notes: This figure displays the breadth of courses taken across fields for students in the analysis sample. Subfigure (a) presents the distribution of course fields taken by undergraduates in the analysis sample, while subfigure (b) shows the distribution of the number of fields taken separately by students' final major.

Figure 2: Distribution of Courses Taken



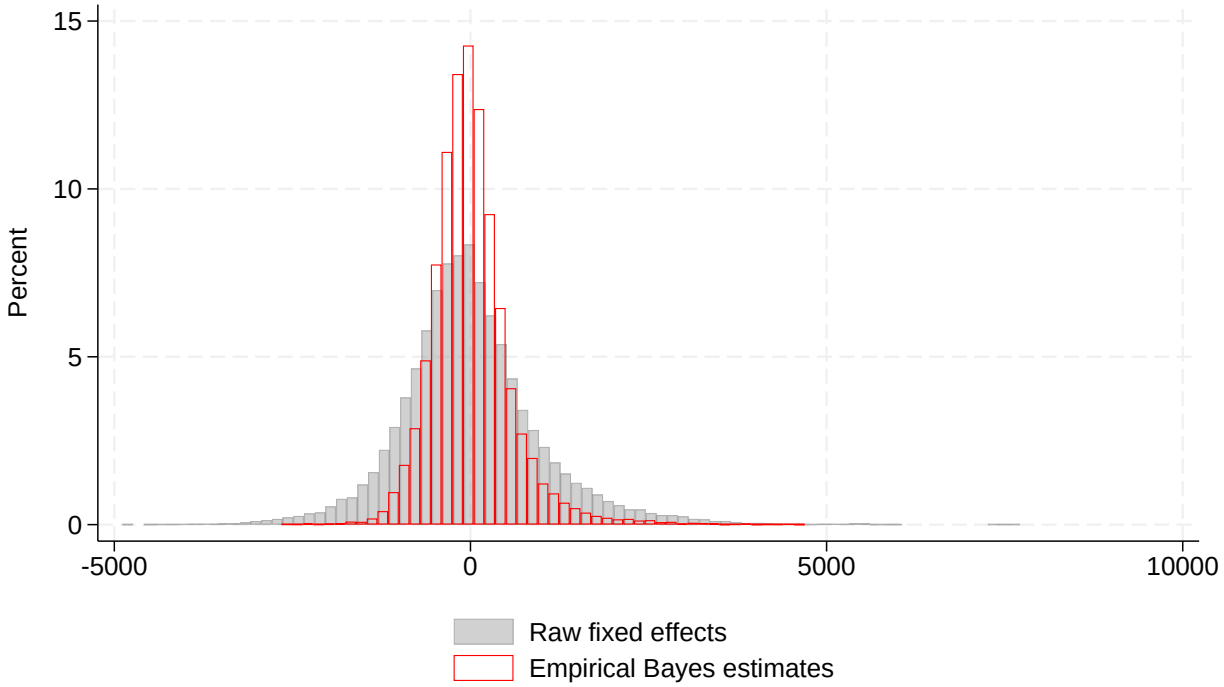
(a) Proportion of Courses Taken Across Fields



(b) Proportion of Courses Taken Across Fields by Major

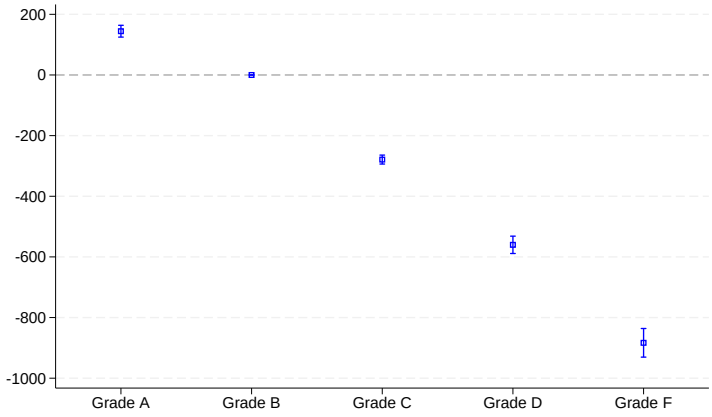
Notes: This figure displays the distribution of courses taken acroos fields of study. Subfigure (a) shows the proportion of courses taken in each field across all students in the analysis sample, while subfigure (b) shows the proportion of courses taken in each field by students' final major.

Figure 3: Distribution of Course Value-Added

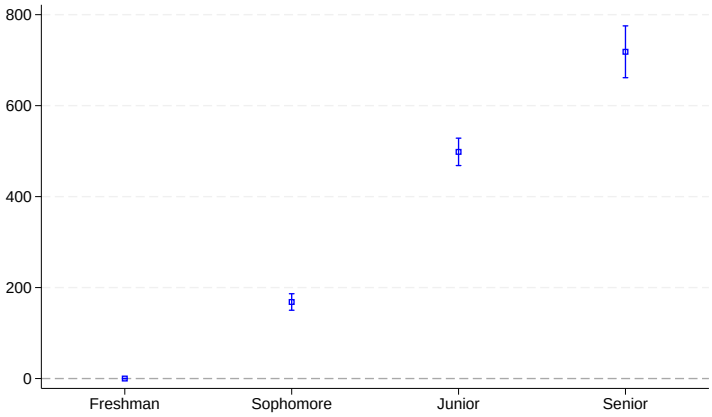


Notes: The figure displays the distribution of raw course value-added estimated using course fixed effects (in grey) and shrunken course value-added using the empirical Bayes shrinkage method (in red).

Figure 4: The Return to College Courses by Academic Grade and by Course Level



(a) By Academic Grade



(b) By Course Level

Notes: The dependent variable is the residualized earnings for each individual as described in Section 3. Estimates in subfigures (a) and (b) are obtained using the academic grade (grades A, B, C, D, and F) and course level (freshman, sophomore, junior, and senior) indicators, respectively. "Controls" are listed in Table 1. All estimates in each panel are from one regression that includes cohort-by-high school, cohort-by-university, and major fixed effects. The sample covers courses taken by undergraduate students who are degree recipients, including failed courses. The estimated returns to course fields in each grade are relative to courses with a B grade in subfigure (a) and relative to freshman courses in subfigure (b). For each point estimate, we show 95% confidence intervals from standard errors that are clustered at the cohort-university level.

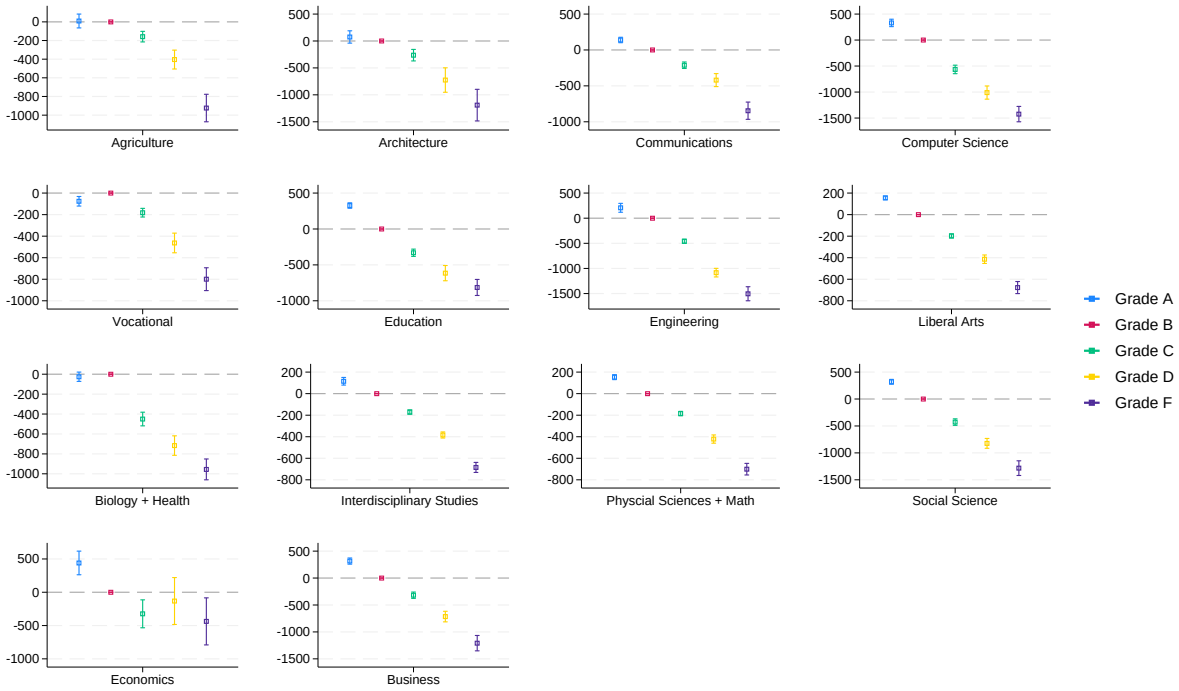
Appendix Tables and Figures

Table A1: The Return to College Courses Across Fields by Student Major

	Residualized Earnings													
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)
Agriculture	35.645		15.969	-16.099	-82.576	119.850	218.991***	1.917	-391.027***	197.858***	-388.991***	93.746*	102.066	-144.910***
	(24.342)		(49.721)	(71.336)	(124.096)	(83.005)	(78.007)	(66.909)	(54.504)	(47.422)	(122.063)	(54.824)	(72.033)	(44.875)
Architecture	235.463***	108.582		111.729	-690.797***	1,096.085***	-61.366	-79.324	96.948	546.771***	-65.292	5.384	99.468	-228.589**
	(82.272)	(87.227)		(154.012)	(189.942)	(106.378)	(110.342)	(138.560)	(78.356)	(52.020)	(92.078)	(83.263)	(86.854)	(104.812)
Communications	77.097***	57.490	36.079		-70.505	-37.766	99.995	231.966***	-268.232***	70.365	83.942	20.773	-72.454	-66.753**
	(18.594)	(54.906)	(53.693)		(75.104)	(29.498)	(68.378)	(43.417)	(55.289)	(45.770)	(61.089)	(31.947)	(89.291)	(30.813)
Computer Science	443.172***	57.488	-20.987	178.636***		204.168***	361.085***	135.267***	133.083***	210.912***	256.145***	220.398***	-110.907	-47.613**
	(26.564)	(35.515)	(19.855)	(44.872)		(40.287)	(63.023)	(51.983)	(49.691)	(52.783)	(68.945)	(53.068)	(150.854)	(22.766)
Vocational	195.300***	17.363	11.943	-27.599	-187.430**		-108.654	146.593***	38.994	76.826**	21.633	36.901**	-40.572	-69.535**
	(19.148)	(37.436)	(26.381)	(30.775)	(72.322)		(68.151)	(27.060)	(45.945)	(31.495)	(35.670)	(17.700)	(81.505)	(33.564)
Education	310.797***	357.639***	-158.401	31.683	13.529	-156.654***	6.003	705.917***	-283.714***	228.968***	189.252***	209.961***	-317.225	-293.287***
	(33.940)	(47.420)	(97.979)	(51.940)	(134.134)	(32.499)	(173.884)	(39.967)	(61.132)	(23.127)	(67.354)	(43.467)	(197.637)	(63.680)
Engineering	297.929***	-10.271	193.502	-266.194*	-64.303	753.854***		343.483***	-107.839	297.631**	-152.993**	-215.887*	-673.811***	-621.883***
	(22.978)	(75.592)	(162.596)	(154.836)	(52.881)	(70.365)		(103.542)	(156.591)	(120.955)	(64.885)	(110.207)	(157.157)	(65.387)
Liberal Arts		-6.663	-28.897**	-68.501***	-178.443***	23.608	60.711*		-73.337***	92.539***	18.978	-44.808***	-47.867	-144.324***
		(16.765)	(14.365)	(14.279)	(35.953)	(15.607)	(32.577)		(15.949)	(20.488)	(21.212)	(10.237)	(48.754)	(15.362)
Biology + Health	117.626***	-123.548***	-1.521	80.443*	23.514	-195.534***	-452.115***	26.757		-14.410	-216.226***	-33.364**	-99.040	-247.615***
	(25.862)	(17.618)	(31.795)	(46.740)	(69.501)	(22.335)	(78.170)	(25.990)		(30.188)	(30.356)	(16.808)	(74.913)	(43.731)
Interdisciplinary Studies	-113.981***	-60.469	24.161	1.997	-842.348***	77.567	43.362	77.563**	-125.029***		-39.569	-12.493	-70.943	-78.871
	(43.980)	(56.088)	(57.285)	(59.891)	(121.523)	(49.501)	(82.248)	(35.528)	(43.198)		(70.957)	(34.788)	(125.783)	(52.270)
Physical Sciences + Math	-49.313***	-50.183**	1.119	-5.628	-77.515**	65.377***	-90.194***	25.760	-278.767***	142.879***		-58.612***	-144.925***	-177.228***
	(13.900)	(19.713)	(13.337)	(23.002)	(35.695)	(14.580)	(18.238)	(16.658)	(19.691)	(24.026)		(14.695)	(54.422)	(21.598)
Social Science	38.847***	2.431	-34.813***	-42.615**	-124.149***	53.401***	1.521	44.477***	-114.043***	27.385	-14.075		-97.281**	-178.156***
	(11.380)	(26.565)	(12.769)	(16.436)	(38.850)	(16.216)	(46.053)	(13.948)	(19.878)	(21.996)	(22.653)		(47.293)	(21.495)
Economics	96.726***	293.470***	-13.690	98.375*	-264.972***	99.171***	-31.174	229.296***	18.736	170.357***	278.443***	183.546***		-168.079***
	(22.095)	(46.843)	(50.461)	(52.708)	(59.748)	(36.648)	(59.800)	(50.158)	(62.415)	(53.835)	(85.142)	(53.978)		(15.643)
Business	374.403***	241.681***	30.108	318.696***	-78.662*	547.175***	321.122***	429.187***	247.975***	293.606***	373.556***	565.857***	99.456***	
	(26.143)	(33.339)	(32.814)	(43.074)	(47.594)	(47.281)	(78.394)	(59.890)	(79.610)	(52.578)	(70.641)	(44.601)	(29.586)	
Excluded Field	Lib. Arts	Ag.	Architecture	Comm.	Comp. Sci	Voc.	Engineering	Bio & Health	Interdisc.	Sci. & Math	Soc. Sci.	Econ.	Business	Lib. Arts
Controls	X	X	X	X	X	X	X	X	X	X	X	X	X	X
Cohort-HS & Cohort-Univ FE	X	X	X	X	X	X	X	X	X	X	X	X	X	X
Major FE	X	X	X	X	X	X	X	X	X	X	X	X	X	X
Observations	6,711,738	291,765	43,942	376,132	210,531	761,446	616,089	693,133	1,116,738	390,319	184,199	822,140	68,363	1,136,843
Adjusted R-squared	0.204	0.567	0.876	0.454	0.580	0.404	0.350	0.323	0.309	0.501	0.591	0.314	0.677	0.317

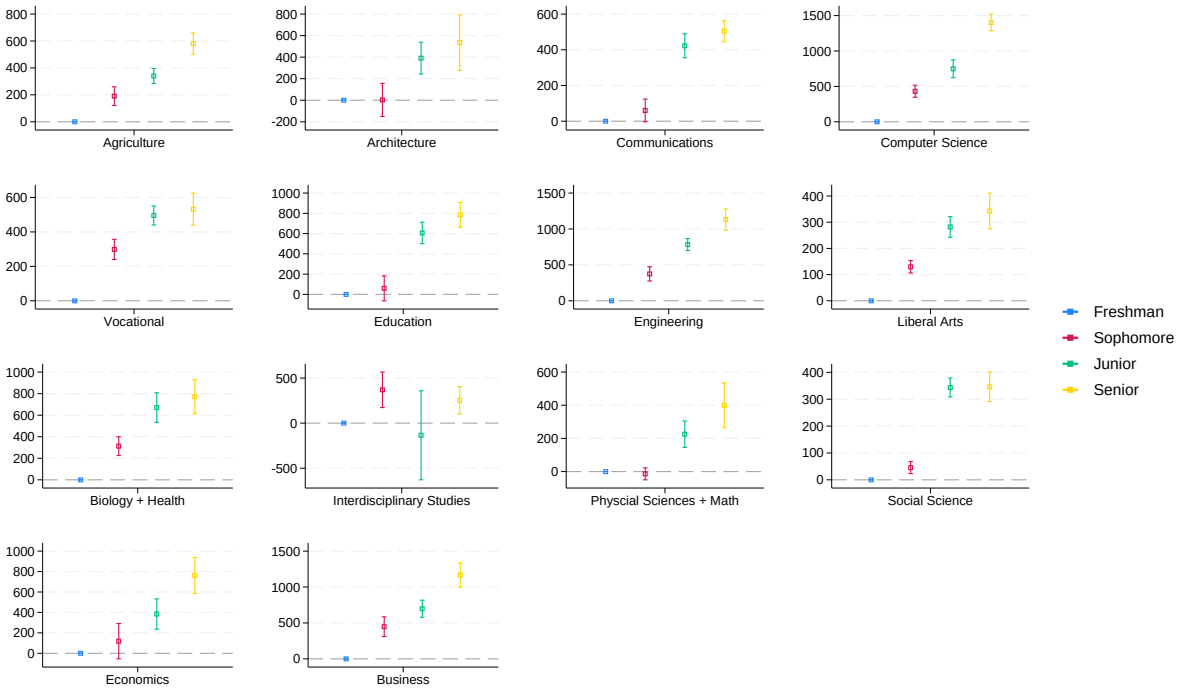
Notes: The dependent variable is the residualized earnings for each individual as described in Section 3. Estimates of field fixed effects are shown "Controls" are listed in Table 1. All estimates include cohort-by-high school, cohort-by-university, and major fixed effects. Column (1) includes undergraduate students who are degree recipients, while the following columns separate the sample by students' major. The estimated returns to course fields in columns (1) are relative to liberal arts (the excluded category), while estimates in the following columns are relative to the same field as students' major. Note that there are no students with an education major from a four-year university, as this major is not offered in Texas. Standard errors clustered at the cohort-university level are in parentheses.

Figure A1: The Return to College Courses Differences between Fields by Academic Grade



Notes: The dependent variable is the residualized earnings for each individual as described in Section 3. Estimates are obtained using the interaction terms between course taken indicator in a field and the grade of each course. "Controls" are listed in Table 1. Estimates in blue, red, green, yellow, and purple are course taken terms interacted with grades A, B, C, D, and F, respectively. All estimates are from one regression that includes cohort-by-high school, cohort-by-university, and major fixed effects. The sample covers courses taken by undergraduate students who are degree recipients, including failed courses. The estimated returns to course fields in each grade are relative to courses with a grade B. Note that there is no four-year education major in Texas. Standard errors clustered at the cohort-university level are in parentheses.

Figure A2: The Return to College Courses Differences between Fields by Course Level



Notes: The dependent variable is the residualized earnings for each individual as described in Section 3. Estimates are obtained using the interaction terms between course taken indicator in a field and the level of each course. "Controls" are listed in Table 1. Estimates in blue, red, green, and yellow are course taken terms interacted with course levels freshman, sophomore, junior, and senior, respectively. All estimates are from one regression that includes cohort-by-high school, cohort-by-university, and major fixed effects. The sample covers courses taken by undergraduate students who are degree recipients, including failed courses. The estimated returns to course fields in each grade are relative to freshman-level courses. Note that there is no four-year education major in Texas. Standard errors clustered at the cohort-university level are in parentheses.

Table A2: Regressions between VAs Estimated with Different Specifications

	Baseline (1)	Student Characteristics (2)	Student Achievement (3)	HS Course Taking (4)	Class Level Means (5)	All Controls (6)
Panel A. With Fixed-Effects						
Baseline	–					
Student Characteristics	1.0007	–				
Student Achievement	0.9981	0.9956	–			
HS Course Taking	0.9916	0.9895	0.9928	–		
Class Level Means	0.9787	0.9808	0.9792	0.9847	–	
All Controls	0.9447	0.9491	0.9459	0.9551	0.9780	–
Panel B. Without Fixed-Effects						
Baseline	–					
Student Characteristics	1.0005	–				
Student Achievement	0.9981	0.9916	–			
HS Course Taking	0.9664	0.9604	0.9673	–		
Class Level Means	0.8899	0.8897	0.8926	0.9127	–	
All Controls	0.6437	0.6469	0.6467	0.6681	0.8087	–

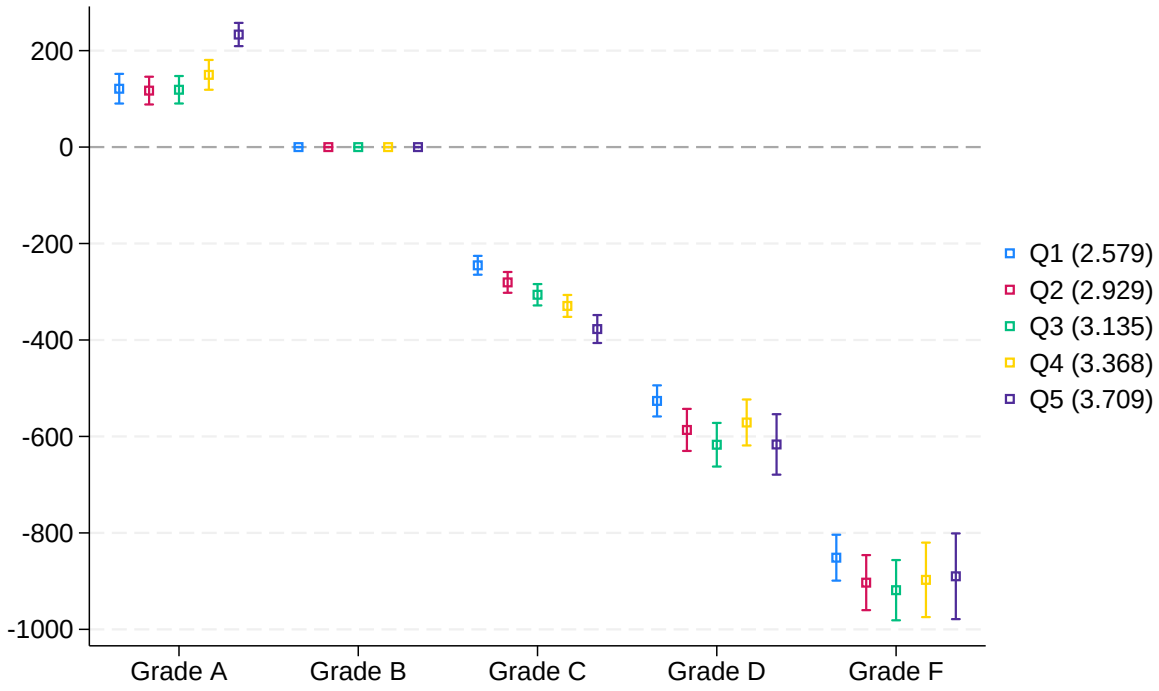
Notes: The table reports correlated estimates between course value-added estimated with different specifications. 'Baseline' in column (1) uses base specification, while the following specifications in columns (2)-(6) remove student characteristics, student achievement, high-school course taking, class level means, and all these controls, respectively. The fixed effects (i.e., cohort-by-high school, cohort-by-university, and major fixed effects) are included in specifications in Panel A and not in Panel B.

Table A3: Robustness: The Return to College Courses by Field - Removing Controls

	Residualized Earnings					
	(1)	(2)	(3)	(4)	(5)	(6)
Agriculture	35.645	33.062	34.547	61.266**	111.288***	135.854***
	(24.342)	(24.335)	(24.405)	(24.650)	(22.884)	(23.922)
Architecture	235.463***	231.156***	236.423***	254.402***	254.930***	270.649***
	(82.272)	(83.345)	(82.473)	(82.742)	(79.328)	(80.716)
Communications	77.097***	74.121***	76.836***	93.760***	48.720***	54.928***
	(18.594)	(18.981)	(18.462)	(19.362)	(16.096)	(17.075)
Computer Science	443.172***	448.399***	443.258***	466.368***	386.495***	411.909***
	(26.564)	(26.740)	(26.502)	(27.316)	(35.995)	(36.858)
Vocational	195.300***	195.499***	194.568***	219.825***	150.768***	162.132***
	(19.148)	(19.376)	(19.178)	(18.818)	(15.964)	(16.860)
Education	310.797***	316.317***	313.154***	321.858***	312.293***	333.033***
	(33.940)	(34.176)	(34.143)	(34.015)	(31.563)	(32.944)
Engineering	297.929***	300.958***	295.731***	326.667***	248.029***	279.147***
	(22.978)	(23.185)	(23.015)	(23.731)	(24.240)	(24.591)
Biology + Health	117.626***	119.681***	120.677***	139.151***	50.874	73.787**
	(25.862)	(26.398)	(25.979)	(26.109)	(32.418)	(34.176)
Interdisciplinary Studies	-113.981***	-114.251***	-114.962**	-108.104**	-17.301	-6.127
	(43.980)	(43.861)	(44.469)	(45.284)	(41.248)	(42.908)
Physical Sciences + Math	-49.313***	-49.778***	-46.456***	-32.854**	-53.581***	-30.124*
	(13.900)	(13.697)	(13.899)	(14.466)	(16.082)	(16.226)
Social Science	38.847***	39.003***	38.600***	52.124***	33.348***	42.739***
	(11.380)	(11.398)	(11.459)	(11.756)	(9.861)	(10.564)
Economics	96.726***	94.149***	97.554***	121.856***	163.640***	192.607***
	(22.095)	(22.316)	(22.165)	(23.014)	(27.425)	(28.907)
Business	374.403***	372.799***	376.028***	397.633***	361.738***	386.903***
	(26.143)	(26.494)	(26.011)	(26.868)	(29.616)	(30.869)
Controls: Student Characteristics	X		X	X	X	
Controls: Student Achievement	X	X		X	X	
Controls: HS Course Taking	X	X	X		X	
Controls: Class Level Means	X	X	X	X		
Cohort-HS & Cohort-Univ FE	X	X	X	X	X	X
Major FE	X	X	X	X	X	X
Observations	6,711,738	6,711,738	6,711,738	6,711,738	6,711,738	6,711,738
Adjusted R-squared	0.204	0.200	0.203	0.200	0.194	0.182

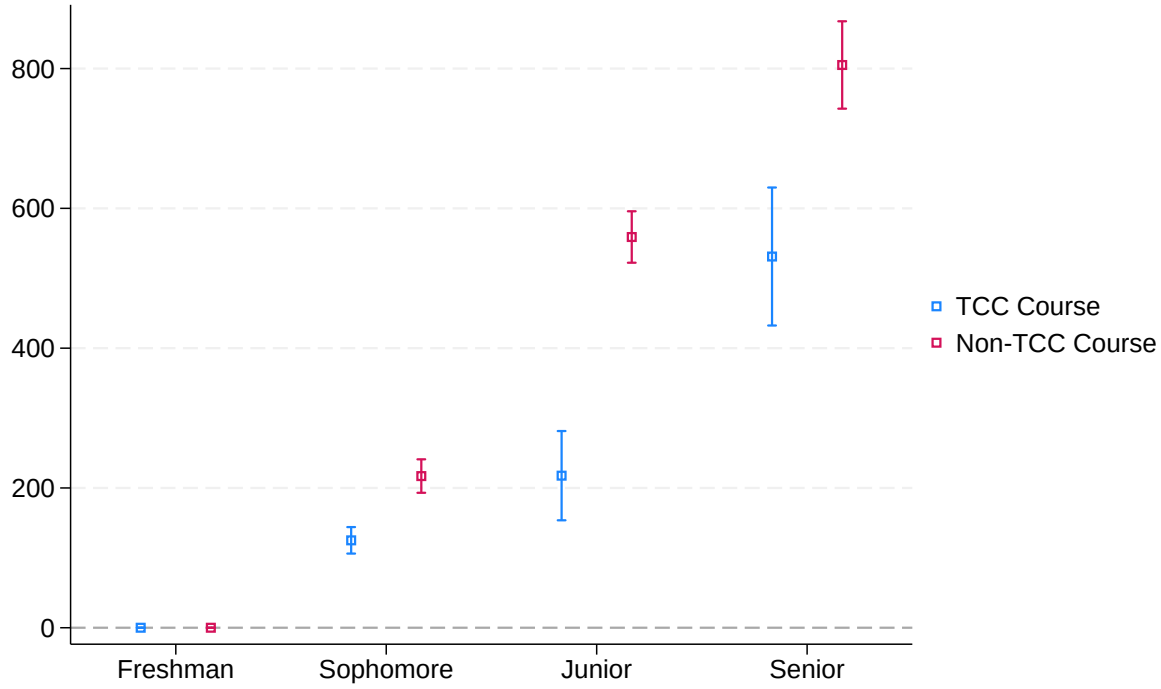
Notes: The dependent variable is the residualized earnings for each individual as described in Section 3. The estimates are obtained using equation (3). "Controls" are listed in Table 1. All estimates include cohort-by-high school, cohort-by-university, and major fixed effects. We use the baseline specification in column (1), while removing student characteristics, student achievement, high-school course taking, class level means, and all these controls in columns (2), (3), (4), (5), and (6), respectively. All estimated returns to course fields are relative to liberal arts (the excluded category). Standard errors clustered at the cohort-university level are in parentheses.

Figure A3: Robustness: The Return to College Courses by Academic Grade and Course Average Grade Quintile



Notes: The dependent variable is the residualized earnings for each individual as described in Section 3. Estimates in subfigures (a) and (b) are obtained using the academic grade (grades A, B, C, D, and F) and course level (freshman, sophomore, junior, and senior) indicators, respectively. Subfigure (a) further separates the sample by quintile of class-level grade means, while subfigure (b) separates the sample by Texas Core Curriculum (TCC) and non-TCC courses. "Controls" are listed in Table 1. All estimates in each panel are from one regression that includes cohort-by-high school, cohort-by-university, and major fixed effects. The sample covers courses taken by undergraduate students who are degree recipients, including failed courses. The estimated returns to course fields in each grade are relative to courses with a B grade in subfigure (a) and relative to freshman courses in subfigure (b). For each point estimate, we show 95% confidence intervals from standard errors that are clustered at the cohort-university level.

Figure A4: The Return to College Courses by Course Level and Core Curriculum Status



Notes: The dependent variable is the residualized earnings for each individual as described in Section 3. Estimates in subfigures (a) and (b) are obtained using the academic grade (grades A, B, C, D, and F) and course level (freshman, sophomore, junior, and senior) indicators, respectively. Subfigure (a) further separates the sample by quintile of class-level grade means, while subfigure (b) separates the sample by Texas Core Curriculum (TCC) and non-TCC courses. "Controls" are listed in Table 1. All estimates in each panel are from one regression that includes cohort-by-high school, cohort-by-university, and major fixed effects. The sample covers courses taken by undergraduate students who are degree recipients, including failed courses. The estimated returns to course fields in each grade are relative to courses with a B grade in subfigure (a) and relative to freshman courses in subfigure (b). For each point estimate, we show 95% confidence intervals from standard errors that are clustered at the cohort-university level.

Table A4: Correlation between Course Value-Added and Characteristics Composition of Enrolled Students

	Course Value-Added			
	(1)	(2)	(3)	(4)
Math Standardized Score	-11.156***	-13.119***	-11.344***	-13.591***
	(3.779)	(4.467)	(3.813)	(4.479)
Read Standardized Score	-12.710**	18.106***	-12.269**	18.399***
	(5.265)	(4.927)	(5.178)	(4.800)
Top Ten Percentile Math	19.335***	17.321***	19.805***	17.645***
	(7.265)	(5.646)	(7.399)	(5.729)
Top Ten Percentile Reading	6.904	-15.852***	6.255	-16.703***
	(6.103)	(4.795)	(6.028)	(4.728)
70th-90th Percentile	3.239	4.144	4.085	5.034
	(4.770)	(4.332)	(4.848)	(4.392)
70th-90th Percentile	4.673	-5.170	4.153	-5.690*
	(4.088)	(3.541)	(3.971)	(3.397)
Black	-30.509***	-35.766***	-30.709***	-36.029***
	(4.279)	(5.157)	(4.292)	(5.289)
Hispanic	-12.805***	-8.669**	-12.962***	-9.036**
	(4.459)	(4.108)	(4.463)	(4.184)
Asian	-22.036*	-34.315***	-22.040*	-34.598***
	(11.790)	(11.494)	(11.812)	(11.533)
Male	11.167	2.491	10.886	2.366
	(20.505)	(10.947)	(20.572)	(10.926)
Gifted	-8.148**	-7.514*	-8.508**	-8.112**
	(3.933)	(3.857)	(3.881)	(3.780)
At Risk	-8.950**	-8.261**	-8.427**	-7.892**
	(3.513)	(3.595)	(3.556)	(3.599)
Economically Disadvantaged	2.900	0.224	3.119	0.375
	(3.827)	(3.094)	(3.868)	(3.115)
Cohort-Univ FE	X	X	X	X
Cohort-HS FE		X		X
Major FE		X		X
Excluding "Ethnicity - Other"			X	X
Observations	6,711,771	6,711,771	6,563,257	6,563,257

Notes: The dependent variable is the estimated course value-added. Columns (1)-(2) use the full sample, while columns (3)-(4) exclude students whose ethnicity is "Other". We include cohort-by-university fixed effects in the odd columns and include additional cohort-by-high school fixed effects and major fixed effects in even columns. Standard errors clustered at the cohort-university level are in parentheses.