Teaching for College and Teaching for Work:

Curriculum and Economic Opportunity in Community Colleges*

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Abstract

Community colleges serve the dual mission of preparing students for transfer to four-year colleges and for entry into the labor market, with returns that vary widely across students and programs. This paper studies how these returns depend on what students are taught. We link 605,915 syllabi from 40 Texas community colleges to administrative student records to estimate the effects of course content on educational attainment and earnings. Our design uses variation in current content conditional on prior content and instructor identity to account for student selection into courses. For students in academic programs, content aligned with equivalent four-year courses increases transfer and bachelor's degree completion. General alignment with local labor demand diverts students from the transfer pathway, reducing both outcomes. Holding this general alignment fixed, stronger preparation for occupations related to students' fields of study improves academic students' attainment. For vocational students, general alignment with local labor demand does not improve outcomes, but stronger preparation for occupations related to their programs raises earnings. These findings identify curriculum as a determinant of community-college returns and emphasize the importance of alignment between curriculum and students' educational and occupational pathways.

JEL Classification: I23, I24, I26, J24, J31

Keywords: Community Colleges, Course Content, Skills, Instructors, Economic Mobility

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1 Introduction

Community colleges are a primary point of entry into U.S. higher education and a major provider of workforce training. With open admissions and low tuition, they serve nearly 10.5 million students, including a disproportionate share of first-generation and low-income students (Bailey et al., 2015; American Association of Community Colleges, 2025). These institutions pursue two distinct objectives. Academic programs prepare students to transfer to four-year institutions and earn bachelor's degrees, while vocational programs prepare students to enter the labor market directly (Cohen et al., 2014). Yet completion and transfer rates remain low, and labor-market returns vary widely across credentials and fields (Bailey et al., 2015; Jepsen et al., 2014; Stevens et al., 2019; Dadgar and Trimble, 2015). Improving outcomes along both pathways is central to community colleges' role in economic mobility.

The content of community college courses is central to both objectives. Students preparing to transfer need material they can build on in subsequent four-year college coursework, while those entering the workforce need skills they can apply on the job. Even within the same course, instructors can emphasize material that serves these objectives to different degrees. Course content may therefore be an important source of variation in community-college returns, and one that colleges and instructors can adjust directly. This paper asks how different dimensions of community college course content shape student progress along academic and vocational pathways, and when teaching for college and teaching for work are complements rather than substitutes.

Answering these questions presents three challenges. The first is data: administrative records identify course titles, credits, programs, and credentials, but do not record the material covered in the classroom. The second is measurement. Assessing how content prepares students for further education and work requires comparing it with two different benchmarks: the curriculum at four-year institutions and the skills demanded by employers. The third is selection. Students choose courses and instructors, instructors choose what to teach, and colleges design curricula in response to their students and local economies. Comparisons across students, courses, or colleges therefore combine the effects of content with selection. Estimating the causal effects of course content on student outcomes requires variation in what students are taught that they did not select.

In this paper, we address these challenges by linking 605,915 syllabi from 40 Texas community colleges to administrative records on students' educational attainment and earnings. We use syllabi to measure how closely course content matches the material taught in equivalent four-year courses and the skills demanded by local employers. To account for student selection, we use variation

in current content conditional on prior content and instructor identity, comparing students within the same college, major, and entry cohort. We find that content aligned with equivalent four-year courses increases transfer and bachelor's degree completion among students in academic programs. Broad alignment with local labor demand diverts these students from the transfer pathway, reducing both outcomes. Holding this general alignment fixed, stronger preparation for occupations related to students' fields of study improves academic students' attainment. For vocational students, course content aligned to the general local labor demand does not improve outcomes, but content matching occupations related to students' fields raises students' earnings. Alignment of course content to student pathways and fields of study is therefore critical. Teaching for work can even support teaching for college when the skills taught connect to students' fields.

Our measures of course content are constructed directly from syllabus text. Academic relevance (AR) is the average textual similarity between a community-college syllabus and syllabi for corresponding courses at seven Texas four-year universities. The Texas Common Course Numbering System identifies equivalent lower-division academic courses across institutions, allowing us to compare the material taught within a common course designation. To construct general labor-market relevance (GLMR), we identify the frequency of terms from 28 families of skills (such as health care, marketing, or legal) in each syllabus and weight each family by its relative prevalence among recorded skill mentions in local job postings. Major-specific labor-market relevance (MLMR) uses the same syllabus content but calculates demand weights from postings in occupations connected to the student's major. The two labor-market measures thus differ in the jobs used to define demand.

We begin our analysis by showing that syllabi vary substantially along each dimension of content. Community-college syllabi have an average AR of 0.181, compared with 0.168 for pairs of four-year syllabi with the same course number. Community-college courses are therefore broadly aligned with their four-year counterparts on this measure. Vocational courses contain more labor-market-relevant content than academic courses. Fields and courses together account for most of the explained variation in all three measures, while institutions contribute especially strongly to general labor-market relevance in academic courses. This suggests that colleges may differ in how far they bring their workforce mission into academic teaching. Vocational courses have an explicit occupational purpose; incorporating skills for local employment into academic courses may depend more on institutional priorities and the jobs available nearby. AR is nearly uncorrelated with either labor-market measure. GLMR and MLMR are closely but not perfectly related; their differences

allow us to distinguish broad local demand from demand in occupations associated with students' fields.

We next ask whether these differences in course content matter for students. To estimate the effects of our three dimensions of content, we exploit a useful feature of the course registration process at Texas community colleges. Texas HB 2504 requires public institutions to make course information available by the seventh day after classes begin; the current syllabus need not be posted when registration opens (Biasi and Ma, 2026). Students can thus select an instructor and consult prior syllabi, while the updated syllabus is usually not available. This feature implies that, for students entering the community college in the same year and with the same initially declared major, the content of a given course is as good as randomly assigned conditional on lagged content and the instructor. Our empirical strategy thus compares students in the same program, with the same instructors and similar prior course content, who are exposed to different current content. The identifying assumption is that, conditional on these controls, changes in content are unrelated to other determinants of student outcomes. The small explanatory power of observed student and instructor characteristics for content updates supports this assumption.

With this empirical design, we begin by studying the effect of academic relevance on students' educational outcomes and earnings. Among academic students, a one-standard-deviation (SD) increase in AR raises the probability of transfer to a four-year institution by 1.9 percentage points (pp) and BA completion by 1.3 pp. Relative to mean rates of 22% and 11%, respectively, these are increases of 8.6% and 11.8%. These results show that differences in the material taught in formally equivalent courses affect students' progress toward a four-year degree.

The educational gains vary across students. Students with a higher predicted probability of completing a bachelor's degree based on observed characteristics (such as high school test scores, major, gender, ethnicity and measures of academic and economic disadvantage) experience larger increases in transfer and bachelor's degree attainment from higher academic relevance. The gains are also larger for students who are not academically or economically disadvantaged, particularly for bachelor's degree attainment.

The average earnings effect of AR is close to zero. This estimate is consistent with the modest average earnings gain that additional bachelor's degrees would generate. For illustration, if completing a bachelor's degree raises earnings by 30%, a 1.3-pp increase in attainment would imply an average earnings gain of about 0.34% through degree completion alone. This gain lies within the 95% confidence interval around our estimate. However, earnings gains increase with students'

baseline probability of completing a BA. At a predicted probability of 50%, a one-standard-deviation increase in AR raises earnings by approximately 8%. The educational and earnings results thus suggest that students with stronger initial prospects are better positioned to benefit from academically relevant coursework. Aligning content with four-year curricula can therefore improve outcomes while also widening gaps within community colleges.

Next, we examine how labor-market relevance shapes outcomes along the academic and vocational pathways. Broad alignment with local demand diverts academic students from the transfer pathway. A one-SD increase in GLMR reduces AA attainment by 5.8 pp, transfer by 9.6 pp, and BA completion by 6.4 pp, while increasing attainment of other community-college credentials by 1.3 pp. The reductions in transfer and BA completion are smaller when relevance is defined using occupations associated with the student's major: 5.2 and 2.6 pp, respectively. These differences show that the educational consequences of labor-market-oriented content depend on which jobs it prepares students to perform.

To distinguish the role of occupational targeting from broad alignment with local demand, we construct a measure of occupational tilt, defined as the difference between the standardized values of MLMR and GLMR. We then estimate the effect of tilt holding GLMR fixed, capturing greater preparation for occupations connected to the student's field at a given level of general labor-market alignment. Greater occupational tilt raises all three educational outcomes: AA attainment, transfer, and BA completion. These findings suggest that teaching skills used in occupations related to students' fields can make the career value of further education more apparent, encouraging them to persist and pursue a four-year degree. We find no detectable average earnings effects of either labor-market measure among academic students.

For vocational students, preparation for occupations related to their field produces substantial earnings gains. A one-SD increase in MLMR raises log earnings by 0.120, or approximately 13%. Vocational earnings also increase with occupational tilt, holding GLMR fixed, while GLMR alone has no detectable average earnings effect. The estimated gains from MLMR are larger for academically or economically disadvantaged students. One interpretation is that occupationally relevant coursework helps compensate for gaps in prior preparation or fewer opportunities to acquire job skills outside college.

Taken together, these results emphasize the importance of alignment between course content and student pathways. Academic content helps students in academic programs, while connecting instruction to occupations in students' fields can support further education in academic programs

and raise earnings in vocational programs. These findings give colleges a concrete way to pursue their two missions through choices about what to teach within existing programs. The contrasting patterns of heterogeneity also suggest that those choices can shape the distribution of gains: academic alignment benefits students with stronger initial prospects most, while occupational preparation offers particularly large estimated gains to disadvantaged vocational students.

Related literature. This paper contributes to research on curriculum and the returns to higher education. Earlier work uses detailed coursework and curricular reforms to study the earnings returns to what students learn (Jacobson et al., 2005; Arteaga, 2018; Hamermesh and Donald, 2008; Light and Schreiner, 2019). Recent studies use syllabus text to measure exposure to frontier knowledge and workplace activities (Biasi and Ma, 2022; Chau et al., 2023), and Biasi and Ma (2026) estimate the effects of frontier knowledge using syllabus updates at four-year universities. We contribute to this literature by identifying and estimating the effects of course content in community colleges, institutions that prepare students for both further education and direct labor-market entry. Measuring content relative to these two objectives shows how the effects of curriculum differ across students' educational and occupational pathways. The analysis also identifies a specific input through which instructors can affect student outcomes, complementing evidence on instructor effectiveness (Carrell and West, 2010; Fairlie et al., 2014).

Second, we contribute to the literature on community colleges and economic mobility. Research on credits, credentials, and vocational programs documents substantial variation in returns across fields and awards (Kane and Rouse, 1995; Jepsen et al., 2014; Stevens et al., 2019; Grosz, 2020). Work on community-college access shows that these institutions expand entry into higher education while also diverting some students from four-year entry (Rouse, 1995; Mountjoy, 2022). Our work demonstrates that course content is an important determinant of success among students already enrolled in community colleges. Variation within institutions, programs, entry cohorts, and instructors connects curricular choices to both BA attainment and vocational earnings. With our analysis, we extend the study of community-college returns to an instructional input that colleges and instructors can change without changing students' access to an institution or program.

Third, the paper contributes to research on skill demand and the supply of skills through education. Studies of employer job postings document differences in skill requirements across firms and occupations (Deming and Kahn, 2018; Hershbein and Kahn, 2018). Related work measures the skills associated with college majors and how institutions adjust degree production and coursework to changes in labor demand (Hemelt et al., 2023; Conzelmann et al., 2023); evidence on major

choice establishes the earnings consequences of students' allocation across fields (Kirkebøen et al., 2016; Andrews et al., 2024). Cnossen et al. (2025) measure skills in vocational curricula and estimate their earnings returns. We contribute to this body of research by connecting employer skill demand directly to the material taught in individual courses and estimating the returns to their alignment. Comparing broad and major-specific demand, including in a joint specification, identifies the occupations used to guide the curriculum as a consequential choice. For vocational students, the earnings gains come from content directed toward jobs associated with their field.

2 Institutional Setting

2.1 Community Colleges in the United States

Community colleges are largely public, predominantly two-year institutions that provide open-access postsecondary education. Their dual mission combines academic preparation for transfer to four-year institutions with vocational and technical training for employment (Cohen et al., 2014; Bailey et al., 2015). This role was articulated in the 1947 Truman Commission's call to extend free public education through the first two years of college and integrate vocational and liberal education (Cohen et al., 2014).

In 2025, the sector comprised 1,024 institutions: 924 public, 64 independent, and 36 tribal. Credit programs enrolled approximately 6.4 million students in fall 2023, accounting for 39% of U.S. undergraduates; 66% of these community-college students attended part-time. Noncredit enrollment is estimated at 4.1 million, bringing combined enrollment to approximately 10.5 million (American Association of Community Colleges, 2025).

Community colleges generally offer open admissions and charge low tuition. Admission to the institution does not necessarily guarantee admission to every program, as some specialized programs have separate entry requirements. In 2024–2025, average annual tuition and fees at public community colleges were $4,050 for in-district students, compared with $11,610 for in-state students at public four-year institutions (American Association of Community Colleges, 2025). Low tuition and broad access make community colleges an important entry point for first-generation and low-income students, as well as adults combining education with work or family responsibilities (Bailey et al., 2015).

Fields and programs. The curricular scope of community colleges spans general education in mathematics, natural sciences, social sciences, and the humanities, as well as specialized occupa-

tional coursework. Colleges also provide developmental instruction to prepare students for college-level coursework (Cohen et al., 2014; Bailey et al., 2015).

Credit-bearing programs fall into three broad categories:

1. *Academic transfer programs*, typically leading to Associate of Arts (AA) or Associate of Science (AS) degrees. These programs cover coursework comparable to the first two years of a four-year degree and prepare students for further study in fields such as biology, economics, and psychology.

2. *Applied and vocational programs*, leading to degrees such as the Associate of Applied Science (AAS). These programs prepare students for employment in fields such as nursing, information technology, automotive technology, and advanced manufacturing.

3. *Occupational certificates*, which provide focused training in particular skills or occupations, including welding and heating, ventilation, and air conditioning. These programs vary in length and often prepare students for relatively rapid labor-market entry.

Colleges also offer noncredit workforce training and adult education, which may lead to noncredit certificates (Cohen et al., 2014; Bailey et al., 2015).

Students enter these programs with different objectives. Some intend to transfer after completing general education requirements, with or without first earning an associate's degree. Others seek occupational training with an immediate labor-market payoff, upgrade their skills, change careers, or return to education after time out of school (Bailey et al., 2015). These objectives shape the courses students take and the uses they expect to make of their education.

2.2 The Texas Context

Texas's public community colleges are organized into 50 locally governed districts. Elected boards oversee colleges and set local policies, including tuition and property tax rates. Revenues combine state support, local property taxes, tuition and fees, and federal funding (Texas Higher Education Coordinating Board, 2023).

Open admissions and low tuition characterize the Texas sector. Tuition is generally lower for students residing within a college's taxing district than for other Texas residents, reinforcing the local role of these institutions. Colleges respond to local educational and workforce needs while operating within statewide arrangements that connect their academic programs to public four-year universities.

2.3 Common Course Numbering and the Texas Core Curriculum

Texas uses common course numbering and a statewide core curriculum to facilitate transfer between institutions. These arrangements serve complementary purposes: the Texas Common Course Numbering System (TCCNS) identifies equivalencies between individual courses, while the Texas Core Curriculum establishes a common framework for general education requirements.

TCCNS is a voluntary collaboration among participating colleges and universities that identifies equivalent lower-division academic courses. Common designations allow students and institutions to determine how a course taken at one institution corresponds to a course at another. For example, the University of Texas at Austin's PSY 301 and Austin Community College's PSYC 2301 are both titled *Introduction to Psychology* and correspond to the common designation TCCNS PSYC 2301. Universities may retain their own course numbers while reporting the corresponding TCCNS designations. Coverage is limited to courses included in the equivalency system; it does not extend to every lower-division university course or to vocational coursework.[1] We use these equivalencies to match community-college courses to their four-year counterparts.

The Texas Core Curriculum specifies the general education component of academic undergraduate degrees at public institutions. Under the revised framework implemented in fall 2014, the core comprises 42 semester credit hours distributed across foundational component areas.[2] Institutions select their own approved courses within this framework, subject to statewide requirements and learning objectives.

Students who complete the core at one Texas public institution can transfer it as a block to another, satisfying the receiving institution's core requirements without repeating that coursework. Students who transfer before completing the core receive credit toward the receiving institution's core for the core courses they have completed.[3]

Common course definitions and statewide learning requirements leave room for differences in readings, applications, and the emphasis placed on particular topics. Students at different institutions, or in different offerings of the same course, can therefore encounter different material within formally equivalent coursework. This combination of common course designations and local instructional discretion allows us to compare the content of community-college and four-year courses and study how differences in what students are taught affect their outcomes.

[1] See the Texas Common Course Numbering System.

[2] These include communication, mathematics, life and physical sciences, language/philosophy/culture, creative arts, American history, government/political science, social and behavioral sciences, and a component-area option.

[3] See the Texas Higher Education Coordinating Board's *Elements of the Texas Core Curriculum* (April 2018). The core predates the 2014 revision; revised rules were adopted in 2011 and implemented in fall 2014.

3 Data

Our analysis combines the text of approximately one million course syllabi with administrative records on students and instructors and data on employer skill demand. Syllabi describe course content; the administrative records link that content to the students who studied it and their subsequent attainment and earnings.

3.1 Course Syllabi

Texas's House Bill 2504 requires public institutions to post syllabi online for undergraduate classroom courses offered for credit and retain them for at least two years after posting.[4] We collected 605,915 syllabi by scraping the websites of 40 Texas public community colleges.[5] We restrict both the syllabus and linked student analyses to 2011–2024. Coverage varies across institutions and begins later at many colleges; Appendix B describes the institutional coverage and collection procedure.

We complement this corpus with approximately 400,000 syllabi from seven public four-year institutions: Stephen F. Austin State University, Sam Houston State University, Texas A&M University, the University of Houston–Clear Lake, UT Austin, UT Dallas, and West Texas A&M University. These syllabi provide the benchmark for measuring the academic relevance of community-college course content.

We match lower-division academic courses across sectors using annual crosswalks from the Texas Common Course Numbering System (TCCNS), which identifies equivalent freshman- and sophomore-level academic courses. For each year, we use the crosswalk then in effect to map institution-specific course numbers to common designations, accounting for changes in course numbering over time.[6] This procedure allows us to compare the content of courses with the same formal designation. The matched academic sample comprises 426,242 community-college syllabi and 11,532 four-year syllabi; only a minority of lower-division courses in the four-year corpus have a TCCNS designation. We also retain 156,655 vocational community-college syllabi, which do not have TCCNS designations and are not matched to four-year courses.

Within each institution, we identify courses by course code and section, and instructors by their administrative identifiers. A syllabus is a document, typically corresponding to one course–section–

[4] The requirement applies beginning in fall 2010. See HB 2504, enrolled version, Sections 1 and 4: https://capitol.texas.gov/tlodocs/81R/billtext/html/HB02504F.htm. Appendix C describes the posting deadline and its implications for course selection. Prior work examining college syllabi (e.g. Nowogrodzki, 2016; Biasi and Ma, 2022; Chau et al., 2023) draws on the Open Syllabus Project, which has limited coverage of community colleges.

[5] The repositories of the remaining ten colleges could not be collected using our automated procedures.

[6] See the system's description and course-equivalency database at https://tccns.org/.

term. Panel (a) of Table 1 summarizes the syllabus samples.

Table 1: Summary Statistics of Syllabi, Students, and Instructors

	Academic community college	Vocational community college	Four-year institutions
Panel (a): Syllabi			
# syllabi	426,242	156,655	11,532
# courses	50,967	61,172	
Average # sections	6.811	1.791	
Average # instructors	3.806	1.445	
Panel (b): Students			
High school exam rank	57.145	51.567	68.504
	(17.724)	(18.142)	(15.288)
Share economically disadvantaged	0.446	0.499	0.328
	(0.497)	(0.500)	(0.470)
High school-county characteristics			
Avg exam rank of high school	57.381	55.713	71.972
	(7.959)	(8.443)	(3.774)
Share economically disadvantaged in high school	0.463	0.477	0.319
	(0.192)	(0.193)	(0.176)
Median income in home county ($)	69,727	70,476	72,969
	(18,410)	(21,000)	(18,883)
Outcomes			
Graduates with CC Degree	0.304	0.350	
	(0.460)	(0.477)	
Earnings after CC degree ($)	10,941	11,481	
	(5,962)	(6,388)	
Transfers to four-year	0.223	0.109	
	(0.416)	(0.311)	
Graduates with Bachelor's Degree	0.107	0.049	0.548
	(0.309)	(0.217)	(0.498)
Earnings after Bachelor's degree ($)	13,110	13,038	13,259
	(6,466)	(6,538)	(6,908)
# students	120,206	30,219	808,192
Panel (c): Faculty			
Share female	52.250	52.810	44.690
Share part-time	30.140	26.280	44.130
Share taught in CC			8.628
Share taught in four-year university	29.670	8.377	
Share with BA	4.330	23.240	
Share with MA	69.580	36.040	
Share with PhD	21.490	7.630	
Tenure at Institution	9.192	8.037	5.815
	(6.913)	(6.609)	(5.355)
Salary ($)	41,481	45,387	25,084
	(30,358)	(29,617)	(23,241)

Notes: Summary statistics of syllabi, students, and faculty in the analysis samples. Standard deviations are reported in parentheses when available. Student shares are proportions; faculty shares are percentages. Earnings are quarterly and expressed in 2025 dollars.

3.2 Students and Instructors

We obtain student information from linked administrative records maintained by the Texas Education Research Center (ERC), combining data from the Texas Higher Education Coordinating Board (THECB), the Texas Education Agency (TEA), and the Texas Workforce Commission (TWC).

THECB records report enrollment, majors, course transcripts, grades, and degree attainment for students at Texas public two-year, four-year, and health-related institutions. The linked records also identify enrollment and degree attainment at Texas private four-year institutions. Enrollment and degree records extend back to the 1990s, while the transcript data required for our analysis begin in academic year 2011–2012. Community-college records classify both students and courses as academic or vocational. We define transfer as enrollment at a Texas public or private four-year institution following community-college enrollment, and measure bachelor's-degree attainment using degrees awarded by these institutions. We do not observe out-of-state enrollment.

We use course transcripts to link students to syllabi and faculty teaching assignments to link students and courses to instructors. THECB faculty records also report instructors' education, employment history, and pay. Because syllabus availability varies across colleges and years, we retain only students whose course records can be linked to at least one syllabus. Within institution–year–semester cells covered by the syllabus corpus, more than 90% of enrollment records match to at least one syllabus.

We use TEA high-school examination records to measure students' academic preparation before college. Specifically, we calculate percentile ranks in mathematics and reading test scores within high-school graduation cohort and subject.[7] We also measure economic and academic disadvantage at college entry. Economic disadvantage indicates that a student meets a federal poverty criterion or qualifies for public assistance or need-based financial aid (see Appendix D for details). Academic disadvantage indicates a need for remedial college coursework, assessed before exposure to course content.

Finally, we link students to TWC unemployment-insurance wage records, which report quarterly earnings from employment covered by the Texas unemployment-insurance system. We express earnings in 2025 dollars and follow students' observed earnings histories beginning at college exit. Appendix D describes the observation window and earnings-sample restrictions.

[7] The records span the TAAS, TAKS, and STAAR assessment regimes. SAT and ACT scores are available for only a subset of community-college students. For students with multiple attempts, we use the last attempt; students missing the required TEA test-score information are excluded from the analysis sample. Appendix D describes the construction of examination percentiles and other baseline controls.

Panel (b) of Table 1 summarizes the student sample, which includes 120,206 academic and 30,219 vocational community-college students, alongside a comparison sample of 808,192 four-year students. Vocational students are more likely to be economically disadvantaged (with a rate of 50%, compared with 45% of academic students and 33% of four-year students). They also have lower high-school test-score ranks. Among academic students, 30% earn a community-college credential, 22% transfer to a four-year institution, and 11% earn a bachelor's degree. The corresponding shares among vocational students are 35%, 11%, and 5%. Among bachelor's-degree recipients, community-college students earn approximately $13,000 per quarter, similar to students in the four-year comparison sample. Average quarterly earnings after earning a community-college credential are approximately $10,900 for academic students and $11,500 for vocational students.

Panel (c) describes the faculty sample. Most instructors work full-time. Among community-college instructors teaching academic courses, 30% previously taught at a four-year institution, compared with 8% of those teaching vocational courses. Academic-course instructors also have higher educational attainment: 70% hold master's degrees and 21% hold Ph.D.s, compared with 36% and 8%, respectively, among vocational-course instructors.

3.3 Labor-Market Skills and Occupations

We measure employer skill demand using Lightcast job postings. Each posting records the year, location, occupation, and skills requested by the employer, drawn from a taxonomy of more than 30,000 skills. We group these skills into 28 families using Lightcast's classification and aggregate recorded skill mentions by county and year. Appendix Figure A1 lists the skill families and shows their shares of recorded skill mentions in Texas postings in 2010, 2015, and 2018.

We combine these data with occupational information from O*NET and a crosswalk provided by the National Center for Education Statistics (NCES) linking fields of study to occupations. The crosswalk connects educational programs (i.e., degree-major pairs) classified under the Classification of Instructional Programs (CIP) to occupations classified under the Standard Occupational Classification (SOC), thus identifying the occupations for which programs in a given field provide relevant education and training.[8] We use these links to identify the occupations associated with each student's major.

[8]The NCES CIP–SOC crosswalk and accompanying documentation are available at https://nces.ed.gov/ipeds/cipcode/resources.aspx?y=56. A version linking CIP codes to O*NET occupations, based on the NCES data, is available at https://www.onetcenter.org/crosswalks.html.

4 Measuring Course Content

We use syllabus text to measure course content relative to the two objectives of community colleges. *Academic relevance* (AR) captures similarity to corresponding courses at four-year institutions. *General labor-market relevance* (GLMR) captures coverage of skills demanded across all local jobs. *Major-specific labor-market relevance* (MLMR) captures coverage of skills demanded in local occupations related to a student's major. These measures distinguish preparation for further study from preparation for work, and broad labor-market alignment from alignment with the student's field.

4.1 Academic Relevance

Academic relevance measures how closely the content of a community-college course resembles that of its four-year counterparts. The intuition is that alignment with four-year curricula can prepare students for the coursework they encounter after transfer. We use the Texas Common Course Numbering System (TCCNS) to identify equivalent courses. For example, Austin Community College's PSYC 2301 and UT Austin's PSY 301 are both titled *Introduction to Psychology* and correspond to the common designation TCCNS PSYC 2301. These equivalencies identify courses with common descriptions and learning objectives, while syllabi reveal differences in readings, applications, and emphasis. Our comparison focuses on academic community-college courses and corresponding lower-division courses at four-year institutions.

Following Biasi and Ma (2026), we represent each syllabus as a vector whose coordinates correspond to terms in a common dictionary. The dictionary contains the words, bigrams, and trigrams that appear as keywords in academic publications in OpenAlex. We weight each term using its frequency within the syllabus and its prevalence in earlier documents, following the Term Frequency–Backward Inverse Document Frequency (TF–BIDF) approach of Biasi and Ma (2022).

Let n_{dk} denote the number of occurrences of dictionary term k in document d, $\mathcal{K}$ the dictionary, and $\mathcal{D}_{<t}$ the reference corpus of documents dated before year t. For syllabus s, term frequency and backward inverse document frequency are

$$\mathrm{TF}_{sk} = \frac{n_{sk}}{\sum_{\ell \in \mathcal{K}} n_{s\ell}}, \qquad \mathrm{BIDF}_{k,t} = \log\left(\frac{|\mathcal{D}_{<t}|}{\sum_{d \in \mathcal{D}_{<t}} \mathbf{1}\{n_{dk} > 0\}}\right). \tag{1}$$

TF measures the term's share of all dictionary-term occurrences in the syllabus. BIDF gives greater

weight to terms that appear in fewer earlier documents. The resulting syllabus vector has elements

$$v_{sk} = \mathrm{TF}_{sk}\,\mathrm{BIDF}_{k,t(s)},$$

where $t(s)$ is the syllabus year. Thus, a term receives greater weight when it appears frequently in a syllabus but is uncommon across earlier documents. Appendix B describes text extraction and vectorization.

For a community-college syllabus s and a four-year syllabus f, cosine similarity is

$$c_{sf} = \frac{\mathbf{v}_s' \mathbf{v}_f}{\|\mathbf{v}_s\| \|\mathbf{v}_f\|}. \tag{2}$$

With nonnegative weights and nonzero vectors, this measure ranges from zero to one. It equals zero when the vectors have no positively weighted terms in common and one when they are proportional. Multiplying all term counts in either document by the same factor leaves the cosine unchanged.

A simple example illustrates the scale of this measure. Suppose two syllabi each contain 100 distinct terms, with each term appearing once and receiving equal weight. If the syllabi share 20 terms, their cosine similarity is $20/\sqrt{100 \times 100} = 0.20$: the shared terms account for 20% of each syllabus. Increasing the number of shared terms from 20 to 30 raises similarity from 0.20 to 0.30. This example gives a direct interpretation in terms of overlap; with TF–BIDF weighting, similarity also reflects how frequently terms appear within each syllabus and how common they are in earlier documents.

Let $F(s)$ be the set of four-year syllabi with the same TCCNS number as s. Academic relevance is the average of the individual cosine similarities:

$$\mathrm{AR}_s = \frac{1}{|F(s)|} \sum_{f \in F(s)} c_{sf}. \tag{3}$$

Each four-year syllabus in the comparison set receives equal weight. We also calculate average similarity among four-year syllabi with the same TCCNS number, which provides a benchmark for the variation in content within the four-year sector. We compare community-college and four-year syllabi from the same year. The comparison set therefore follows the content of the corresponding four-year courses over time.

To examine variation across four-year institutions, we also construct comparisons with

UT Austin and Texas A&M, the two state flagships. Appendix Tables A9 and A10 report estimates using the alternative flagship benchmark.

4.2 General Labor-Market Relevance

General labor-market relevance combines the skill content of a syllabus with employer demand for those skills in the surrounding labor market. We use job-posting data from Lightcast covering more than 30,000 skills. The cleaned data contain 28 named families (Appendix Figure A1). We construct the measure in three steps.

First, for each county q in Texas, we calculate family k's share of recorded skill mentions in local postings in a baseline year, denoted by ω_{qk}. The source construction first calculates shares within county–month cells and then aggregates them to county–year weights. Because postings can list several skills, this is a share of skill mentions rather than a share of distinct postings. Second, we search each syllabus for the words and phrases in the skill dictionary and calculate the frequency of terms belonging to each family, ϕ_{sk}. Third, we weight these syllabus frequencies by local demand:

$$\text{GLMR}_s = \sum_{k=1}^{28} \phi_{sk}\omega_{q(s)k}, \tag{4}$$

where $q(s)$ is the county of the college offering a course with syllabus s. A syllabus receives a higher value when it devotes more content to skill families that employers request frequently across all jobs in that county and year. We measure employer demand in 2010, and hold these weights fixed across syllabus years. Each skill-family frequency in local job postings is divided by the sum of frequencies across all skill families in the county. Syllabus skill counts are constructed using SkillNER, which matches full phrases and alternative word forms, combines expressions referring to the same skill, and aggregates retained mentions into skill families. We retain matches with scores of at least 0.65, remove misleading dictionary variants such as "page," "section," and "powerpoint," and exclude generic skills such as Teaching, Research, Planning, and Scheduling.

4.3 Major-Specific Labor-Market Relevance

General LMR can assign substantial weight to skills demanded in jobs unrelated to a student's field. To account for this, we construct a major-specific LMR using demand in occupations connected to the student's major. We identify these occupations using the NCES field-to-occupation crosswalk and O*NET occupational information, then calculate each named family's share of recorded skill mentions in local postings for the relevant occupations. Denote these county–major weights by

ω_{qgk}. We combine them with the same syllabus frequencies used in GLMR:

$$\text{MLMR}_{sg} = \sum_{k=1}^{28} \phi_{sk}\omega_{q(s)gk}, \tag{5}$$

where g denotes a given major. The two labor-market measures therefore differ in the jobs used to define demand. GLMR weights skills using all local jobs; MLMR weights them using jobs connected to the student's major g. While GLMR is constant for a given syllabus, the same syllabus can have different MLMR values for students in different majors. We use the NCES crosswalk linking CIP fields of study to occupations. For students in general studies or with undeclared majors, we set MLMR equal to GLMR. Major-specific demand weights also use 2010 postings and are normalized by the sum of skill-family frequencies within the relevant county–occupation group.

4.4 Individual Skill Families

We also examine the earnings effects of exposure to each skill family, ϕ_{sk}, separately for academic and vocational students. These estimates complement the aggregate measures by showing which types of skill content generate gains along each pathway.

5 Differences in Course Content Across Courses

We begin by documenting differences in academic and labor-market relevance across courses. We benchmark community-college courses against their four-year counterparts and compare the labor-market content of academic and vocational courses. We then examine how the measures relate to one another and how much of their variation is associated with fields, courses, institutions, and instructors.

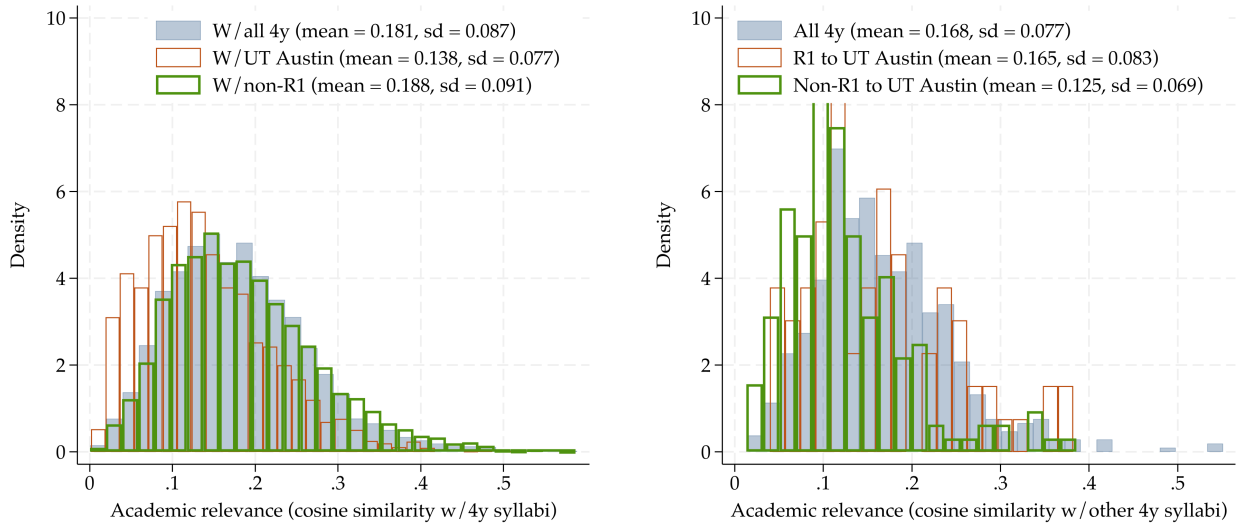
5.1 Academic Relevance

Community-college courses are, on average, slightly more similar to their four-year counterparts than four-year courses are to one another. Average AR among community-college courses is 0.181, with a standard deviation of 0.087 (Figure 1, panel (a)). The corresponding mean among four-year courses is 0.168, with a standard deviation of 0.077 (panel (b)). In both sectors, the standard deviation is nearly half the mean, indicating substantial variation in how closely courses resemble their four-year counterparts.

The comparison institution also determines the magnitude of the measured academic relevance. Community-college courses have an average similarity of 0.138 to courses at UT Austin, the most se-

lective institution in our sample, compared with 0.188 to courses at non-R1 universities. Differences also emerge within the four-year sector: average similarity to UT Austin is 0.165 among courses at other R1 universities and 0.125 among courses at non-R1 universities. Community-college curricula thus more closely resemble those at non-selective institutions. These differences also suggest that formal course equivalencies leave room for differences in content within and across sectors.

Figure 1: Distribution of Academic Relevance, by Institution Type



(a) Community-college courses

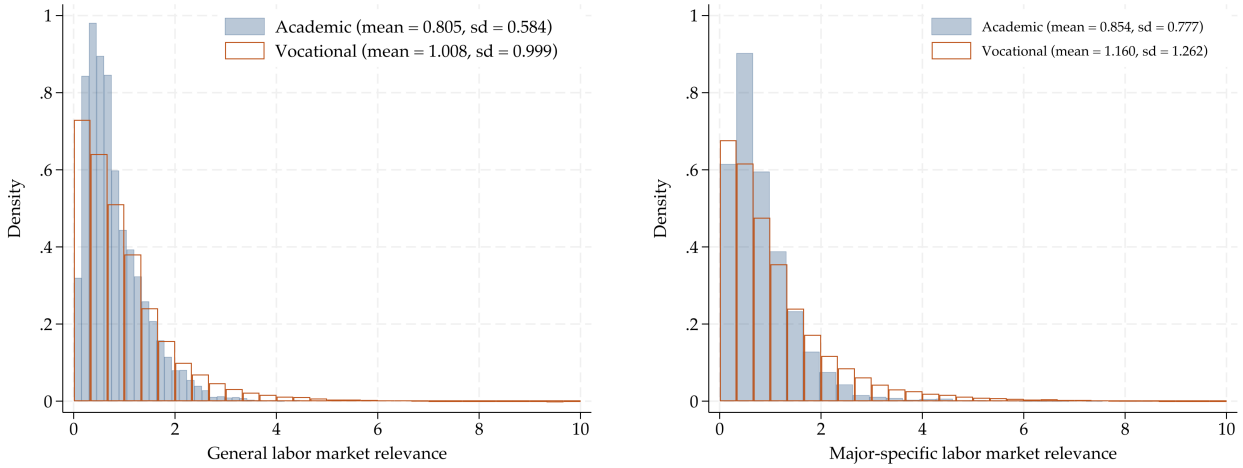
(b) Four-year courses

Notes: AR is a syllabus's average cosine similarity to four-year syllabi with the same TCCNS course number and year. Panel (a) shows its distribution across community-college courses, using alternative sets of comparison institutions. Panel (b) reports the corresponding comparisons among four-year courses. Values of 0.6 or greater are omitted from the histograms so that the main mass of each distribution remains visible; the means and standard deviations reported in the legends use all nonmissing observations.

5.2 Labor-Market Relevance

Vocational courses place greater emphasis on locally demanded skills than academic courses under both the general and major-specific measures. Average general LMR is 1.008 among vocational courses and 0.805 among academic courses, with standard deviations of 0.999 and 0.584, respectively (Figure 2, panel (a)). The difference is larger for major-specific LMR: the mean is 1.160 among vocational courses and 0.854 among academic courses, with standard deviations of 1.262 and 0.777 (panel (b)). These patterns are consistent with the occupational focus of vocational instruction, particularly when demand is measured within occupations related to the field. Both measures also have long right tails, reflecting courses with especially high concentrations of demanded skills.

Figure 2: Distribution of General and Major-Specific Labor-Market Relevance, by Course Type



(a) General labor-market relevance

(b) Major-specific labor-market relevance

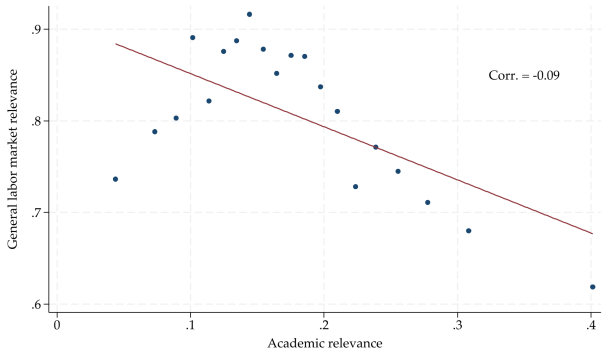
Notes: General LMR weights syllabus skill content by demand across all local jobs. Major-specific LMR uses demand in occupations related to the major. The measures are defined in Section 4. The figure reports their unstandardized distributions separately for academic and vocational courses. Values of 10 or greater are omitted from the histograms so that the main mass of each distribution remains visible; the means and standard deviations reported in the legends use all nonmissing observations.

5.3 Relationships Among Measures of Course Content

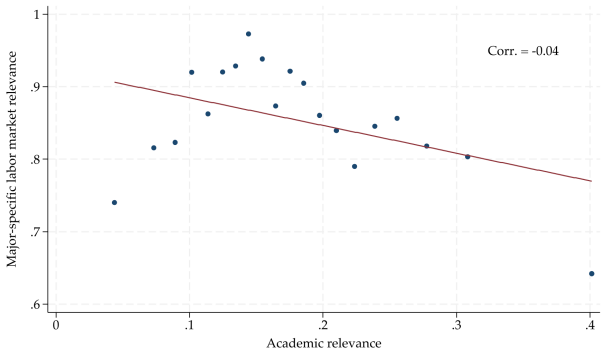
Academic relevance is nearly uncorrelated with either measure of labor-market relevance (Figure 3). Its correlation with general LMR is -0.09, and its correlation with major-specific LMR is -0.04. A course's similarity to four-year curricula therefore provides little information about its alignment with locally demanded skills. The measures thus capture distinct dimensions of instruction corresponding to community colleges' two missions.

General and major-specific LMR are more closely related, with a correlation of 0.80. This implies that courses that emphasize skills demanded across the local labor market also tend to emphasize skills demanded in occupations associated with their field. Because this correlation is not perfect, courses with similar alignment to broad local labor demand can still differ in how closely their content matches the skills demanded in occupations related to their field. We use this variation below to examine how the educational and earnings effects of labor-market-oriented content depend on the jobs it prepares students to perform.

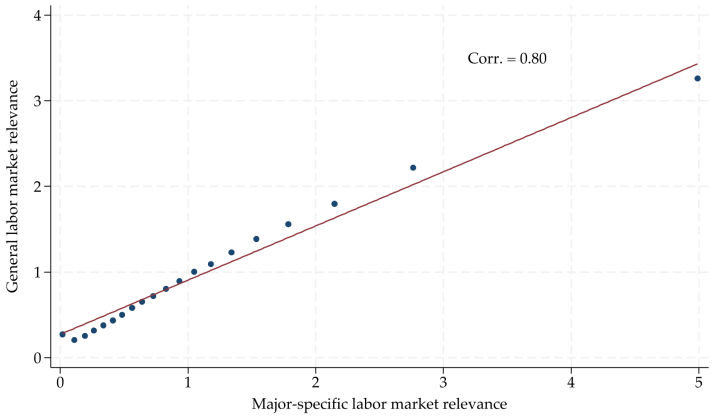
Figure 3: Relationships Among Academic and Labor-Market Relevance Measures



(a) Academic relevance and general labor-market relevance



(b) Academic relevance and major-specific labor-market relevance



(c) General and major-specific labor-market relevance

Notes: Each panel presents an unconditional binned scatterplot. Panels (a) and (b) use academic community-college courses, for which AR is defined. Panel (c) uses academic and vocational courses. Circles denote bin means and solid lines denote linear fits. Correlations are calculated using the underlying observations.

5.4 Explaining the Variation in Course Content

We next examine how much of the variation in content is explained by the subjects and courses students take, the colleges they attend, and the instructors who teach them. Locating these differences helps us understand how academic and labor-market alignment relate to the organization of instruction. Differences across fields and courses may reflect disciplinary requirements, while differences across colleges and instructors may reflect institutional priorities and individual teaching choices.

To do this, we regress each content measure on five sets of fixed effects: year, field, course, institution, and instructor. These factors overlap: instructors specialize in particular subjects, and institutions offer different combinations of courses. The additional explanatory power of a factor therefore depends on which other factors are already included. We use a Shapley–Owen decomposition to allocate this shared explanatory power. The procedure treats each set of fixed effects as a group and averages its incremental contribution to adjusted R^2 across all possible orders in which the groups enter the regression.[9]

Table 2 reports these contributions. Dividing each contribution by the full model's adjusted R^2 gives its share of explained variation.

We find that fields and courses account for most of the explained variation in academic relevance. Their contributions are 0.370 and 0.314, respectively, together representing 94% of the total. Institutions and instructors contribute 0.035 and 0.007. This concentration suggests that alignment with four-year curricula is closely tied to the subjects being taught. One interpretation is that some fields and courses have more widely shared expectations about the material students should learn, making alignment between community colleges and universities easier to sustain.

Institutions play a larger role in general LMR, particularly among academic courses. They account for 34% of explained variation in that sample, compared with 25% for fields and 27% for courses. This pattern is consistent with colleges differing in how strongly they incorporate locally demanded skills into instruction designed to prepare students for transfer. Their local economic environments may therefore influence the workplace applications and skills emphasized even in

[9] For group j, the contribution is

$$\phi_j = \sum_{T \subseteq V \setminus \{j\}} \frac{|T|!(K - |T| - 1)!}{K!} \left[\bar{R}^2(T \cup \{j\}) - \bar{R}^2(T) \right],$$

where $\bar{R}^2(S)$ is the adjusted R^2 from a regression of the content measure on the fixed effects in set S, V is the full set of groups, $K = |V| = 5$, and $\bar{R}^2(\varnothing) = 0$. The contributions sum to the full model's adjusted R^2.

academic courses.[10]

Fields and courses play a stronger role in the labor-market relevance of vocational instruction. Together, they account for 70% of explained variation in general LMR among vocational courses. Their combined share rises to 85% for major-specific LMR, compared with 78% among academic courses. These patterns are consistent with occupational requirements providing a more specific guide to the skills taught within a field. Such requirements may be especially influential in vocational programs, where coursework is designed around preparation for particular jobs.

Instructors account for less than 5% of explained variation in each labor-market measure. These contributions concern differences in average content associated with instructor identity. The empirical analysis below examines how students respond to changes in content over time, conditional on instructor identity and prior course content.

Table 2: Shapley–Owen Decomposition of Variance in Course Content

	AR	General LMR		Major-specific LMR	
	Academic	Academic	Vocational	Academic	Vocational
	(1)	(2)	(3)	(4)	(5)
Year	0.003	0.071	0.010	0.008	0.002
Field	0.370	0.196	0.225	0.167	0.100
Course	0.314	0.206	0.141	0.229	0.105
Institution	0.035	0.263	0.122	0.082	0.023
Instructor	0.007	0.036	0.024	0.018	0.010
Total	0.729	0.772	0.521	0.505	0.240

Notes: Each entry is the average incremental adjusted R^2 from adding the indicated group of fixed effects across all possible orderings of the five groups. Contributions sum to the full model's adjusted R^2. Columns distinguish academic and vocational community-college courses.

6 Estimating the Effects of Course Content: Research Design

Estimating the effects of course content requires accounting for how students and instructors select into it. Students choose courses partly on the basis of what they expect to learn. Instructors may design content based on the characteristics of their students, and colleges may design curricula around their programs and local economies. These choices can generate a spurious correlation between course content and student outcomes even in the absence of a causal effect.

[10]The labor-market measures reflect both syllabus content and demand weights. Because the weights vary across counties, the institutional component can capture geographic differences in the skills used to evaluate course content as well as differences in curricula. For major-specific LMR, the occupational benchmark also varies by field.

Following Biasi and Ma (2026), our research design exploits a useful feature of the Texas course registration process. At registration, students are generally unable to see the updated syllabus and can only choose courses based on prior syllabi and instructor identity. To identify the causal effect of content, we therefore compare students in the same program and entry cohorts who were exposed to courses with different content, while holding fixed prior content and instructor identity.

6.1 Baseline Model

Consider student i, who enters college j in major g and cohort e. For a given content measure, let C_i denote the student's course offerings, recorded at census dates, for which that measure is observed. Let m_s denote the standardized content of offering s. For MLMR, the measure also depends on the student's major. Average exposure is

$$\bar{m}_i = \frac{1}{|C_i|} \sum_{s \in C_i} m_s. \tag{6}$$

Each course receives equal weight, and standardization occurs before averaging across the student's courses.

For student outcome y_i, the baseline model is

$$y_i = \beta \bar{m}_i + X_i' \delta + \lambda_{jge} + \epsilon_i, \tag{7}$$

where X_i contains student characteristics and λ_{jge} denotes college-by-major-by-entry-cohort fixed effects. Student controls include high-school mathematics and reading test-score percentiles, calculated within graduation cohort and subject, and indicators for economic and academic disadvantage at college entry. Appendix D describes these variables and the associated sample restrictions.

The fixed effects compare students who enter the same college and major in the same cohort, accounting for shared program requirements and course availability. Students within these groups can nevertheless choose different courses for reasons related to their preparation, preferences, or expected outcomes. Average content exposure may therefore remain correlated with ϵ_i, biasing OLS estimates of β.

6.2 Identification Strategy: Updates to Course Content

Texas's HB 2504 requires public institutions to post current syllabi no later than seven days after classes begin. Since course registration opens before this deadline, access to the updated syllabus is not guaranteed when students choose courses. Students can instead draw on prior syllabi and

instructor identity to form expectations about what they will learn. Revisions to course content can subsequently change what they are taught relative to those expectations, but are unobserved at registration. Appendix C documents the statewide rule and institution-specific posting policies.

We account for expected content by controlling for the content of prior offerings and for instructor identity. Let $p(s)$ denote the prior offering corresponding to offering s, and let C_i^{lag} denote the student's course offerings for which prior content is observed. We define measures of content of prior offerings as

$$\bar{m}_i^{\text{lag}} = \frac{1}{|C_i^{\text{lag}}|} \sum_{s \in C_i^{\text{lag}}} m_{p(s)}. \tag{8}$$

Our estimating equation thus augments equation (7) with measures of content of prior offerings and instructor fixed effects:

$$y_i = \beta \bar{m}_i + \gamma \bar{m}_i^{\text{lag}} + X_i' \delta + \lambda_{jge} + \sum_{\ell \in L_i} \varphi_\ell + \epsilon_i, \tag{9}$$

where L_i is the set of instructors who teach student i. These indicators are not mutually exclusive, as a student typically takes courses with several instructors.

Lagged exposure captures differences in the prior content of students' chosen courses. Instructor fixed effects account for persistent differences in content and teaching across instructors, while college-by-major-by-entry-cohort fixed effects absorb conditions shared by students entering the same program and cohort. The coefficient β is identified by differences in current exposure remaining after accounting for these controls.

In models of earnings, we pool repeated observations for up to nine years after college exit and include fixed effects for years since exit and calendar year. Throughout the analysis, we cluster standard errors at the college-by-major-by-entry-cohort level. This allows the error term ϵ_i to be correlated across students in the same entering group, as well as across repeated earnings observations for the same student.

Identifying assumptions. Our research design rests on one maintained assumption: current exposure is unrelated to other determinants of student outcomes after conditioning on lagged exposure, student characteristics, and the fixed effects. This condition has three substantive implications.

First, students must not select into the content updates used for identification. They may choose courses based on prior content and instructor reputation, but the controls must account for the information that makes their current exposure predictable and related to their outcomes. This restriction

also applies to schedule changes after updated syllabi become available.[11]

Second, instructors' revisions must be unrelated to changes in their students' unobserved characteristics, conditional on the controls. This condition would be violated, for example, if instructors revised their content in response to unobserved characteristics of the students in their class.

Third, content updates must not systematically coincide with other changes in instruction that also affect outcomes. Examples are changes in grading practices or instructor effort.

Evidence on content updates. The registration and posting schedule motivates the first condition by allowing students to choose courses before seeing the revised material. As an additional piece of evidence in support of this condition, Table 3 tests whether course updates can be predicted by a set of characteristics of the students who take each course and the instructors who teach it. The corresponding joint F-statistics are 1.29, 1.10, and 1.16, indicating that these characteristics have limited explanatory power for measured content updates.

7 Effects of Academic Relevance

We now turn to the central question of the paper: does course content help community colleges advance their academic and workforce objectives? We begin by studying the effects of academic relevance (AR) on academic students' degree attainment, transfer to four-year institutions, and earnings. We first estimate average effects, then examine how they vary with students' baseline preparation and disadvantage status.

7.1 Academic Relevance and Educational Outcomes

Exposure to courses with higher academic relevance helps students progress along the transfer pathway. A one-SD increase in AR raises the probability of transferring to a four-year institution by 1.9 pp and of earning a bachelor's degree (BA) by 1.3 pp (Table 4, columns 3 and 4, significant at the 1% and 5% levels, respectively). These effects correspond to increases of 8.6% and 11.8% relative to the respective sample means of 22% and 11%. Using a BA attainment rate of 65% among students who start at a four-year college as a benchmark, the estimated increase closes 2.4% of the unconditional gap in BA attainment between community-college and four-year entrants and nearly 40% of the gap conditional on transferring.[12]

[11] Our course sets reflect enrollment at census dates, which can follow syllabus publication. The assumption therefore covers additions and drops before those dates. Because exposure averages content across the student's observed courses, it also requires that subsequent course choices and syllabus coverage do not generate a correlation between measured exposure and unobserved determinants of outcomes.

[12] The unconditional gap is $65 - 11 = 54$ pp, so the gain closes $1.3/54 \times 100 = 2.4\%$. A separate illustrative calculation holds the transfer rate fixed at 22%. Under this assumption, the implied conditional BA-completion rate rises from 11/22

Table 3: Course Content Updates and Student and Instructor Characteristics

	Academic relevance (1)	General LMR, academic courses (2)	General LMR, vocational courses (3)
Students			
Share White	0.151*	-0.033	-0.014
	(0.085)	(0.023)	(0.034)
Share Black	0.060	-0.010	0.051
	(0.092)	(0.025)	(0.038)
Share Hispanic	0.099	-0.023	-0.004
	(0.085)	(0.023)	(0.034)
High school rank	0.0001	-0.0003	0.0002
	(0.0008)	(0.0002)	(0.0003)
Share academically disadvantaged	0.048	0.008	0.030*
	(0.029)	(0.009)	(0.015)
Share economically disadvantaged	0.081*	-0.003	-0.005
	(0.037)	(0.008)	(0.013)
Faculty			
Age	0.0009*	0.0002	-0.0003
	(0.0005)	(0.0002)	(0.0004)
Male	0.004	0.000	-0.004
	(0.009)	(0.004)	(0.009)
White	0.017	0.007	0.014
	(0.025)	(0.011)	(0.027)
Black	0.011	0.013	0.024
	(0.030)	(0.015)	(0.029)
Hispanic	0.050*	0.005	0.025
	(0.028)	(0.012)	(0.029)
Bachelor's	0.037	-0.008	-0.003
	(0.041)	(0.014)	(0.010)
Master's	0.020	-0.002	0.000
	(0.030)	(0.012)	(0.010)
Ph.D.	0.011	0.000	
	(0.031)	(0.012)	
Taught at a four-year institution	-0.002	0.007*	0.005
	(0.010)	(0.004)	(0.013)
Part-time	0.007	-0.005	0.001
	(0.011)	(0.004)	(0.008)
Specification			
Institution × field × year fixed effects	X	X	X
N	12,805	42,291	45,117
R^2	0.044	0.034	0.063
F-statistic	1.286	1.102	1.156

Notes: Dependent variables are standardized content updates; the lag specification conditions current content on lagged content. Student race and disadvantage shares are scaled to one standard deviation. All columns include institution-by-field-by-year fixed effects. Standard errors, clustered at the college-by-major-by-entry-cohort level, are in parentheses. Blank cells denote omitted estimates. * $p < 0.10$.

By contrast, AR does not appear to affect the likelihood that students obtain an AA or another community-college credential. Since students generally do not need a community college degree to transfer to a four-year institution, this pattern suggests that greater academic relevance primarily helps students advance beyond community college.

Table 4: Effects of Academic Relevance on Educational Outcomes

	Attains AA degree	Attains other CC degree	Transfers to four-year	Attains BA
	(1)	(2)	(3)	(4)
Academic relevance	0.008	-0.005	0.019***	0.013**
	(0.006)	(0.003)	(0.007)	(0.006)
Mean dep. var.	0.23	0.07	0.22	0.11
Instructor fixed effects	X	X	X	X
College–major–entry-cohort FE	X	X	X	X
Adjusted R^2	0.567	0.619	0.443	0.410
N	101,097	101,097	101,097	101,097

Notes: Estimates from equation (9) for students in academic programs. Academic relevance is standardized as described in Section 6.1. The dependent variables are indicators for completion of an Associate of Arts or Associate of Science degree (AA/AS; column 1), completion of another community-college degree or credential (column 2), transfer to a Texas four-year institution (column 3), and bachelor's degree attainment (column 4). All specifications control for lagged academic relevance, instructor fixed effects, and college–major–entry-cohort fixed effects. Standard errors are clustered at the college–major–entry-cohort level. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

7.1.1 Differences in Impacts: Baseline BA Probability and Student Advantage

The benefits of academically relevant content may depend on how well prepared students are to pursue a four-year degree. To capture this dimension, we construct each student's predicted probability of eventually completing a BA (*baseline BA probability*) using characteristics measured at or before community-college entry. We estimate a linear probability model of BA attainment using major at community-college enrollment, high-school test scores, ethnicity, gender, academic-disadvantage status, economic-disadvantage status, and high-school fixed effects. We use the fitted values as baseline BA probabilities, replacing predictions below zero with zero and predictions above one with one. The mean predicted probability is 22%, and the maximum is 60%.

To study whether the returns to AR vary by students' baseline prospects, we augment equation (9) with baseline probability and its interaction with AR. The coefficient on AR therefore measures

= 50.0% to 12.3/22 = 55.9%, closing (55.9 - 50.0)/(65 - 50.0) × 100 = 39.4% of the conditional gap. This calculation should be interpreted as descriptive, because it does not incorporate the estimated increase in transfer.

its effect for a student with a baseline BA probability of zero; the interaction coefficient describes how that effect changes as baseline BA probability increases.

Estimates of this specification, albeit imprecise, suggest that students with stronger baseline prospects benefit more from academically relevant content. At a baseline BA probability of zero, the estimated effects of AR are much smaller than in our main specification, and equal to -0.5 pp for AA attainment, 0.1 pp for attainment of other community college degrees, 0.5 pp for transfer, and -0.3 pp for BA attainment (p-values equal to 0.669, 0.893, 0.714, and 0.790, respectively; Table 5). The interaction terms are instead positive and large: A 10 pp increase in baseline BA probability corresponds to an additional AR effect of 0.69 pp on AA attainment (p-value = 0.211), 0.73 pp on transfer (p-value = 0.238), and 0.79 pp on BA attainment (p-value = 0.157), and a 0.26 pp reduction in attainment of other credentials (p-value = 0.338). Taken at face value, these estimates imply that, for a student with a 50% baseline probability of obtaining a BA, a one-SD increase in AR increases AA degree completion by 2.9 pp, transfer by 4.2 pp, and BA attainment by 3.6 pp while reducing other community college degree attainment by 1.2 pp. The same effects are 0.2 pp, 1.3 pp, 0.5 pp, and -0.2 pp for a student with a baseline probability of only 10%. While imprecise, these results suggest a positive gradient in the benefits along the transfer pathway.

In panel (a) of Figure 4, we additionally examine differences by academic and economic disadvantage at entry. The effects on transfer are positive and significant for both disadvantaged and non-disadvantaged students. The point estimates for BA completion are larger for students without the corresponding disadvantage. Together, these patterns suggest that stronger alignment with four-year curricula can encourage transfer across groups, while students with stronger preparation and greater resources may be better positioned to translate that opportunity into a bachelor's degree.

7.2 Academic Relevance and Students' Earnings

We next study the effects of academic relevance on students' post-college earnings. The average earnings estimate is close to zero: the estimate of β in equation (9), using the logarithm of quarterly earnings as the outcome variable and pooling data across quarters, is -0.008 log points (p-value = 0.414; Table 6, column 1). This estimate is consistent with the earnings gains implied by the increase in BA attainment. For illustration, a 30% earnings return to a BA and a 1.3 pp increase in attainment imply an average earnings gain of approximately 0.34% through additional degree completion, well

Table 5: Effects of Academic Relevance on Educational Outcomes: Heterogeneity by Predicted BA Completion

	Attains AA degree	Attains other CC degree	Transfers to four-year	Attains BA
	(1)	(2)	(3)	(4)
Academic relevance	-0.005	0.001	0.005	-0.003
	(0.012)	(0.007)	(0.014)	(0.012)
AR × baseline BA probability	0.069	-0.026	0.073	0.079
	(0.055)	(0.027)	(0.062)	(0.056)
Mean dep. var.	0.23	0.07	0.22	0.11
Instructor fixed effects	X	X	X	X
College–major–entry-cohort FE	X	X	X	X
Adjusted R^2	0.568	0.619	0.444	0.411
N	101,097	101,097	101,097	101,097

Notes: Estimates from equation (9) for students in academic programs, augmented with baseline BA probability and its interaction with AR. Baseline BA probability is constructed as described in the text. Academic relevance is standardized as described in Section 6.1. The dependent variables are indicators for completion of an Associate of Arts or Associate of Science degree (AA/AS; column 1), completion of another community-college degree or credential (column 2), transfer to a Texas four-year institution (column 3), and bachelor's degree attainment (column 4). All specifications control for lagged academic relevance, instructor fixed effects, and college–major–entry-cohort fixed effects. Standard errors are clustered at the college–major–entry-cohort level. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

within the confidence interval of our estimate.[13]

These average estimates, though, mask substantial heterogeneity by students' baseline prospects of completing a BA. Column 2 of Table 6 reports estimates from a specification that interacts AR with each student's predicted baseline BA probability. The coefficient on AR is negative at -0.071 log points (or -6.9 pp), while the interaction is 0.0291 log points (34%); both are significant at the 1% level. These estimates imply that a one-SD increase in AR reduces earnings by approximately 4.1% for students with a baseline BA probability of 10% and raises earnings by 7.7% for students with a baseline probability of 50%. This gradient suggests that the earnings value of academic preparation depends on students' prospects along the transfer pathway.

The estimates by disadvantage status show a similar pattern (Figure 4, panel (b)). For academically disadvantaged students, the earnings estimate is negative but statistically insignificant; for students without academic disadvantage, it is close to zero. For economically disadvantaged students, the estimated effect is approximately -2.4% and statistically significant, compared with a positive but insignificant estimate of approximately 1.5% for students without economic disadvantage.

Finally, column 3 of Table 6 tests whether the earnings effects of AR vary linearly with experience, measured as years since college exit. We find no evidence of such a pattern. The coefficients on AR and its interaction with experience are 0.001 and -0.001, respectively, and both are indistinguishable from zero (with p-values of 0.967 and 0.639).

8 Labor-Market Relevance

The results so far indicate that aligning community-college courses with their four-year counterparts helps students progress along the transfer pathway. We now examine the effects of alignment with skills demanded by employers. We use two metrics that capture different dimensions of the workforce objective. General labor-market relevance (GLMR) measures alignment with skills demanded across *all* jobs in the local labor market. Major-specific labor-market relevance (MLMR) weights skills according to demand in occupations related to the student's major. Comparing their effects allows us to examine how the educational and earnings consequences of preparation for work depend on which occupations the curriculum prepares students to enter.

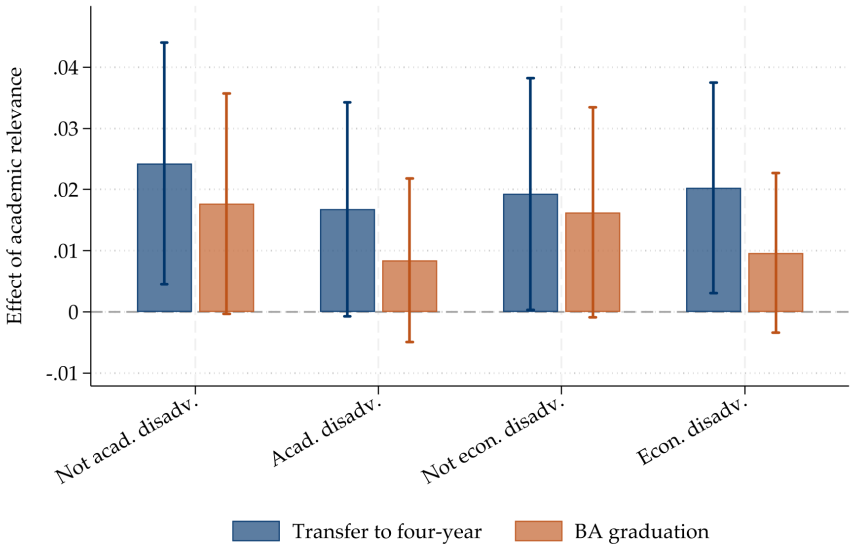
[13] In a simple calculation applying the same BA earnings premium to additional completers, the implied effect on log earnings is $0.013 \times \log(1.30) = 0.0034$, or approximately 0.34%.

Table 6: Effects of Academic Relevance on Earnings

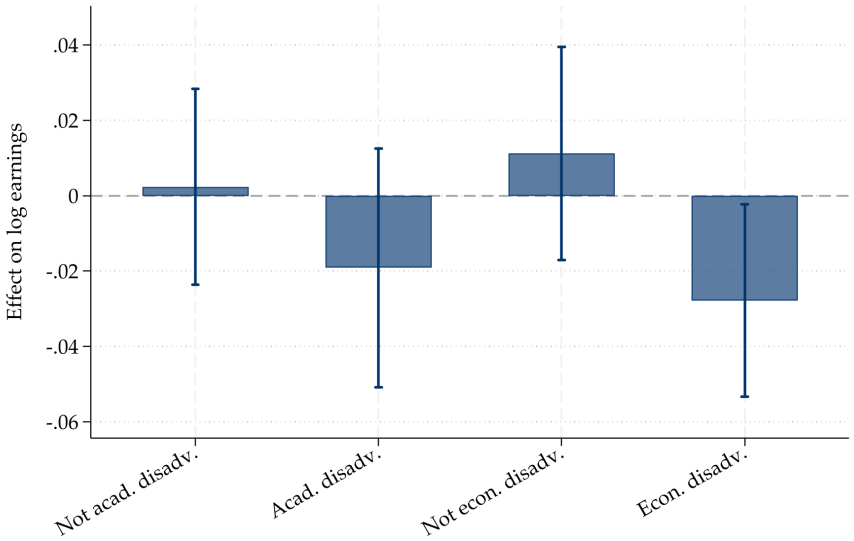
	(1)	(2)	(3)
Academic relevance	-0.008	-0.071***	0.001
	(0.010)	(0.022)	(0.018)
Academic relevance × baseline BA probability		0.291***	
		(0.090)	
Academic relevance × experience			-0.001
			(0.002)
Instructor fixed effects	X	X	X
College–major–entry-cohort FE	X	X	X
Potential-experience controls	X	X	X
Calendar-year fixed effects	X	X	X
Adjusted R^2	0.383	0.383	0.383
N	569,970	569,970	569,970

Notes: Estimates from equation (9) for students in academic programs, pooling quarterly earnings observations after college exit. Academic relevance is standardized as described in Section 6.1. The dependent variable is the natural logarithm of quarterly earnings. Column 2 interacts AR with baseline BA probability, constructed as described in the text. Column 3 interacts AR with experience, measured as years since college exit. All specifications control for lagged academic relevance, potential experience, instructor fixed effects, college–major–entry-cohort fixed effects, and year fixed effects. Standard errors are clustered at the college–major–entry-cohort level. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Figure 4: Effects of Academic Relevance, by Disadvantage Status



(a) Transfer and BA attainment



(b) Log earnings

Notes: Estimates and 95% confidence intervals from equation (9) for students in academic programs, with AR interacted with an indicator for academic or economic disadvantage in separate specifications. The "non-disadvantaged" bars report the coefficient on AR; the "disadvantaged" bars report the sum of that coefficient and the corresponding interaction coefficient. Academic relevance is standardized as described in Section 6.1. The dependent variables are indicators for transfer to a Texas four-year institution and bachelor's degree attainment (panel (a), blue and orange bars, respectively), and the natural logarithm of quarterly earnings (panel (b)). Panel (b) pools quarterly earnings observations after college exit. All specifications control for lagged academic relevance, instructor fixed effects, and college–major–entry-cohort fixed effects; panel (b) additionally controls for potential experience (defined as the number of years elapsed since college exit) and year fixed effects. Standard errors are clustered at the college–major–entry-cohort level.

8.1 Educational Outcomes of Academic Students

We begin with the educational outcomes of students in academic programs. Our first result is that higher general labor-market relevance moves academic students away from the transfer pathway. A one-SD increase in GLMR lowers AA attainment by 5.8 pp, transfer by 9.6 pp, and BA attainment by 6.4 pp (Table 7, panel A, all significant at the 1% level). At the same time, it increases attainment of other community-college credentials by 1.3 pp. Greater exposure to skills demanded across the local labor market thus shifts students' educational trajectories toward credentials associated with direct labor-market entry and away from the four-year pathway.

The estimated reductions in transfer and BA attainment are smaller when labor-market relevance is defined using occupations related to students' majors. A one-SD increase in MLMR lowers transfer by 5.2 pp and BA completion by 2.6 pp, with no significant effect on AA completion (Table 7, panel B). These comparisons suggest that the educational consequences of preparation for work depend on the jobs students are being prepared to perform.

8.2 General Labor-Market Relevance and Occupational Tilt

GLMR and MLMR are closely related, with a correlation of 0.8 (Figure 3, panel (c)). Both use the same syllabus skill frequencies, weighted by demand across different sets of occupations. To distinguish the role of occupational targeting from broad labor market alignment, we estimate their effects jointly. We express this specification in terms of GLMR and *occupational tilt*, defined as major-specific minus general relevance. Letting GLMR_i and MLMR_i denote each student's average exposure to the corresponding standardized course measures,

$$\mathrm{OT}_i = \mathrm{MLMR}_i - \mathrm{GLMR}_i. \tag{10}$$

Higher tilt therefore indicates greater alignment with occupations related to the student's field relative to alignment with the broader local labor market. We then estimate

$$\begin{aligned} y_i = \beta_G \mathrm{GLMR}_i + \beta_T \mathrm{OT}_i + \gamma_G \mathrm{GLMR}_i^{\mathrm{lag}} + \gamma_T \mathrm{OT}_i^{\mathrm{lag}} \\ + X_i'\delta + \lambda_{jge} + \sum_{\ell \in L_i} \varphi_\ell + \epsilon_i, \end{aligned} \tag{11}$$

with the additional time controls described above for earnings. The coefficient β_T measures the effect of greater alignment with occupations related to the student's field, holding general labor-market relevance fixed. The coefficient β_G captures a common increase in both relevance measures:

holding their difference fixed, a one-unit increase in GLMR also raises MLMR by one unit. Equivalently, the current-content terms can be written as

$$(\beta_G - \beta_T)\text{GLMR}_i + \beta_T \text{MLMR}_i.$$

The occupational-tilt specification therefore estimates the same model as jointly including GLMR and MLMR, while giving the coefficients a direct interpretation in terms of common alignment and occupational targeting.

Estimates of this model are in panel C of Table 7. Holding GLMR fixed, greater occupational alignment improves academic students' educational outcomes. A one-unit increase in tilt raises AA attainment by 6.6 pp, transfer by 4.8 pp, and BA completion by 5.4 pp. These estimates are significant at the 1%, 5%, and 1% levels, respectively.

These results clarify how the educational effects of preparation for work depend on its occupational focus. Holding occupational tilt fixed, a common increase in general and major-specific relevance—captured by the coefficient on GLMR in panel C of Table 7—still reduces AA attainment, transfer, and BA completion. At a given level of general relevance, however, stronger preparation for occupations connected to students' fields supports progress along the transfer pathway. One interpretation is that teaching skills used in these occupations makes the career value of further education more apparent, encouraging students to persist and pursue a four-year degree.

8.3 Earnings

We next examine whether alignment with employer skill demand translates into higher earnings, distinguishing students in academic and vocational programs.

8.3.1 Academic Students

Among academic students, the average earnings estimates are close to zero: -0.017 log points for GLMR and -0.016 for MLMR, neither statistically significant (Table 8, panels A and B, column 1). The joint specification yields a similar pattern. Holding GLMR fixed, the coefficient on occupational tilt is -0.007 (standard error 0.024), while the coefficient on GLMR is -0.019 (standard error 0.019); both are statistically indistinguishable from zero (panel C, column 1).

We also examine whether these effects differ by academic and economic disadvantage at entry (Figure 5, panels (a) and (b)). The estimates are negative and generally statistically indistinguishable from zero across groups for both GLMR and MLMR, consistent with the average results.

Table 7: Effects of Labor-Market Relevance on Academic Students' Educational Outcomes

	Attains AA degree	Attains other CC degree	Transfers to four-year	Attains BA
	(1)	(2)	(3)	(4)
Panel A: General LMR				
General LMR	-0.058***	0.013**	-0.096***	-0.064***
	(0.011)	(0.006)	(0.013)	(0.011)
Mean dep. var.	0.23	0.07	0.22	0.11
Adjusted R^2	0.560	0.614	0.444	0.409
N	113,416	113,416	113,416	113,416
Panel B: Major-specific LMR				
Major-specific LMR	-0.018	0.005	-0.052***	-0.026*
	(0.013)	(0.007)	(0.017)	(0.014)
Mean dep. var.	0.23	0.07	0.22	0.11
Adjusted R^2	0.559	0.614	0.443	0.409
N	113,416	113,416	113,416	113,416
Panel C: General LMR and occupational tilt				
General LMR	-0.036***	0.010	-0.078***	-0.045***
	(0.013)	(0.008)	(0.017)	(0.014)
Occupational tilt	0.066***	-0.008	0.048**	0.054***
	(0.017)	(0.009)	(0.020)	(0.018)
Mean dep. var.	0.23	0.07	0.22	0.11
Adjusted R^2	0.560	0.614	0.444	0.410
N	113,416	113,416	113,416	113,416
Instructor fixed effects	X	X	X	X
College–major–entry-cohort FE	X	X	X	X

Notes: Panels A and B report estimates from equation (9) for students in academic programs, using general labor-market relevance (GLMR) and major-specific labor-market relevance (MLMR), respectively. Panel C reports estimates from equation (11), which jointly includes GLMR and occupational tilt. GLMR and MLMR are standardized before averaging across students' courses, as described in Section 6.1. Occupational tilt is the difference between these average exposures, MLMR minus GLMR, and is not separately standardized. The dependent variables are indicators for completion of an Associate of Arts or Associate of Science degree (AA/AS; column 1), completion of another community-college degree or credential (column 2), transfer to a Texas four-year institution (column 3), and bachelor's degree attainment (column 4). All specifications control for lagged versions of the main explanatory variables, instructor fixed effects, and college–major–entry-cohort fixed effects. Panel C includes both lagged GLMR and lagged occupational tilt. Standard errors are clustered at the college–major–entry-cohort level. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

As with AR, however, the earnings effects increase with students' baseline likelihood of completing a BA. The interaction coefficients are 0.225 for GLMR and 0.240 for MLMR, both significant at the 10% level (panels A and B, column 2). These estimates imply that, for students with a baseline BA probability of 50%, a one-SD increase in GLMR raises earnings by approximately 4.1%, while the corresponding increase in MLMR raises earnings by 4.4%. At a baseline BA probability of 10%, the implied effects are instead -4.8% and -5.2%, respectively. Academic and labor-market-oriented content thus both have more favorable earnings effects among students who enter community college better positioned to complete a four-year degree.

The earnings effect of MLMR also becomes more favorable with experience (panel B, column 3). Allowing the effect to vary linearly with years since college exit yields a coefficient of -0.061 log points at exit and an interaction coefficient of 0.007, significant at the 5% and 10% levels, respectively. The fitted profile therefore implies an initially negative effect that approaches zero roughly nine years after exit. For GLMR, we find no evidence of a linear change with experience: the interaction coefficient is -0.003, with a standard error of 0.003 (panel A, column 3).

8.3.2 Vocational Students

For vocational students, alignment with occupations related to their field produces substantial earnings gains. A one-SD increase in MLMR raises log earnings by 0.120, or 12.7%, with a standard error of 0.057 (Table 8, panel B, column 4). The estimate is significant at the 5% level. The corresponding GLMR estimate is -0.022 (standard error 0.026) and statistically indistinguishable from zero (panel A, column 4).

The experience specifications provide little evidence that these effects change linearly with years since college exit (column 5). For MLMR, the estimated effect at exit is 0.132 log points, while the interaction with experience is -0.002 (standard error 0.009). The GLMR interaction is also -0.002 (standard error 0.005). Neither interaction is statistically significant.

The joint specification confirms the value of targeting occupations related to students' majors. Holding GLMR fixed, a one-unit increase in occupational tilt raises vocational students' log earnings by 0.138, or 14.8% (panel C, column 4). The standard error is 0.059, and the estimate is significant at the 5% level. A common one-unit increase in GLMR and MLMR, holding tilt fixed, also raises earnings: the coefficient on GLMR is 0.101 log points, or approximately 10.6%, significant at the 10% level. This coefficient captures an increase in both dimensions of relevance, including stronger preparation for occupations related to students' fields. The positive tilt coefficient further shows that strengthening this occupational connection raises vocational earnings even at a given

level of general labor-market relevance.

Table 8: Effects of Labor-Market Relevance on Earnings

	Academic students			Vocational students	
	(1)	(2)	(3)	(4)	(5)
Panel A: General labor-market relevance					
General LMR	-0.017	-0.072**	-0.001	-0.022	-0.011
	(0.016)	(0.034)	(0.024)	(0.026)	(0.037)
General LMR × baseline BA probability		0.225*			
		(0.126)			
General LMR × experience			-0.003		-0.002
			(0.003)		(0.005)
Adjusted R^2	0.380	0.380	0.380	0.579	0.579
N	646,372	646,372	646,372	146,311	146,311
Panel B: Major-specific labor-market relevance					
Major-specific LMR	-0.016	-0.077*	-0.061**	0.120**	0.132*
	(0.018)	(0.041)	(0.030)	(0.057)	(0.072)
Major-specific LMR × baseline BA probability		0.240*			
		(0.145)			
Major-specific LMR × experience			0.007*		-0.002
			(0.004)		(0.009)
Adjusted R^2	0.380	0.380	0.380	0.579	0.579
N	646,372	646,372	646,372	146,311	146,311
Panel C: General LMR and occupational tilt					
General LMR	-0.019			0.101*	
	(0.019)			(0.058)	
Occupational tilt	-0.007			0.138**	
	(0.024)			(0.059)	
Adjusted R^2	0.380			0.579	
N	646,372			146,311	
Instructor fixed effects	X	X	X	X	X
College–major–entry-cohort FE	X	X	X	X	X
Potential-experience controls	X	X	X	X	X
Calendar-year fixed effects	X	X	X	X	X

Notes: Panels A and B report GLMR and MLMR estimates from equation (9); panel C reports the joint GLMR and occupational-tilt specification in equation (11). Columns 1–3 use academic students and columns 4–5 vocational students. The outcome is log quarterly earnings. Columns 1 and 4 report average effects, column 2 interacts content with baseline BA probability, and columns 3 and 5 interact content with experience. Content measures are standardized before averaging; occupational tilt is MLMR minus GLMR without further standardization. Specifications include the corresponding lagged content, instructor, college–major–entry-cohort, experience, and calendar-year fixed effects. Standard errors are clustered at the college–major–entry-cohort level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Heterogeneity by student disadvantage Alignment with occupations related to students' fields produces larger earnings gains for disadvantaged vocational students (Figure 5, panel (d)). For

academically disadvantaged students, a one-SD increase in MLMR raises log earnings by approximately 0.22, compared with 0.08 for students without academic disadvantage. The corresponding estimates are approximately 0.17 for economically disadvantaged students and 0.05 for students without economic disadvantage. GLMR, by comparison, has no detectable earnings effect in any subgroup (panel (c)).

These patterns suggest that occupation-specific instruction may be particularly valuable for students who enter college with weaker academic preparation or fewer economic resources. One interpretation is that these students rely more heavily on college coursework to acquire the skills employers demand. Strengthening the connection between vocational curricula and students' intended occupations may therefore help compensate for differences in the preparation and opportunities students bring to college.

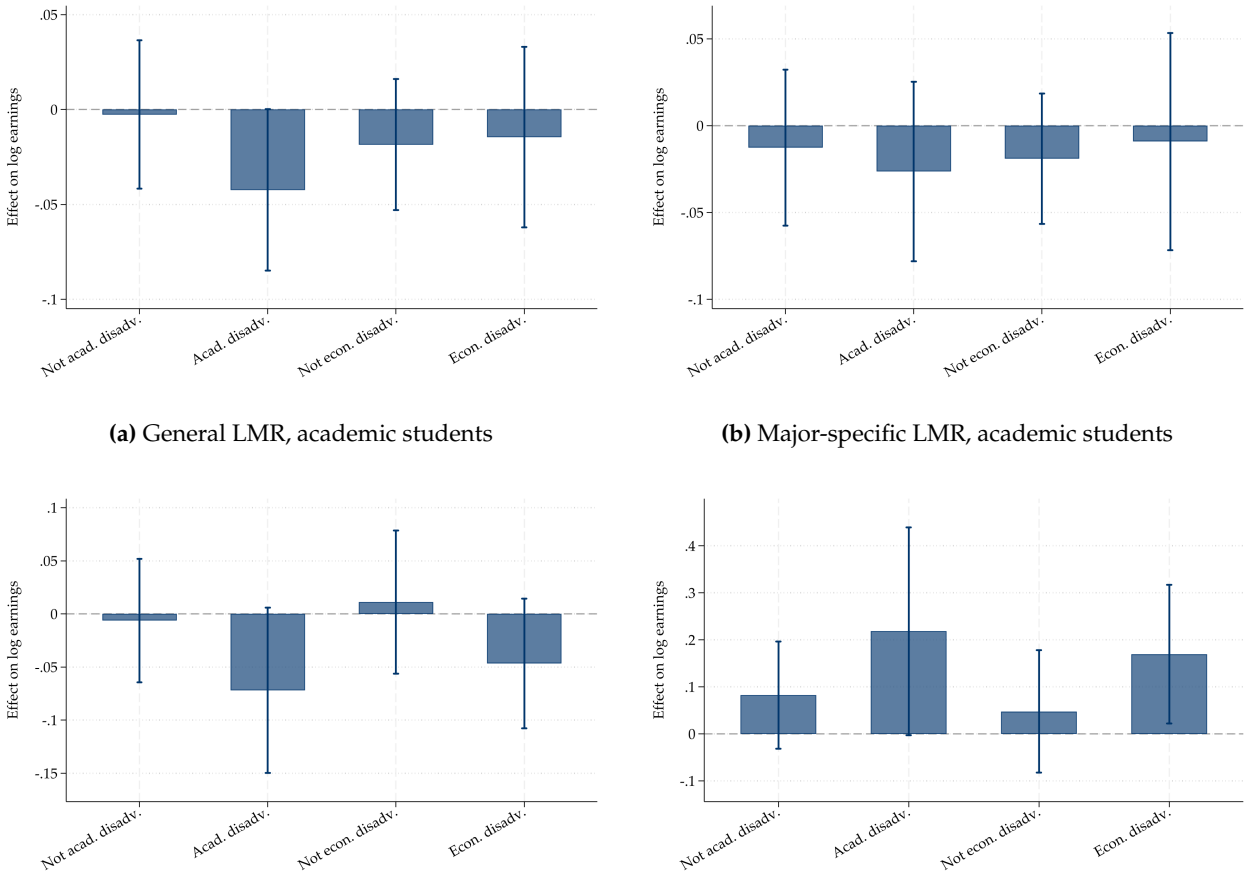
8.3.3 Timing of Earnings Effects

We next examine how the earnings effects of labor-market relevance evolve after college exit and whether their timing differs by student disadvantage. Job-related skills may help students secure better jobs immediately after college, or their value may grow as students gain experience and advance in their careers. To distinguish these patterns, we allow the effects of each content measure to vary linearly with years since college exit and by academic or economic disadvantage. Figure 6 reports the implied effects at exit and nine years later.

Among academic students, the estimated effects of major-specific relevance become more favorable over time in every subgroup (panel (b)). The estimates are initially negative and approach zero by year nine. The largest improvement is among economically disadvantaged students, for whom the estimated effect rises from -0.101 to 0.023 log points. General labor-market relevance follows a different pattern: its estimated effects are close to zero at exit and become more negative over time across all groups (panel (a)). For academically disadvantaged students, for example, the estimate declines from -0.001 to -0.050 log points.

Among vocational students, the timing of the MLMR effects differs markedly by disadvantage status (panel (d)). Initial point estimates are positive in every subgroup and larger among students without the corresponding disadvantage. For students without academic disadvantage, the estimated effect declines from 0.165 log points at exit to 0.011 nine years later; for academically disadvantaged students, it rises from 0.113 to 0.285. The same pattern appears by economic disadvantage: the estimate declines from 0.165 to -0.038 for students without economic disadvantage and rises from 0.104 to 0.209 for economically disadvantaged students. The GLMR profiles show

Figure 5: Average Earnings Effects of Labor-Market Relevance, by Disadvantage Status



(a) General LMR, academic students

(b) Major-specific LMR, academic students

(c) General LMR, vocational students

(d) Major-specific LMR, vocational students

Notes: Estimates and 95% confidence intervals from equation (9), with each content measure interacted with an indicator for academic or economic disadvantage in separate specifications. Panels (a) and (b) report results for academic students; panels (c) and (d) report results for vocational students. The content measure is general labor-market relevance (GLMR) in panels (a) and (c), and major-specific labor-market relevance (MLMR) in panels (b) and (d). The "non-disadvantaged" bars report the coefficient on the content measure; the "disadvantaged" bars report the sum of that coefficient and the corresponding interaction coefficient. The content measures are standardized as described in Section 6.1. The dependent variable is the natural logarithm of quarterly earnings, pooling observations after college exit. All specifications control for the corresponding lagged content measure, instructor fixed effects, college–major–entry-cohort fixed effects, potential experience (defined as the number of years elapsed since college exit), and calendar-year fixed effects. Standard errors are clustered at the college–major–entry-cohort level.

no comparable pattern across the two dimensions of disadvantage (panel (c)).

These point estimates suggest that the larger average MLMR gains among disadvantaged vocational students develop over the years following college exit. One interpretation is that these students take longer to find jobs in which they can fully use the occupation-specific skills acquired in college, or that these skills provide a foundation for subsequent learning and career advancement.

8.4 Which Skills Help Which Students?

Our results suggest that the benefits of preparation for work depend on the occupations students are being prepared to enter. We further explore this relationship by examining the earnings effects of individual skill families. We estimate a separate regression for each skill family using our lagged-content specification. Appendix Figure A2 compares the resulting estimates for vocational students, on the horizontal axis, and academic students, on the vertical axis.

Several skill families have different earnings patterns across the two tracks. Finance has a positive and significant estimate for academic students and a negative (though insignificant) estimate for vocational students, while education displays the reverse pattern: a negative effect for academic students and a positive insignificant effect for vocational students. Human-resources content has positive estimates in both tracks, with a significant effect for academic students. Lastly, information technology has negative and statistically significant estimates in both tracks. Taken together, these patterns suggest that the value of particular skills may depend on how they complement the rest of a student's training and the occupations that training prepares them to enter.

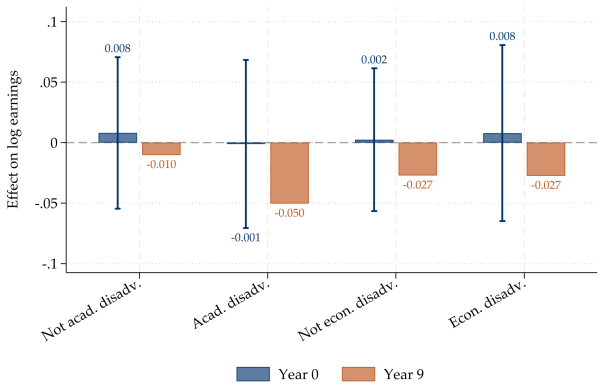
8.5 Robustness

We probe the robustness of our estimates and further explore the mechanisms driving them by examining whether the results depend on how we account for instructor characteristics and on the four-year curricula used to measure academic relevance.

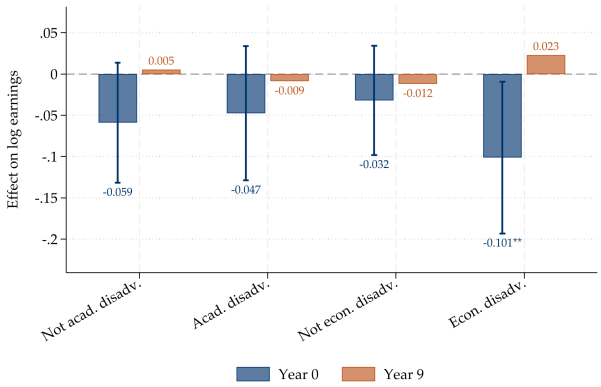
8.5.1 Instructor fixed effects.

Instructors can directly affect student outcomes through teaching practices, grading, and advising, in addition to the content they teach. If these contributions are correlated with course content, omitting instructor fixed effects allows the content coefficients to capture both. To account for this, our main estimates reported earlier controlled for instructor fixed effects. However, comparing specifications with and without these controls helps assess the importance of accounting for persistent differences across instructors.

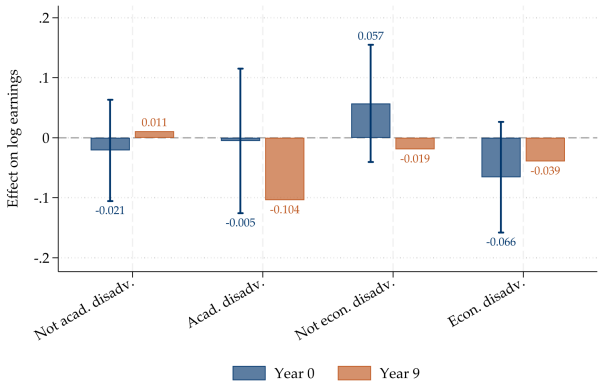
Figure 6: Earnings Effects of Labor-Market Relevance at College Exit and Nine Years Later



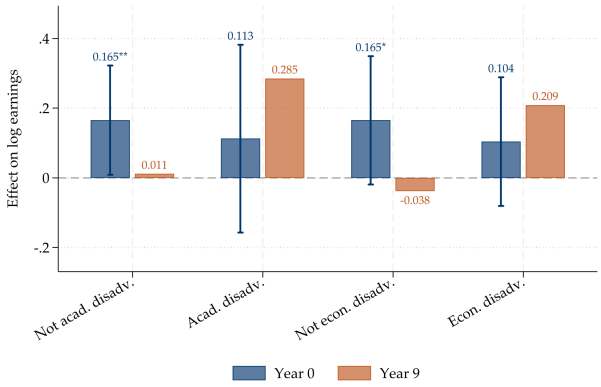
(a) General LMR, academic students



(b) Major-specific LMR, academic students



(c) General LMR, vocational students



(d) Major-specific LMR, vocational students

Notes: Estimated effects on the natural logarithm of quarterly earnings from equation (9), allowing the effects of course content to vary linearly with years since college exit and by academic or economic disadvantage in separate specifications. Panels (a) and (b) report results for academic students; panels (c) and (d) report results for vocational students. The content measure is general labor-market relevance (GLMR) in panels (a) and (c), and major-specific labor-market relevance (MLMR) in panels (b) and (d). The content measures are standardized as described in Section 6.1. For each subgroup, let b denote the estimated content effect at college exit and d its estimated change per year. The blue and orange bars report the fitted effects at years zero and nine, b and $b + 9d$, respectively. For non-disadvantaged students, these coefficients are the content coefficient and its interaction with experience; for disadvantaged students, they additionally incorporate the corresponding interactions with the disadvantage indicator. All specifications control for the corresponding lagged content measure, instructor fixed effects, college–major–entry-cohort fixed effects, potential experience, and calendar-year fixed effects. Standard errors are clustered at the college–major–entry-cohort level. Capped lines show 95% confidence intervals for year-zero effects. Stars refer to year-zero effects: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Excluding instructor fixed effects yields larger estimates of the impact of AR on educational outcomes. The coefficients for transfer and BA attainment are 7.9 and 4.1 pp, respectively, compared with 1.9 and 1.3 pp in the baseline specification (Appendix Table A1). These larger estimates are consistent with a positive association between academic alignment and instructor characteristics that also affect educational success. The effects of GLMR and MLMR on transfer and BA attainment stay negative. The distinction between general and major-specific labor-market relevance also remains: GLMR has larger negative coefficients for transfer and BA attainment than MLMR, while conditional occupational tilt has positive coefficients for AA attainment, transfer, and BA completion (Appendix Table A2).

Earnings estimates of labor-market relevance, though, differ when we exclude instructor fixed effects. The coefficient on GLMR is positive at 0.038 log points for both academic and vocational students, while the coefficient on MLMR is positive at 0.037 for academic students. These estimates are statistically significant, whereas their baseline counterparts are close to zero (Appendix Table A4). The positive vocational earnings estimates for MLMR and occupational tilt remain, at 0.102 and 0.071 log points, respectively (panels B and C, column 4). The AR earnings interaction with baseline BA probability also remains positive and significant, at 0.341 (Appendix Table A3).

One interpretation for these results is that instructors who emphasize skills demanded by employers also bring industry experience, professional connections, or knowledge of hiring practices that help students find better jobs. These contributions can raise earnings independently of the content recorded in their syllabi. The positive earnings coefficients without instructor fixed effects vis-à-vis a zero effect with instructor fixed effects may therefore largely reflect the benefits of studying with these instructors, above and beyond the effects of what they teach. These comparisons thus suggest that broad labor-market alignment is correlated with other instructor-related advantages, while the vocational earnings gains from occupation-specific content remain after accounting for persistent instructor differences.

8.5.2 Changes within an instructor's course.

Our baseline models with instructor fixed effects account for persistent differences across instructors. An instructor's effectiveness may, however, also vary across the courses they teach. To account for these differences, we replace instructor fixed effects with instructor-by-course fixed effects. This specification uses changes in measured content across offerings of the same course taught by the same instructor, absorbing persistent differences specific to each instructor–course pair.

Effects on educational outcomes are largely robust with this alternative specification. The AR

effects on transfer and BA attainment are 1.7 and 1.3 pp, compared with baseline estimates of 1.9 and 1.3 pp (Appendix Table A5). GLMR continues to reduce AA attainment, transfer, and BA completion, with effects of 7.2, 10.4, and 7.4 pp, respectively. The corresponding MLMR estimates are smaller, including reductions of 4.9 pp in transfer and 2.1 pp in BA attainment (Appendix Table A6). The educational results therefore persist when comparisons are restricted to variation within an instructor's course.

Average earnings estimates are more sensitive to this restriction. The AR coefficient is -0.020 log points, significant at the 10% level (Appendix Table A7). Among vocational students, the MLMR coefficient remains positive at 0.064, although it is smaller and less precisely estimated than in the baseline specification, with a standard error of 0.091. The GLMR coefficient is -0.103, significant at the 5% level (Appendix Table A8).

8.5.3 Alternative academic-relevance benchmark.

Four-year institutions differ in what they teach, so the academic-relevance measure may depend on which institutions supply the comparison syllabi. We assess this sensitivity by reconstructing AR using only equivalent courses at UT Austin and Texas A&M, the two state flagships. Courses at these institutions may cover more advanced material or place greater demands on students' prior preparation. Closer alignment with their curricula could therefore strengthen preparation for subsequent four-year coursework, but it could also be a poorer fit for community-college students' existing knowledge and intended transfer destinations. The flagship benchmark allows us to examine whether the gains from academic alignment extend to curricula that may offer more demanding preparation while being less closely matched to the students community colleges serve.

Using this alternative measure, we find effects on transfer and BA attainment close to those obtained using our main measure (Appendix Table A9). The average earnings coefficient is 0.014 log points and is not statistically distinguishable from zero, while the interaction with baseline BA probability remains positive and significant, at 0.165 (Appendix Table A10). Both the gains along the transfer pathway and the larger earnings returns among students with stronger initial BA prospects therefore remain using this alternative definition of academic relevance.

9 Discussion and Conclusion

This paper identifies course content as an important source of variation in the returns to community college. Combining syllabi with administrative records from Texas, we measure alignment with four-year curricula and with skills demanded in the labor market and show that what stu-

dents are taught shapes their progression through college and their subsequent earnings. Among academic students, greater academic relevance raises transfer and BA completion, with larger earnings returns among students with a higher baseline probability of completing a BA. Greater general labor-market relevance instead diverts academic students from the transfer pathway. Among vocational students, alignment with labor demand raises earnings only when it is tied to the occupations most closely related to the student's major.

Our findings complement evidence that community-college returns vary across access margins, credits, credentials, programs, and fields (Kane and Rouse, 1995; Jepsen et al., 2014; Stevens et al., 2019; Grosz, 2020; Mountjoy, 2022). Our results locate an additional source of variation within institutions, programs, cohorts, and instructors. They also complement evidence from four-year universities that the knowledge taught in courses affects educational progress and earnings (Biasi and Ma, 2026). Community colleges make the objective of the curriculum especially important because the same institutions prepare students for transfer and for direct labor-market entry. The effects of content depend on which of these pathways it supports.

Our results have several policy implications. First, they speak directly to the challenge of improving bachelor's completion through the community-college transfer pathway, where low attainment limits an important route to economic mobility (Velasco et al., 2024). We identify course content as a margin through which colleges can improve both transfer and eventual degree completion. A one-SD increase in academic relevance raises BA attainment by 1.3 pp, closing approximately 2.4% of the unconditional attainment gap relative to the four-year-starter benchmark discussed above. Since standard administrative data reveal little about this dimension, syllabus-based measures could complement the information colleges use to review transfer pathways. Second, job postings can inform curriculum design, but the relevant occupations must be defined in relation to the program's objectives. Broad alignment with local skill demand can move academic students away from the transfer pathway, while stronger alignment with occupations related to students' majors, holding general alignment fixed, supports academic students' progress and raises vocational students' earnings.

The variation in our design comes from changes in content across course offerings. Evaluations of coordinated curriculum reforms could establish whether larger changes generate similar effects and how those effects depend on the content being added or displaced. A second question is how students' initial preparation shapes their ability to use the content they encounter. The positive earnings gradients by baseline BA probability suggest that curricular changes and inter-

ventions that improve college preparation may complement one another. Longer earnings panels could also clarify how the returns to occupational content evolve as students accumulate experience and change jobs. Answering these questions would help guide curriculum design toward the educational and occupational pathways that community colleges serve.

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Appendix A Additional Tables and Figures

Table A1: Effects of Academic Relevance on Educational Outcomes, Without Instructor Fixed Effects

	Attains AA degree	Attains other CC degree	Transfers to four-year	Attains BA
	(1)	(2)	(3)	(4)
Panel A: Baseline specification				
Academic relevance	0.108***	-0.010***	0.079***	0.041***
	(0.008)	(0.004)	(0.007)	(0.006)
Mean dep. var.	0.23	0.07	0.22	0.11
Instructor fixed effects				
College–major–entry-cohort FE	X	X	X	X
Adjusted R^2	0.152	0.141	0.199	0.217
N	101,097	101,097	101,097	101,097
Panel B: baseline BA probability interaction specification				
Academic relevance	0.076***	0.010	0.042***	0.011
	(0.017)	(0.008)	(0.014)	(0.012)
AR $\times$ baseline BA probability	0.133*	-0.089***	0.159***	0.135***
	(0.068)	(0.034)	(0.060)	(0.052)
Mean dep. var.	0.23	0.07	0.22	0.11
Instructor fixed effects				
College–major–entry-cohort FE	X	X	X	X
Adjusted R^2	0.156	0.141	0.203	0.220
N	101,097	101,097	101,097	101,097

Notes: Estimates of equation (9) without instructor fixed effects, for students in academic programs. Academic relevance is standardized as described in Section 6.1. The dependent variables are indicators for completion of an Associate of Arts or Associate of Science degree (AA/AS; column 1), completion of another community-college degree or credential (column 2), transfer to a Texas four-year institution (column 3), and bachelor's degree attainment (column 4). All specifications control for lagged academic relevance and college–major–entry-cohort fixed effects. Standard errors are clustered at the college–major–entry-cohort level. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table A2: Effects of Labor-Market Relevance on Educational Outcomes, Without Instructor Fixed Effects

	Attains AA degree	Attains other CC degree	Transfers to four-year	Attains BA
	(1)	(2)	(3)	(4)
Panel A: General labor-market relevance				
General LMR	-0.045***	0.084***	-0.097***	-0.069***
	(0.012)	(0.008)	(0.011)	(0.009)
Mean dep. var.	0.23	0.07	0.22	0.11
Adjusted R^2	0.131	0.183	0.197	0.217
N	113,416	113,416	113,416	113,416
Panel B: Major-specific labor-market relevance				
Major-specific LMR	-0.005	0.081***	-0.060***	-0.040***
	(0.015)	(0.010)	(0.015)	(0.011)
Mean dep. var.	0.23	0.07	0.22	0.11
Adjusted R^2	0.131	0.181	0.195	0.216
N	113,416	113,416	113,416	113,416
Panel C: General LMR and occupational tilt				
General LMR	-0.015	0.087***	-0.073***	-0.050***
	(0.015)	(0.010)	(0.014)	(0.010)
Occupational tilt	0.102***	0.017	0.076***	0.061***
	(0.021)	(0.012)	(0.020)	(0.017)
Mean dep. var.	0.23	0.07	0.22	0.11
Adjusted R^2	0.131	0.184	0.197	0.217
N	113,416	113,416	113,416	113,416
Instructor fixed effects				
College–major–entry-cohort FE	X	X	X	X

Notes: Estimates for students in academic programs, omitting instructor fixed effects. Panels A and B report estimates from equation (9) for students in academic programs, using general labor-market relevance (GLMR) and major-specific labor-market relevance (MLMR), respectively. Panel C reports estimates from equation (11), which jointly includes GLMR and occupational tilt. GLMR and MLMR are standardized before averaging across students' courses, as described in Section 6.1. Occupational tilt is the difference between these average exposures, MLMR minus GLMR, and is not separately standardized. The dependent variables are indicators for completion of an Associate of Arts or Associate of Science degree (AA/AS; column 1), completion of another community-college degree or credential (column 2), transfer to a Texas four-year institution (column 3), and bachelor's degree attainment (column 4). All specifications control for lagged versions of the main explanatory variables, and college–major–entry-cohort fixed effects. Panel C includes both lagged GLMR and lagged occupational tilt. Standard errors are clustered at the college–major–entry-cohort level. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table A3: Effects of Academic Relevance on Earnings, Without Instructor Fixed Effects

	(1)	(2)	(3)
Academic relevance	0.001	-0.075***	0.003
	(0.010)	(0.021)	(0.017)
Academic relevance × baseline BA probability		0.341***	
		(0.090)	
Academic relevance × experience			0.000
			(0.002)
Instructor fixed effects			
College–major–entry-cohort FE	X	X	X
Potential-experience controls	X	X	X
Calendar-year fixed effects	X	X	X
Adjusted R^2	0.277	0.278	0.277
N	569,970	569,970	569,970

Notes: Estimates from equation (9) for students in academic programs, pooling quarterly earnings observations after college exit and omitting instructor fixed effects. The dependent variable is the natural logarithm of quarterly earnings. Column 2 interacts AR with baseline BA probability, constructed as described in the text. Column 3 interacts AR with experience, measured as years since college exit. All specifications control for lagged academic relevance, potential experience, college–major–entry-cohort fixed effects, and year fixed effects. Standard errors are clustered at the college–major–entry-cohort level. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table A4: Effects of Labor-Market Relevance on Earnings, Without Instructor Fixed Effects

	Academic students			Vocational students	
	(1)	(2)	(3)	(4)	(5)
Panel A: General labor-market relevance					
General LMR	0.038***	0.010	-0.003	0.038**	0.016
	(0.014)	(0.033)	(0.025)	(0.017)	(0.032)
General LMR × baseline BA probability		0.107			
		(0.124)			
General LMR × experience			0.006*		0.003
			(0.004)		(0.004)
Adjusted R^2	0.280	0.280	0.280	0.354	0.354
N	646,372	646,372	646,372	146,311	146,311
Panel B: Major-specific labor-market relevance					
Major-specific LMR	0.037**	-0.012	-0.036	0.102**	0.025
	(0.017)	(0.042)	(0.030)	(0.042)	(0.062)
Major-specific LMR × baseline BA probability		0.183			
		(0.154)			
Major-specific LMR × experience			0.011***		0.013
			(0.004)		(0.009)
Adjusted R^2	0.280	0.280	0.280	0.353	0.353
N	646,372	646,372	646,372	146,311	146,311
Panel C: General LMR and occupational tilt					
General LMR	0.039**			0.097**	
	(0.017)			(0.041)	
Occupational tilt	0.011			0.071*	
	(0.023)			(0.042)	
Adjusted R^2	0.280			0.355	
N	646,372			146,311	
Instructor fixed effects					
College–major–entry-cohort FE	X	X	X	X	X
Potential-experience controls	X	X	X	X	X
Calendar-year fixed effects	X	X	X	X	X

Notes: Estimates without instructor fixed effects; the dependent variable is the natural logarithm of earnings. Panels A and B report GLMR and MLMR estimates from equation (9); panel C reports the joint GLMR and occupational-tilt specification in equation (11). Columns 1–3 use academic students and columns 4–5 vocational students. The outcome is log quarterly earnings. Columns 1 and 4 report average effects, column 2 interacts content with baseline BA probability, and columns 3 and 5 interact content with experience. Content measures are standardized before averaging; occupational tilt is MLMR minus GLMR without further standardization. Specifications include the corresponding lagged content, college–major–entry-cohort, experience, and calendar-year fixed effects. Standard errors are clustered at the college–major–entry-cohort level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A5: Effects of Academic Relevance on Educational Outcomes, With Instructor–Course Fixed Effects

	Attains AA degree	Attains other CC degree	Transfers to four-year	Attains BA
	(1)	(2)	(3)	(4)
Academic relevance	0.002	-0.005	0.017**	0.013*
	(0.007)	(0.004)	(0.008)	(0.007)
Mean dep. var.	0.23	0.07	0.22	0.11
Instructor–course fixed effects	X	X	X	X
College–major–entry-cohort FE	X	X	X	X
Adjusted R^2	0.637	0.699	0.529	0.485
N	101,097	101,097	101,097	101,097

Notes: Estimates for students in academic programs, replacing instructor fixed effects in equation (9) with instructor–course fixed effects. Academic relevance is standardized as described in Section 6.1. The dependent variables are indicators for completion of an Associate of Arts or Associate of Science degree (AA/AS; column 1), completion of another community-college degree or credential (column 2), transfer to a Texas four-year institution (column 3), and bachelor's degree attainment (column 4). All specifications control for lagged academic relevance, instructor-by-course fixed effects, and college–major–entry-cohort fixed effects. Standard errors are clustered at the college–major–entry-cohort level. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table A6: Effects of Labor-Market Relevance on Educational Outcomes, With Instructor–Course Fixed Effects

	Attains AA degree	Attains other CC degree	Transfers to four-year	Attains BA
	(1)	(2)	(3)	(4)
Panel A: General labor-market relevance				
General LMR	-0.072***	0.007	-0.104***	-0.074***
	(0.014)	(0.007)	(0.016)	(0.013)
Mean dep. var.	0.23	0.07	0.22	0.11
Adjusted R^2	0.638	0.711	0.533	0.488
N	113,416	113,416	113,416	113,416
Panel B: Major-specific labor-market relevance				
Major-specific LMR	-0.030**	0.002	-0.049***	-0.021
	(0.014)	(0.008)	(0.018)	(0.015)
Mean dep. var.	0.23	0.07	0.22	0.11
Adjusted R^2	0.637	0.710	0.533	0.488
N	113,416	113,416	113,416	113,416
Instructor–course fixed effects	X	X	X	X
College–major–entry-cohort FE	X	X	X	X

Notes: Estimates for students in academic programs, replacing instructor fixed effects with instructor–course fixed effects. Panels A and B report estimates from equation (9) for students in academic programs, using general labor-market relevance (GLMR) and major-specific labor-market relevance (MLMR), respectively. GLMR and MLMR are standardized before averaging across students' courses, as described in Section 6.1. The dependent variables are indicators for completion of an Associate of Arts or Associate of Science degree (AA/AS; column 1), completion of another community-college degree or credential (column 2), transfer to a Texas four-year institution (column 3), and bachelor's degree attainment (column 4). All specifications control for lagged versions of the main explanatory variables, instructor-by-course fixed effects, and college–major–entry-cohort fixed effects. Panel C includes both lagged GLMR and lagged occupational tilt. Standard errors are clustered at the college–major–entry-cohort level. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table A7: Effects of Academic Relevance on Earnings, With Instructor–Course Fixed Effects

	(1)
Academic relevance	-0.020*
	(0.011)
Instructor–course fixed effects	X
College–major–entry-cohort FE	X
Potential-experience controls	X
Calendar-year fixed effects	X
Adjusted R^2	0.442
N	569,970

Notes: Estimates from equation (9) for students in academic programs, pooling quarterly earnings observations after college exit and with instructor-by-course fixed effects. Academic relevance is standardized as described in Section 6.1. The dependent variable is the natural logarithm of quarterly earnings. All specifications control for lagged academic relevance, potential experience, instructor-by-course fixed effects, college–major–entry-cohort fixed effects, and year fixed effects. Standard errors are clustered at the college–major–entry-cohort level. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table A8: Effects of Labor-Market Relevance on Earnings, With Instructor–Course Fixed Effects

	Academic students	Vocational students
	(1)	(2)
Panel A: General labor-market relevance		
General LMR	-0.028	-0.103**
	(0.019)	(0.048)
Adjusted R^2	0.445	0.642
N	646,372	146,311
Panel B: Major-specific labor-market relevance		
Major-specific LMR	-0.030	0.064
	(0.021)	(0.091)
Adjusted R^2	0.445	0.642
N	646,372	146,311
Instructor–course fixed effects	X	X
College–major–entry-cohort FE	X	X
Potential-experience controls	X	X
Calendar-year fixed effects	X	X

Notes: Estimates with instructor-by-course fixed effects; the dependent variable is the natural logarithm of earnings. Panels A and B report GLMR and MLMR estimates from equation (9). Column 1 use academic students and column 2 vocational students. The outcome is log quarterly earnings. Content measures are standardized before averaging. Specifications include the corresponding lagged content, instructor-by-course, college–major–entry-cohort, experience, and calendar-year fixed effects. Standard errors are clustered at the college–major–entry-cohort level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A9: Effects of Flagship Academic Relevance on Educational Outcomes

	Attains AA degree	Attains other CC degree	Transfers to four-year	Attains BA
	(1)	(2)	(3)	(4)
Panel A: Baseline specification				
Flagship academic relevance	0.014**	-0.003	0.017**	0.012*
	(0.006)	(0.003)	(0.007)	(0.006)
Mean dep. var.	0.23	0.07	0.22	0.11
Instructor fixed effects	X	X	X	X
College–major–entry-cohort FE	X	X	X	X
Adjusted R^2	0.575	0.625	0.445	0.412
N	94,457	94,457	94,457	94,457
Panel B: baseline BA probability interaction specification				
Flagship academic relevance	0.000	-0.001	0.018	0.001
	(0.012)	(0.007)	(0.015)	(0.013)
Flagship AR $\times$ baseline BA probability	0.070	-0.010	0.007	0.057
	(0.050)	(0.027)	(0.058)	(0.052)
Mean dep. var.	0.23	0.07	0.22	0.11
Instructor fixed effects	X	X	X	X
College–major–entry-cohort FE	X	X	X	X
Adjusted R^2	0.576	0.625	0.446	0.413
N	94,457	94,457	94,457	94,457

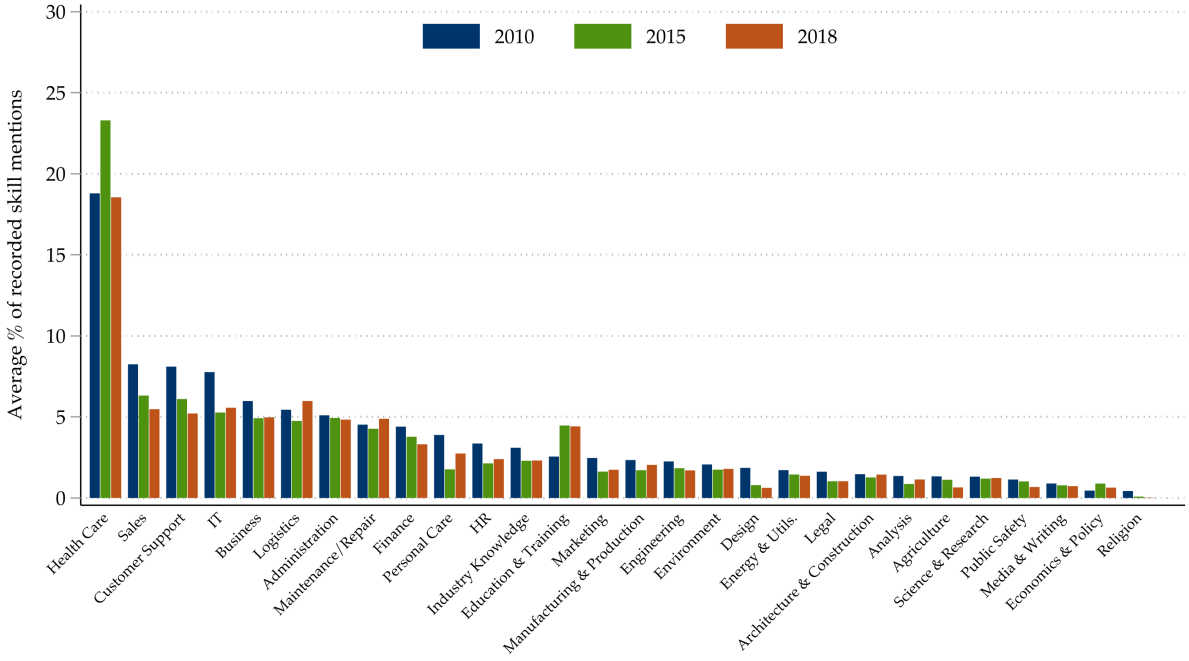
Notes: Estimates for students in academic programs, using AR constructed from comparisons with syllabi at UT Austin and Texas A&M. Academic relevance is standardized as described in Section 6.1. The dependent variables are indicators for completion of an Associate of Arts or Associate of Science degree (AA/AS; column 1), completion of another community-college degree or credential (column 2), transfer to a Texas four-year institution (column 3), and bachelor's degree attainment (column 4). All specifications control for lagged academic relevance, instructor fixed effects, and college–major–entry-cohort fixed effects. Standard errors are clustered at the college–major–entry-cohort level. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table A10: Effects of Flagship Academic Relevance on Earnings

	(1)	(2)	(3)
Flagship academic relevance	0.014	-0.024	0.023
	(0.009)	(0.020)	(0.016)
Flagship academic relevance × baseline BA probability		0.165**	
		(0.075)	
Flagship academic relevance × experience			-0.001
			(0.002)
Instructor fixed effects	X	X	X
College–major–entry-cohort FE	X	X	X
Potential-experience controls	X	X	X
Calendar-year fixed effects	X	X	X
Adjusted R^2	0.385	0.385	0.385
N	545,762	545,762	545,762

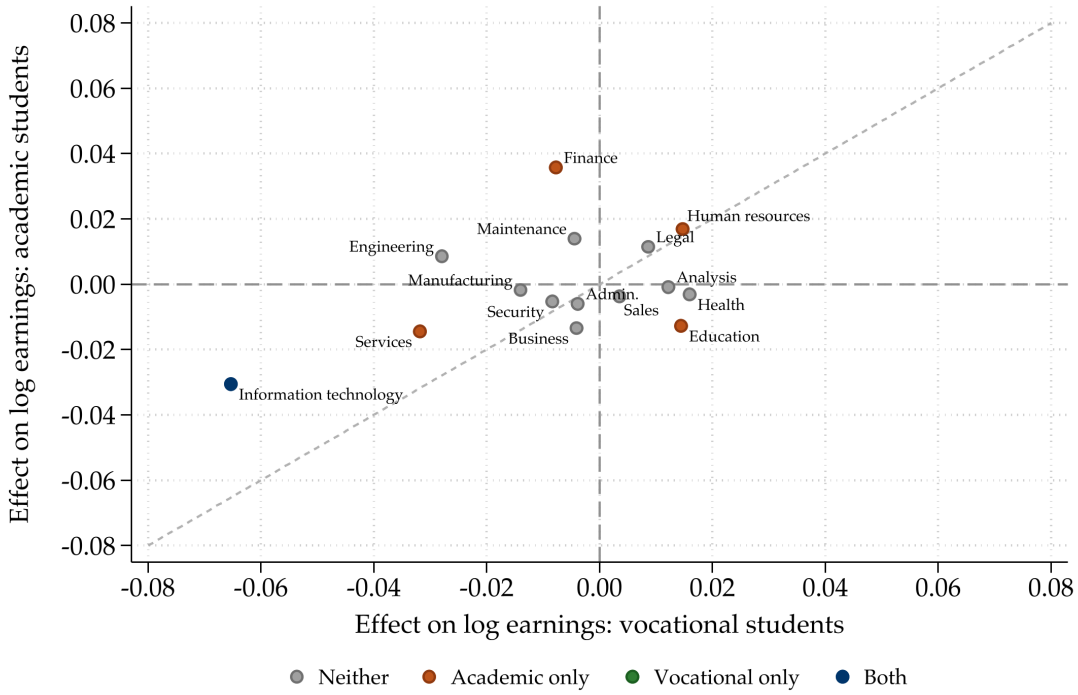
Notes: Estimates from equation (9) for students in academic programs, pooling quarterly earnings observations after college exit and using AR constructed from comparisons with syllabi at UT Austin and Texas A&M. Academic relevance is standardized as described in Section 6.1. The dependent variable is the natural logarithm of quarterly earnings. Column 2 interacts AR with baseline BA probability, constructed as described in the text. Column 3 interacts AR with experience, measured as years since college exit. All specifications control for lagged academic relevance, potential experience, instructor fixed effects, college–major–entry-cohort fixed effects, and year fixed effects. Standard errors are clustered at the college–major–entry-cohort level. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Figure A1: Distribution of Recorded Skill Demand Across Families



Notes: For each county–month, the source variable measures a named family's percentage of all recorded skill mentions in Lightcast postings. Bars average this percentage across observed family–county–month cells in 2010, 2015, and 2018; absent cells are not imputed as zero. The unclassified source category is excluded, leaving 28 named families. A posting with several recorded skills can contribute multiple mentions.

Figure A2: Effects of Specific Skill Families on Log Earnings of Academic and Vocational Students



Notes: Each point represents the estimated earnings effects of one skill family for vocational students (horizontal axis) and academic students (vertical axis). Estimates are from equation (9), with each skill family entered in a separate regression. The dependent variable is the natural logarithm of quarterly earnings, pooling observations after college exit. Marker colors indicate statistical significance at the 10% level: orange denotes significance for academic students only, green for vocational students only, blue for both groups, and gray for neither group. These colors refer to the individual estimates and do not indicate whether the effects differ significantly between groups. The horizontal and vertical dashed lines mark zero; the diagonal dashed line marks equality between the academic and vocational estimates. All specifications control for lagged skill content, instructor fixed effects, college–major–entry-cohort fixed effects, potential experience (years since college exit), and calendar-year fixed effects. Standard errors are clustered at the college–major–entry-cohort level.

Appendix B Syllabi Data Details

B.1 Collecting Syllabi

B.1.1 Community College Syllabi

We collect syllabi from public repositories maintained under Texas's HB 2504 disclosure requirement. For each college, we use automated scripts to download available PDF syllabi from its compliance page or syllabus repository. The collection covers 40 public community colleges; the other ten institutions' repositories could not be collected using our automated procedures. These institutions are listed in Table B1.

We downloaded the four-year syllabi in December 2023 and the community-college syllabi in spring 2025. Some community colleges provide historical syllabi. We restrict the analysis to 2011–2024.

Table B1: Community College Syllabi: Coverage and Sample Size

Institution	# Syl.	Years	Institution	# Syl.	Years
Alvin Community College	3,814	2022–24	Kilgore College	10,956	2014–23
Amarillo College	36,868	2010–24	Laredo College	6,430	2022–24
Angelina College	16,042	2019–24	McLennan Community College	48,891	2010–24
Austin Community College	1,470	2023	Midland College	522	2023
Blinn College	74,412	2012–24	Navarro College	30,377	2000–20
Brazosport College	4,845	2021–24	Northeast Texas Community College	6,970	2016–23
Central Texas College	969	2023	Odessa College	2,463	2021–24
Cisco College	4,731	2018–24	Panola College	366	2023
Clarendon College	460	2023–24	Ranger College	1,186	2022–24
Coastal Bend College	2,645	2018–24	San Jacinto College	27,258	2022–24
College of the Mainland	4,965	2021–24	South Texas College	49,045	2019–24
Collin College	61,474	2019–24	Southwest Texas Junior College	2,224	2023–24
Dallas College	78,007	2021–24	Temple College	1,976	2023–24
Del Mar College	1,223	2023–24	Texas Southmost College	1,240	2023
El Paso Community College	13,704	2011–24	Trinity Valley Community College	5,717	2021–24
Frank Phillips College	205	2023	Tyler Junior College	43,308	2018–24
Galveston College	2,488	2022–24	Vernon College	3,074	2011–24
Hill College	1,368	2022–24	Weatherford College	431	2023
Houston Community College	45,949	2021–24	Western Texas College	336	2023
Howard College	7,016	2021–24	Wharton County Junior College	490	2023
Total				**605,915**	

Notes: Institutional counts and coverage years.

B.1.2 Four-Year University Syllabi

To compare community college syllabi with those from four-year institutions, we additionally collected syllabi from seven public universities in Texas, listed in Table B2. The sample includes the

state's two flagship universities (UT Austin and Texas A&M) and several regional universities. The collection procedure mirrors that for community colleges: we scraped each institution's public syllabus repository, using the public repositories maintained under HB 2504.

Table B2: Four-Year University Syllabi: Coverage and Sources

Institution	Years available	Link
Sam Houston State U	2011–23	https://samweb.shsu.edu/facil0wp/
Stephen F. Austin State U	2009–24	https://orion.sfasu.edu/courseinformation/
Texas A&M U	2013–23	https://howdy.tamu.edu/uPortal/p/public-class-search-ui.ctf1/max/render.uP
UT Austin	2011–23	https://utdirect.utexas.edu/apps/student/coursedocs/nlogon/
UT Dallas	2005–24	https://coursebook.utdallas.edu/
U of Houston–Clear Lake	2010–24	https://saprd.my.uh.edu/psc/saprd/EMPLOYEE/HRMS/c/UHS_SS_CUSTOM.UHS_HB2504_DISPLAY.GBL
West Texas A&M U	2013–24	https://syllabus.wtamu.edu/syllabi/

Notes: Institutions, coverage years, and repository addresses from Biasi and Ma (2026).

B.2 Text Extraction and Cleaning

The text extraction and cleaning procedure follows Biasi and Ma (2026). We first convert all PDF files to text using PyMuPDF.[14] We then clean the extracted text as follows:

(i) We use the Unidecode Python package[15] to convert Unicode text into ASCII text. This step replaces accented letters, symbols, and characters from non-Latin alphabets with their ASCII approximations.

(ii) We remove browser information, often present in the header of a syllabus, by searching for keywords such as "Internet Explorer", "Newer Browser", "JavaScript Enabled", "Cookies Are", "Download Info", "Login", "Log In", "Print", and "Search".

(iii) We convert all text to lowercase.

(iv) We tokenize the text using the NLTK Python Toolkit[16] and strip out punctuation marks, numbers, and HTML tags.

(v) We apply lemmatization using the WordNet Lemmatizer to reduce words to their base form.

[14] https://pymupdf.readthedocs.io/en/latest/
[15] https://pypi.org/project/Unidecode/
[16] https://www.nltk.org/

(vi) We remove stop words using a combined list from the NLTK English stop word corpus and the Stanford CoreNLP stop word list, totaling approximately 280 stop words.[17]

B.3 Identifying Syllabi Sections

We separate descriptions of course content from administrative material. Syllabi generally report course descriptions, learning objectives, readings, and topic outlines, alongside policies concerning grading, attendance, disability accommodations, and academic integrity. The section-parsing procedure uses section-title keywords and document formatting to identify these components, following Biasi and Ma (2026) (Appendix B.1.2). The original procedure retains sections describing content, objectives, outlines, and materials.

The parser identifies section boundaries using title keywords and formatting, including capitalization, numbering, and colons. It retains course descriptions, learning objectives, outlines, and materials and removes instructor contacts, grading information, and administrative policies. If it cannot identify a valid section split, it retains the original text. We extract PDF text page by page and concatenate pages in order before processing. The skill measures use a Burning Glass dictionary of skill names and alternative word forms and SkillNER phrase matching, with the vocabulary filters and score threshold described in Section 4.

B.4 Linking Courses Across Institutions

We use TCCNS equivalencies to link lower-division academic courses at community colleges and four-year institutions. TCCNS identifies freshman- and sophomore-level general academic coursework; it does not provide a common numbering system for all vocational courses. The crosswalk maps an institution's own course number to a common designation.[18] Courses with the same designation form the comparison set for academic relevance, while their syllabi can differ in readings, applications, and topic emphasis.

We use the TCCNS crosswalk corresponding to each year from 2011 through 2024, mapping institution-specific course numbers under the designation in effect when the course was offered. This accommodates course-number changes over time. Academic courses without a TCCNS designation do not enter cross-sector academic-relevance matching. Vocational courses do not have TCCNS designations and are not assigned academic-relevance measures.

B.5 Vectorization

To transform each document into a word vector, we use as a dictionary the set of all unique unigrams, bigrams, and trigrams ever appearing as keywords in approximately 107 million English-language academic articles from OpenAlex, constructed following the procedure described in Biasi and Ma (2026) (Appendix B.2).[19]

From each syllabus, we extract n-grams for $n \in \{1, 2, 3\}$ and retain only those matching a dictionary entry. Each document is then represented as a term-frequency vector, weighted using a backward-looking TF-IDF (TF-BIDF) scheme (Biasi and Ma, 2022, 2026). Specifically, the inverse document frequency for term w at time t is computed only over documents published prior to t, so that terms frequent in earlier documents receive less weight. We compute textual similarity between

[17] The Stanford CoreNLP stop word list is available at https://github.com/stanfordnlp/CoreNLP/blob/master/data/edu/stanford/nlp/patterns/surface/stopwords.txt.

[18] See https://tccns.org/.

[19] OpenAlex is an openly licensed (CC0) catalog of global research maintained by OurResearch (https://openalex.org). From an initial pool of over 261 million records, the final dataset retains approximately 107 million English-language articles with non-empty abstracts. See Biasi and Ma (2026) (Appendix B.2) for details on the filtering and construction of the academic publications dataset.

documents as the cosine similarity of their TF-BIDF-weighted vectors. See Biasi and Ma (2026) (Section 3) for a detailed exposition of the TF-BIDF weighting and cosine similarity procedure.

The common dictionary contains unique one-, two-, and three-word keywords from approximately 107 million English-language academic articles in OpenAlex. We generate the corresponding terms from each syllabus and retain dictionary matches, so all syllabi use the same vector coordinates. Term frequency counts occurrences within the syllabus. Backward inverse document frequency gives lower weight to terms that are prevalent in documents published before the syllabus date. A term absent from a syllabus receives a zero coordinate.

Appendix C Syllabus Visibility at Registration

Texas's disclosure rules distinguish information available from previous course offerings from the updated syllabus for the current term. The statewide deadline falls after classes begin, while students can choose courses and instructors before that deadline. This timing motivates the comparison of current content conditional on prior content and instructor identity. A posting deadline establishes when access must be provided; it does not establish the date on which a particular syllabus first became available.

C.1 Statewide Framework

HB 2504 added Section 51.974 to the Texas Education Code. It requires public institutions, other than medical and dental units, to post syllabi for undergraduate classroom courses offered for credit. The information must be public no later than the seventh day after the first day of classes and remain online for at least two years after its initial posting. The requirement applies beginning in fall 2010.[20]

The statewide rule allows institutions to comply by posting after registration has begun. It therefore does not guarantee access to the current-term syllabus when registration opens. Institution-specific policies can impose earlier deadlines, and instructors can post early. The empirical design accordingly relies on the conditional independence of current content, given prior content, instructor identity, and the other controls. The institutional record explains the timing behind this assumption; the balance analysis examines its observable implications.

Table C1 organizes the institutional documentation using the same classification as Biasi and Ma (2026). We preserve its categories while correcting the institution counts. The evidence includes an Austin Community College announcement from August 2010 and current institutional pages. The date of each document is relevant when using it to describe practices during the estimation period.

Table C1: Institutional Documentation on Syllabus Posting

Documentation	Information provided	Count	Institutions or examples
Tier 1: institution-specific timing cited	Posting deadline; historical validity depends on source date	7	Austin, Angelina, Cisco, Coastal Bend, Hill, Panola, San Jacinto
Tier 2: institution-specific public-access materials	Repository or course-information procedures; timing not established	11	Brazosport, Collin, Dallas, El Paso, Houston, Navarro, Northeast Texas, South Texas, Temple, Tyler, Vernon
Tier 3: statewide baseline	HB 2504 deadline; no additional timing documentation retained	22	Includes Clarendon and the institutions listed below

Notes: Counts of colleges and names by tier of documentation.

C.2 Tier 1: Institution-Specific Timing Documentation

Austin Community College. An official announcement dated August 12, 2010, explains the college's implementation of HB 2504 beginning that fall and specifies the seventh-day posting deadline

[20] HB 2504, enrolled version, Sections 1 and 4: https://capitol.texas.gov/tlodocs/81R/billtext/html/HB02504F.htm. The enacted text establishes both the deadline and its historical applicability.

for syllabi and instructor CVs.[21] This contemporaneous source documents the deadline at the introduction of the statewide requirement.

Cisco College. Cisco's accreditation page describes its HB 2504 procedures and states that syllabi and instructor CVs are made public by the seventh class day and retained for at least two years.[22] This is a statement of the compliance deadline; it does not report actual upload dates.

Coastal Bend College. Coastal Bend's HB 2504 page describes syllabus content requirements and repeats the statutory deadline for making course information available online.[23]

Panola College. Panola's implementation page describes procedures for providing public access by the seventh day after classes begin. It also reports that syllabi have been online in a uniform format since 2008.[24] The page's reference to January 1, 2011, concerns the first compliance-report deadline, rather than the date on which syllabi first became public.

C.3 Tier 2: Public-Access Materials

Collin College. The original paper cites Collin's public course-information page.[25] A repository documents access to syllabi, but its existence does not date the release of the current-term version.

Dallas College. The original paper cites Dallas College's academic calendar.[26] The calendar describes term dates and later-start courses. It provides no direct evidence about syllabus posting.

El Paso Community College. The original appendix cites EPCC's syllabus procedures and an administrative document described as dating to 2011.[27]

Houston Community College. The original paper cites HCC's public syllabus search portal.[28] As with other repositories, the portal's existence does not establish when the current-term syllabus became accessible.

Brazosport College, Navarro College, Northeast Texas Community College, South Texas College, Temple College, Tyler Junior College, and Vernon College. The original paper cites institution-specific public-access pages, syllabi repositories, or handbooks for these seven colleges.[29] These references provide a record of the institutions' disclosure materials.

C.4 Tier 3: Statewide Baseline

The remaining 22 institutions are Alvin Community College, Amarillo College, Blinn College, Central Texas College, Clarendon College, College of the Mainland, Del Mar College, Frank Phillips College, Galveston College, Howard College, Kilgore College, Laredo College, McLennan Community College, Midland College, Odessa College, Ranger College, Southwest Texas Junior College, Texas Southmost College, Trinity Valley Community College, Weatherford College, Western Texas

[21] https://sites.austincc.edu/newsroom/2010/08/12/the-hr-connection-30/.

[22] https://www.cisco.edu/about/accreditation.

[23] https://www.coastalbend.edu/instruction/hb2504.html.

[24] https://www.panola.edu/texas-house-bill-2504.

[25] https://www.collin.edu/academics/programs/publicaccess.html.

[26] https://www.dallascollege.edu/resources/academic-calendar/pages/default.aspx.

[27] https://www.epcc.edu/AboutEPCC/board-of-trustees/board-policy/administrative-procedures/procedures-general-institution; https://www.epcc.edu/AboutEPCC/board-of-trustees/board-policy/administrative-procedures/Documents/GM/6_31_01.pdf.

[28] https://learning.hccs.edu/faculty/syllabus-search.

[29] https://www.brazosport.edu/faculty-staff/instructional-technology/distance-education/house-bill-2504-faculty-info; https://www.navarrocollege.edu/academics/course-syllabi.html; https://www.ntcc.edu/academic-affairs/house-bill-2504; https://www.southtexascollege.edu/academics/pdf/employee-handbook.pdf; https://www.templejc.edu/about-tc/departments/hb2504-course-information; https://www.tjc.edu/info/200344/public_access_to_course_information; https://syllabi.vernoncollege.edu/.

College, and Wharton County Junior College. For these institutions, the documentation retained here consists of the statewide HB 2504 rule. No conclusion about their actual posting dates follows from this classification.

C.5 Registration and Subsequent Schedule Changes

Registration can precede the public-posting deadline by several months. Panola's 2023–2024 calendar, for example, opens registration for fall 2023 on April 5 and lists late registration and schedule changes after classes begin.[30] This example illustrates the difference between initial registration and the schedule ultimately recorded in administrative data.

The transcript-based course set reflects enrollment at the census date.

[30] https://www.panola.edu/sites/default/files/2023-04/2023-2024%20Academic%20Calendar%2C%20Fee%20Chart%2C%20and%20Final%20Exam%20Schedule.pdf.

Appendix D ERC Data Details

D.1 Administrative Records and Linkage

The ERC links students' records across the Texas Higher Education Coordinating Board (THECB), the Texas Education Agency (TEA), and the Texas Workforce Commission (TWC). THECB supplies enrollment, majors, transcripts, credentials, and faculty assignments. The linked records include enrollment and degree attainment at Texas public and private four-year institutions. TEA supplies pre-college examination histories, and the linked administrative records identify economic and academic disadvantage at college entry. TWC supplies quarterly earnings reported by employers to the Texas unemployment-insurance system. Course transcripts, available beginning in academic year 2011–2012, connect students to the courses and instructors represented in the syllabus collection.

D.2 Sample Construction

The summary-statistics sample contains 120,206 academic and 30,219 vocational community-college students. These are distinct from the outcome-specific estimation samples. For example, the main AR attainment estimates use 101,097 academic students. A separate sample of 808,192 four-year students provides the descriptive comparison in Table 1.

The student and syllabus analyses both cover 2011–2024. Because syllabus coverage varies by college and year, we retain only students for whom syllabus-based content measures can be constructed from observed course matches. Students entering before syllabus coverage begins at their college are excluded from the analysis data. Students missing the required TEA high-school test-score information are also excluded. Outcome regressions additionally remove singleton fixed-effect cells, accounting for part of the difference between the academic descriptive sample and the main AR attainment sample. Earnings regressions also require observed earnings.

Across all enrollment records from 2012 through 2024, approximately 20% match to a syllabus. This unconditional rate primarily reflects colleges and periods for which the corpus contains no syllabi. Restricting the denominator to institution-by-year-by-semester cells with syllabus data, the match rate exceeds 90%. Approximately 18% of observed students have only one or two matched courses, while approximately 18% have taken only one or two courses in total. We impose no additional minimum number of syllabus matches beyond the availability of observed content exposure; students with fewer than three matched courses are retained. The vocational descriptive sample does not require observed earnings.

D.3 Course Exposure and Timing

Student exposure averages course content over the set of courses taken, as defined in Section 6. The lagged exposure averages content in prior offerings of those courses. Their construction requires a consistent definition of a course offering across the administrative and syllabus records.

Courses are recorded at the census date. Syllabus matching is annual, averaging course content across terms, and does not require the same instructor in current and prior offerings. We standardize current and lagged content at the course level before constructing each student's unweighted average exposure. Current and lagged exposure are each calculated from their observed matches, and their course sets can differ.

D.4 Baseline Characteristics and Educational Outcomes

High-school examination percentiles measure academic preparation. Administrative indicators measured at college entry capture economic and academic disadvantage. Educational outcomes distinguish AA attainment, other community-college credentials, transfer to a four-year institution,

and bachelor's-degree attainment. Transfer and bachelor's-degree attainment are measured for all students in the relevant analysis group.

High-school examination percentiles are calculated within cells defined by high-school graduation cohort and subject, so students in a cell face the same assessment regime. For students with multiple test attempts, we use the last attempt. Students missing the required TEA high-school test-score information are excluded from the analysis sample. Economic disadvantage is measured at college entry and equals one if the student meets at least one of the following conditions: annual income at or below the federal poverty line; eligibility for Aid to Families with Dependent Children or another public-assistance program; receipt of a Pell Grant or a comparable state program of need-based financial assistance; participation in or eligibility for a program under Title II of the Job Training Partnership Act (JTPA); or eligibility for Food Stamps. Academic disadvantage indicates that a student needs remedial college coursework and is measured at entry, before content exposure.

AA attainment includes AA and AS degrees. Other community-college credentials include AAS degrees and other credit-bearing awards; non-credit credentials are excluded. Transfer is defined as enrollment at a Texas public or private four-year institution after community-college enrollment and does not require junior standing. Transfer and bachelor's-degree attainment include Texas public and private institutions; out-of-state enrollment is not observed.

D.5 Earnings

Earnings come from quarterly TWC wage records. The log-earnings specifications include calendar-year and potential-experience fixed effects. Experience-specific estimates use the same underlying earnings records and follow-up rules.

Earnings are expressed in 2025 dollars. Observations with missing earnings are excluded, while recorded zero earnings remain zero. The earnings observation window begins after students leave college or community college, and experience is measured from that exit.