Student Demand and the Supply of College Courses*

Jacob Light†

February 20, 2026

[Click here for latest version]

Abstract

I study how universities adjust the quantity and content of courses in response to labor market-driven shifts in student demand. Using new course-level data from over 1,000 U.S. institutions spanning two decades, I estimate supply responses to exogenous demand shocks induced by regional labor market changes. Universities adjust course and section supply modestly, expanding more in growing fields than contracting in declining ones. Curricula gradually incorporate in-demand skills, primarily through new course creation rather than revision of existing courses, and disproportionately at research-intensive universities. These findings show that organizational constraints shape how labor market signals translate into human capital production.

JEL Classification: A20, I23, I24, I26, J24.

*Thanks to Nick Bloom, David Figlio, Eric Hanushek, Caroline Hoxby, Chris Karbownik, and Petra Persson for substantial guidance and support. I also thank seminar participants at CUNY, the Federal Reserve Bank of New York, the Hoover Institution, Stanford University, the University of California Santa Barbara, the University of Zurich, Vanderbilt University, the All California Labor Economics Conference, AEFP, the Los Andes Workshop on Economics of Education, NBER Economics of Education, and the Southern Economic Association Conference for helpful feedback. This research was supported by grants from George P. Shultz Dissertation Support Fund at SIEPR, the Institute for Research in the Social Sciences at Stanford University, and the Leonard W. Ely and Shirley R. Ely Graduate Student Fellowship through a grant to the Stanford Institute for Economic Policy Research. All errors are my own.

†Hoover Institution, Stanford University. jdlight@stanford.edu

1 Introduction

Universities play a central role in the economy's adjustment of human capital: they translate labor market signals into instruction and, ultimately, into skills that diffuse through the workforce. This role becomes especially important when technological change alters the tasks firms demand and the skills workers must supply. While technological progress drives long-run growth, its productivity effects depend on whether workers acquire skills that complement new technologies (Romer 1990, Autor et al. 2003).

As technologies evolve, in-demand skills become increasingly specific, making educational content — not just educational attainment — economically consequential (Autor and Thompson 2025). Both descriptive and causal evidence indicate that what students learn plays a first-order role in shaping labor market outcomes. Earnings differences across college majors rival the college wage premium itself (Altonji et al. 2012), and causal evidence shows that both field of study (Bleemer and Mehta 2022) and the content of individual courses (Biasi and Ma 2025) shape graduates' earnings.

A substantial literature documents how students respond to changing returns across fields (Altonji et al. 2016, Patnaik et al. 2021). Far less is known about how universities adjust their instructional capacity. This gap matters because students and universities face fundamentally different adjustment costs. Students can reallocate relatively quickly across fields, particularly where major choice is flexible (Zafar 2011, Stinebrickner and Stinebrickner 2014). Universities, by contrast, must hire specialized faculty, navigate curricular approval processes, and balance short-run demand pressures against longer-run commitments to disciplinary breadth, support for research, and institutional mission (Ehrenberg 2009, Bound and Turner 2007, Bound et al. 2010, Hoxby 2012, Deming and Walters 2017). These features may slow or distort the translation of labor market signals into instruction, generating misalignment between student demand and educational supply. Whether such features are quantitatively important, whether responses differ for expanding versus contracting fields, and how responsiveness varies across institutions are open empirical questions with direct implications for the efficiency of human capital production.

In this paper, I study how universities adjust to labor market-driven shifts in student demand along two margins: the scale of instruction and the content of instruction. I focus on three related questions. First, how responsive is instructional capacity to changes in student demand, and does adjustment occur primarily through the expansion and contraction of sections or through changes in the set of courses offered? Second, how does the content of instruction evolve in response to labor market signals, and to what extent do universities incorporate in-demand skills into curricula over time? Third, do these responses vary systematically across institutions facing different resource constraints, governance structures, and missions? I answer these questions using new data that provide the first systematic view of how universities adjust instructional scale and course content in response to labor market-driven demand shocks. Answering these questions sheds light on whether universities function as flexible adjustment technologies for human capital, or whether organizational constraints introduce a wedge between students' reactions to the labor market and the instruction universities provide.

Analyzing university supply requires detailed data at scale on course offerings and enrollment not available in existing data sources. For this project, I constructed a novel dataset of course catalogs, schedules, and enrollments from 1,018 U.S. colleges and universities spanning more than two decades. The dataset contains 48 million course sections offered since 1994 covering institutions that enroll 56% of all non-profit college students. For a typical course, I observe the title, enrollment, instructor, and a text description of course content.

To estimate supply responses on the extensive margin, I relate changes in course and section offerings to relatively long-term enrollment demand changes using a shift-share instrument based on region-by-field employment growth. The instrumental variables approach is necessary because enrollment is an equilibrium outcome: students cannot enroll in courses that do not exist, and universities' offerings may in turn shape student choices. By isolating variation driven by labor market conditions, the instrument identifies how instructional supply responds to exogenous demand shocks rather than to enrollment changes that reflect both supply constraints and demand. I assess the validity of the extensive margin estimates through a battery of robustness and validation exercises, including tests for pre-trends and anticipation, alternative constructions of the shift-share instrument, sensitivity to influential field-region shocks, and comparisons across institutional and field subsamples.

On the intensive margin, I examine whether the content of instruction shifts in ways that track labor market change. Because curricular adjustments are expressed through language — new topics, tools, and methods appearing in course descriptions — I construct a text-based measure of labor market alignment that links course content to the skill profiles of occupations with different employment growth rates. Each course description is represented as a weighted bundle of words and phrases and projected onto weights derived from the cross-occupation relationship between skill usage and employment growth during the 2010s. Words and phrases disproportionately used in expanding occupations receive higher weight, while those associated with contracting occupations receive lower weight. The resulting index captures the extent to which a course's content resembles the skill bundle of occupations that grew during the decade relative to those that shrank. A course in any field can therefore score highly if it incorporates skills or topics characteristic of fast-growing occupations. The score provides a comparative measure of how course content moves toward or away from the skill profile of growing jobs over time and across institutions. Because course descriptions are brief and may lag behind classroom practice, the measure likely understates short-run within-course adjustments; my focus, therefore, is on long-term changes and I present bounding exercises that confirm the main findings are robust to plausible assumptions about unmeasured within-course changes.

Across both margins, university adjustment is gradual and substantially less than one-for-one. Along the extensive margin, universities respond to changes in student demand by adjusting instructional scale, but these responses are modest relative to demand changes and asymmetric. A 10 percent increase in field-specific demand raises the number of sections by about 5 percent and the number of distinct courses by about 2 percent, with stronger course responses to rising than to falling demand. These estimates imply that even sustained, decade-long demand shifts generate limited expansion in curricular breadth. Most adjustment occurs through offering larger or more frequent sections of existing courses, rather than through the creation of new courses. A counterfactual back-of-the-envelope exercise suggests that absent binding capacity constraints, U.S. institutions would have produced roughly 1.9% more Computer Science majors and 1.4% more Engineering majors between 2009 and 2018, with offsetting reductions in low-demand fields.

Along the intensive margin, course content shifts modestly but systematically toward in-demand skills. On an enrollment-weighted basis, the typical student in 2022-23 is enrolled in a course whose alignment score is 0.092 standard deviations higher than in 2010-11 (0.032 after controlling for changes in field composition). As a benchmark, the total increase corresponds to roughly one-quarter of the alignment gap between a Statistics Principles course and a Data Science course. Shifts controlling for field composition are about eight percent of the same gap. Decomposition results show that adjustment occurs primarily through the introduction of new courses rather than large-scale reorientation of continuing ones. These magnitudes are modest, as most of what universities teach within a field is foundational and does not change from year to year; Intermediate Microeconomics and Organic Chemistry cover durable material regardless of current labor market conditions. The finding is that the margin universities do exercise — primarily the creation of new courses rather than revision of existing ones — is systematically oriented toward the skills profile of expanding occupations.

Responsiveness varies across institution types. Research-intensive, selective, and private universities expand course supply more elastically in growing fields and update curricular content more rapidly, while public, less selective, and teaching-focused institutions rely more heavily on section adjustments and contract more sharply when enrollment declines. Tenure appears to play an offsetting role, protecting courses in declining fields while facilitating expansion in fast-growing ones. Together, these patterns demonstrate that institutional capacity, governance, and resources shape how changes in student demand translate into both the scale and content of instruction.

Interpreting these magnitudes requires care. A one-for-one response of course supply to demand is neither a realistic nor a natural benchmark in higher education, where faculty hiring and training operate on long horizons, and universities maintain curricular breadth for pedagogical and disciplinary reasons. The analysis is, therefore, positive rather than normative: it characterizes how instructional supply adjusts in practice and how institutional features shape the pace and form of that adjustment. When supply responds inelastically, adjustment occurs through larger class sizes rationing in high-demand fields, stasis in low-demand fields, and gradual curricular updating, with new course creation playing a central role. As a result, access to emerging skills expands unevenly across institutions, implying that the translation of labor market demand into human capital accumulation depends not only on student course choices but also on where students enroll.

This paper provides the first systematic evidence on how universities adjust the supply of instruction in response to labor market-driven shifts in student demand along both the scale and content margins and how these responses vary across institutions. While a large literature documents how students respond to changes in returns to education, much less is known about whether and how universities themselves adjust their production technologies when demand shifts. This distinction is central: even when students' latent preferences respond elastically to labor market signals, their realized course-taking and skill acquisition ultimately depend on universities' capacity and willingness to accommodate those shifts. By directly observing course creation, section expansion and contraction, and changes in curricular content, this paper shows that supply responses are gradual and institutionally heterogeneous — creating a wedge between students' preferred and actual educational investments with implications for skill formation and labor market alignment.

The paper contributes most directly to a small but growing literature on supply in higher education. Existing work documents how institutions accommodate enrollment demand at the institution level (Bound and Turner 2007), how instructional costs and technology shape faculty allocation across fields (Johnson and Turner 2009, Courant and Turner 2017, Hemelt et al. 2021), how institutions ration enrollment in high-demand courses (Bleemer and Mehta 2021, Bleemer and Mehta 2022, Mumford et al. 2024), and how grading incentives affect course-taking (Ahn et al. 2019, Denning et al. 2022).[1] Related work by Thomas (2024)

[1] A related literature studies the expansion of for-profit colleges (Deming et al. 2012; Gilpin et al. 2015), focusing on institutional entry and enrollment rather than field-level curricular adjustment.

models university preferences over instructor allocation and introductory course enrollment at a single institution, highlighting welfare trade-offs between access and cost.

I build on this literature by measuring supply responsiveness across a large and diverse set of institutions, over extended time periods, and along margins — course creation, section scaling, and curricular content — that have been largely unobserved in prior work. The scale and coverage of the data enable a unified analysis of how universities adjust instructional breadth and intensity in response to both rising and falling demand.

The paper also contributes new data and methods for characterizing curricular content at scale. Recent work uses text analysis to measure universities' exposure to the research frontier (Biasi and Ma 2025) and to link course content to labor market skills using syllabi (Eggenberger et al. 2018, Chau et al. 2023). These studies demonstrate the promise of textual approaches but rely on samples of syllabi that limit the study of dynamics at the department or university level. I build on this work in two ways. First, I assemble a comprehensive course catalog dataset that records offerings and enrollment for all courses, rather than samples, enabling a systematic characterization of instructional supply and student enrollment responses. Second, I develop a labor market alignment measure that connects course content directly to observed employment growth across occupations, providing an economic benchmark for curricular relevance. This approach draws on recent advances in text-as-data methods (Gentzkow et al. 2019) while grounding the analysis in labor market fundamentals rather than purely textual similarity.

More broadly, the paper speaks to the literature on student responses to changing returns to education. Evidence on how students adjust major choices in response to labor market signals is mixed: some studies find limited sensitivity to wage changes (Beffy et al. 2012, Wiswall and Zafar 2015, Long et al. 2015), while others document more elastic responses to occupation-specific or cyclical shocks (Freeman 1976, Weinstein 2020, Acton 2021, Blom et al. 2021). Contemporaneous work by Conzelmann et al. (2023) documents substantial responsiveness of field-specific degree production to shifts in major-specific labor demand using a related shift-share identification strategy. Both their findings and my first-stage estimates confirm that student enrollment responds elastically to labor market conditions. My contribution is to measure how universities adjust instructional capacity to accommodate these enrollment shifts. By tracking course creation, section expansion and contraction, and changes in curricular content, I provide evidence on the margins through which universities translate demand-driven enrollment growth into instructional supply, and how these margins vary across institution types.

Finally, the paper introduces a novel dataset that enables new research on higher education production. Archival studies use historical university records to examine specific institutional changes (e.g., Andrews and Zhao 2024, Truffa and Wong 2024, Bald 2025). My dataset complements this work by providing systematic, contemporary coverage across hundreds of institutions, with detailed information on course offerings, enrollment, instructional staff, and curricular content over more than two decades. This longitudinal structure supports analyses of curricular evolution, instructional productivity, and the diffusion of new fields and methods across the higher education system.

The rest of the paper proceeds as follows. Section 2 outlines a conceptual framework. Section 3 describes the course catalog dataset and institutional coverage. Section 4 examines adjustments in course and section supply on the extensive margin, while Section 5 analyzes adaptation in course content on the intensive margin. Section 6 concludes.

2 Conceptual framework

This section develops a conceptual framework for how students and universities jointly determine the quantity and content of instruction. The framework highlights the economic forces that shape each side of the market, identifies why instructional supply may respond inelastically to demand, and yields implications that the empirical analysis evaluates. Appendix A provides a partial adjustment model that clarifies how the estimated elasticities map to adjustment frictions.

Instruction in higher education can be viewed as a market. Students demand courses based on expected returns to human capital, tastes, and institutional rules. Because expected returns depend on labor market opportunities, student demand shifts when labor market conditions change. Students can adjust their course-taking relatively quickly, often within a single semester, making enrollment the primary short-run channel through which labor market shocks reach universities.

Universities supply instruction by offering seats in sections of courses. Each margin of supply has a distinct cost structure. Creating a new course requires specialized faculty expertise, preparation, and formal curricular approval — high fixed costs that make course creation lumpy and slow. Adding sections of existing courses requires instructional labor and scheduling capacity but avoids development costs. Expanding seat capacity within existing sections is cheapest in direct terms but may affect instructional technology and quality as size increases. This cost ordering yields a natural implication: when demand shifts, universities should adjust seats most readily, sections next, and courses least.

Observed enrollment is an equilibrium outcome, not a direct measure of student demand. Students cannot enroll in courses that do not exist, and when capacity binds, some students are rationed out of preferred fields and diverted into less-preferred alternatives. Enrollment in constrained fields, therefore, understates demand, while enrollment in substitute fields is inflated. Regressing course supply on enrollment will generally misstate universities' responsiveness because enrollment reflects both demand shifts and supply constraints.[2]

Several structural features of higher education generate supply adjustments that scale less than one-for-one with demand. Instructor labor supply is quasi-fixed: training a PhD takes years, lateral hiring is slow and lumpy, and tenured faculty represent durable commitments regardless of enrollment trends. Demand shocks may be partly transitory, making the option value of waiting high relative to the costs of course creation. And universities commit to offering core courses regardless of demand, creating a floor on instructional capacity.[3]

These features may also generate asymmetric responses, but with different force across margins. The core curriculum floor binds specifically on course quantity: a field can reduce how frequently it offers a foundational course, but eliminating the course entirely would compromise the major. Section quantity, meanwhile, is more flexible. Shifting a course from every semester to once per year is a scheduling decision, not a curricular one. Course quantity should therefore exhibit stronger downward rigidity than section quantity, even when both respond positively to rising demand.

When instructional scale adjusts only partially, universities may also adapt what they teach. Content adjustment can occur by revising existing courses or by creating new ones. Revising an existing course is inexpensive but constrained: a course retains its core identity even as specific topics evolve. Substantive reorientation typically requires creating a new course altogether, incurring the full fixed costs of development. If this distinction holds empirically, the courses that enter the curriculum should be systematically more aligned with expanding occupations than the courses they replace, even when the total number of new courses is small. Section 5 tests this prediction directly.

Finally, universities differ in resources, governance, missions, and the composition of their faculty, and these differences plausibly shape how they adjust. But the direction of influence is not always obvious. Research-intensive universities employ faculty closer to the frontier of their fields, potentially lowering the cost of creating new courses, but they also allocate more faculty time to research, limiting instructional focus. Selective institutions enroll better-prepared students, broadening the set of viable advanced courses, but these institutions have

[2]This logic motivates the instrumental variables strategy in Section 4, which isolates demand shifts driven by labor market conditions external to the university. The resulting demand-mediated elasticity measures whether the institutional pipeline from labor market signal to instructional output is functioning.

[3]These features are analogous to those documented in other settings with specialized labor and durable capital commitments (e.g., Hamermesh and Pfann 1996). When adjustment is costly and partially irreversible, organizations move gradually toward desired capacity rather than adjusting fully each period. Appendix A formalizes this logic using a partial adjustment framework and derives the demand-mediated supply elasticities that the empirical analysis estimates.

long viewed their mission as creating durable knowledge rather than instructing in vocational skills tied to short-term labor market demand. Public institutions may, by mandate, have greater focus on local labor market conditions, but face more layers of governance that slow curricular change. Tenure can slow contraction in declining fields, but long faculty horizons may also lower the perceived cost of investing in new courses.

Rather than resolving these ambiguities theoretically, I treat them as empirical questions. The analyses in Sections 4.5 and 5.3 estimate how elasticities and content adaptation vary across institution types, allowing the data to reveal which institutional features bind in practice and in which direction.

3 Data

3.1 Course catalog dataset

To analyze how higher education institutions adjust course offerings in response to changing student demand, I constructed a unique "course catalog" dataset with detailed course-level information from a sample of U.S. colleges and universities. The dataset includes 48 million course sections offered as early as 1994 from 1,018 institutions, covering 56% of baccalaureate enrollment.[4] I collected the data by scraping universities' online course catalogs and schedules, recording details of each course offered during a specific term.[5]

For a given course, I may observe the name(s) of the instructor(s), the number of sections offered in a year, enrollment in each section, the format of instruction (whether it is in-person or online), and a brief text description of the course content. Appendix Figure A-1 demonstrates the information contained in a typical observation in my dataset.

The dataset broadly reflects characteristics of the population of US universities. While the sample is not truly random, as it only includes universities with online course catalogs, the sample resembles the broader population in several important respects. Table 1 benchmarks the characteristics of schools in the catalog sample against the characteristics of the US higher education system. While the sample aligns closely with the average US four-year institution in aspects like selectivity, cost, and resources, it skews towards larger, public institutions. Extremely small private (often religiously affiliated) institutions are under-represented in this sample.

The course catalog dataset offers unique advantages for researchers. By capturing section-level enrollment and content details, it can measure shifts in student demand years before

[4]While the dataset spans over two decades, the causal analysis focuses on a single post-Great Recession window where labor market shocks are well-measured and stable.

[5]Appendix B summarizes the inclusion criteria for institutions in the course catalog sample and exercises to validate the data.

they manifest in completed majors. Because a major represents only a portion of a student's coursework, course-level data may also provide a more comprehensive snapshot of skill acquisition, reflecting the breadth of knowledge students engage with beyond their primary field of study. Moreover, the dataset provides insight into different margins of course supply — for example, whether a university expands enrollment in a program by expanding existing courses or by creating new courses or eliminating existing courses. The dataset makes it possible to capture short-run supply adjustments that are difficult to observe in degree completion-based outcomes alone.

I impose a series of restrictions to refine the raw course catalog dataset for analysis.[6] I exclude non-classroom-based courses (e.g., independent study, internships), restrict the sample to undergraduate courses, and differentiate between lower- and upper-level courses based on institutional numbering conventions. I further limit the data to complete academic years, excluding summer terms. To standardize classification, I categorize over 48,000 department names into 54 standardized fields (e.g., History, Education, Economics, Engineering).[7] Throughout the analysis, I weight enrollment and course offerings by credit hours.

3.2 Supplemental data sources

I supplement the course data with institution characteristics from the National Center for Education Statistics' Integrated Postsecondary Education Data System (IPEDS). For the IV analysis, I use employment data from IPUMS using the 2009-2018 ACS 1% samples (Ruggles et al. 2023). In Section 5, I document changing course content in relation to student demand using a weighting system that links words or phrases that appear in the course descriptions to the occupations to which they are most distinctive. To do this, I use the text of job descriptions from Lightcast (formerly Burning Glass Technologies). Lightcast collects job descriptions from more than 45,000 online job boards, representing the near-universe of online job posts since 2010. The data include the full text of de-duplicated job postings mapped to six-digit SOC codes.[8]

4 Extensive Margin: adaptation through course quantity

In this section, I estimate long-run elasticities of course and section supply with respect to field-specific student demand. Because course planning and approval operate on multi-year horizons, my preferred specification uses eight-year differences and focuses on upper-level

[6]See Appendix B for details on data processing.

[7]See Appendix C for details on field standardization.

[8]For tractability, I use a sample of job postings: all posts in March, August, and November from 2010-2018. The resulting sample includes more than 2 million job posts.

courses at four-year institutions.[9] Results for lower-level and all undergraduate courses appear in the Appendix.

4.1 Trends in course quantity and enrollment

The conceptual framework in Section 2 describes the margins along which universities can adjust supply: by adjusting the quantity of courses, sections, or seats.[10] [11] To empirically assess how universities modify supply, Figure 1 plots trends in enrollment and supply trends across six broad field groups.[12]

The figure reveals a divergence between course quantity and enrollment growth across fields in instances where enrollment is decreasing or rapidly increasing. The figure documents a shift in enrollment from Humanities and Education towards fields like Business/Economics, STEM, and Computer Science. In high-growth fields like Computer Science, course quantity increased modestly but lagged behind explosive enrollment growth. For fields with declining enrollment, including Education and the Humanities, course quantity remained relatively stable despite sharp enrollment declines. In contrast, fields with modest enrollment growth, such as non-Computer Science STEM and Business/Economics, saw comparable growth in enrollment and course quantity.[13]

This asymmetry points to potential rigidities in two directions. First, downward rigidities make it difficult for institutions to reduce course offerings in response to declining demand. Structural factors, such as commitments to offering foundational skills and the constraints imposed by tenure, contribute to the stability of offerings even as enrollment declines. Commitments to instructors on long-term contracts, such as tenured instructors, regardless of a field's popularity, make the cost of offering courses in less popular fields relatively low.

[9] Upper-level courses are typically numbered in the 300-499 range and comprise advanced core and elective courses. Upper-level courses are the courses over which students have the most discretion in their selection. As a result, fluctuations in enrollment for these courses should more accurately reflect students' changing demand rather than responses to, for example, a university's changing core requirements.

[10] A "course" is an individual class, typically identified by a unique course ID (e.g., Econ 101 or Econ 102), while a "section" is a specific offering of that course. For example, if an institution offers two sections each of Econ 101 and Econ 102 in both the Fall and Spring semesters, the total would be 8 sections for 2 courses in Economics.

[11] I focus on course and section quantity as the primary measures of course supply, due to data limitations of reported seat capacities. Capacities are often implausibly high (e.g., independent study courses, which routinely enroll one student or fewer, list capacity at 999 seats) or remain fixed regardless of enrollment. Since seat counts rarely change systematically and are mechanically linked to sections, courses and sections are the most reliable outcomes.

[12] Skilled trades, professional degree-granting fields, and interdisciplinary departments are excluded. Additional detail on field classification and selection is available in Appendix C.

[13] Computer Science is a unique field for its boom-and-bust cycles. The growth in Computer Science enrollment during the period of my analysis follows a nadir in Computer Science enrollment following the Dot-Com bubble. It is possible that some institutions had surplus capacity in Computer Science to absorb the enrollment surge.

Second, the limited responsiveness of course quantity to the rapid growth in Computer Science enrollment suggests rigidities triggered by surges in demand that outpace institutional capacity for adjustment.

4.2 Empirical Strategy

4.2.1 OLS Specification

Equation 1 shows the OLS specification I use to estimate course quantity elasticity:

$$\Delta y_{i,s,t'} = \alpha \Delta x_{i,t}^{(\text{avg})} + \beta \Delta x_{i,s,t}^{(\text{field})} + \epsilon_{i,s,t} \tag{1}$$

$$\Delta x_{i,s,t}^{(\text{field})} = \Delta x_{i,s,t} - \Delta x_{i,t}^{(\text{avg})} \tag{2}$$

The dependent variable, $\Delta y_{i,s,t'}$, denotes the log change in the quantity of courses offered by institution i in field s over period t'. I calculate this change as a long log difference in the credit-weighted number of courses offered across these periods.[14] The log difference specification differences out any fixed institutional characteristics. Thus, any controls I introduce should pertain to time-varying attributes of universities. To this end, I control for the university's average enrollment growth rate $\Delta x_{i,t}^{(\text{avg})}$, ensuring that the analysis accounts for shifts in course quantity tied to broader university-level changes.

The parameter of interest, β, represents the elasticity of course quantity to relative shifts in enrollment across fields. For clarity, the field-specific enrollment growth rate is adjusted by subtracting the institution's average enrollment growth rate, resulting in $\Delta x_{i,s,t}^{(\text{field})}$.[15]

Because my focus is on estimating how schools adjust, on average, to changing student enrollment, I assign equal weight to each school in the regressions. Within each school, I assign weight to the field-level observations in proportion to the field-level enrollment in

[14] I credit-weight both changes in course quantity and changes in enrollment.

[15] De-meaning is important when testing whether course quantity elasticity differs for fields growing or shrinking relative to the university. Measuring course supply responses to relative, rather than absolute, enrollment changes isolates how universities adjust to field-specific demand shifts. For example, consider two universities where a field grows by 5%: if overall enrollment at the first university increases by 10%, that field is growing more slowly than the institution as a whole and may not warrant expansion beyond the expansion necessary to support the growing university overall. In contrast, if overall enrollment shrinks by 10%, the field is a relative outlier, making it a more natural target for investment. However, differencing out the institution's overall growth rate could introduce bias if overall institutional growth is itself responsive to field-specific demand shifts — for example, if surging STEM demand increases overall enrollment at a technical university. Given that most institutions in my sample are regional public universities, where matriculation is less likely to be driven by specialized field-specific demand shifts, the potential for this bias is limited. Appendix Table A-5 shows results using absolute enrollment changes are substantively identical to my preferred specification.

the base year. This means I give more weight within the institution to fields with greater enrollment to improve precision.

Enrollment is a useful indicator of student demand, particularly for under-subscribed courses capacity constraints do not bind. Conditional on prerequisite structures, scheduling constraints, and degree requirements, students allocate their course-taking across fields in response to differences in preferences, expected returns, and information about labor market conditions. In these environments, enrollment responds quickly to shifting student valuations and provides a reliable measure of demand for instruction. However, enrollment and course supply are mechanically linked: expanding the number of courses in a field increases the available seats and can induce enrollment growth even absent a shift in underlying demand. To reduce mechanical simultaneity, I measure enrollment changes over t and course changes over $t' = t+o$ (one-year offset), so enrollment shifts precede supply responses.[16] This ensures that the enrollment variation used to explain course supply decisions predates the supply response itself. Standard errors are clustered at the institution-by-period level.

4.2.2 IV Specification

When universities do not fully accommodate rising demand, enrollment shifts may not fully reflect changes in latent student demand. For example, when students are rationed out of Computer Science and diverted into, say, an English elective with open seats, OLS treats that English enrollment as demand, making it look like the university is responding to demand in both fields when in fact it is choosing not to respond in Computer Science and the enrollment in English is an artifact of that choice. In such cases, enrollment growth understates demand, and OLS estimates of course quantity elasticities would be biased upward, making universities appear more responsive than they truly are.

To isolate changes in enrollment driven by student preferences rather than institutional supply decisions, I use a shift-share instrumental variables (IV) strategy based on labor market shocks. The instrument combines variation in employment growth[17] across fields with differential exposure to those growth rates across regions, measured at the Census division level.[18] Because labor market growth is driven by macroeconomic forces rather

[16] For example, with an eight-year window, I regress course quantity growth from 2010-11 to 2018-19 on enrollment growth from 2009-10 to 2017-18. Appendix Table A-8 reports estimates under alternative offset and lag lengths; results are stable across specifications.

[17] While it may be more intuitive to think of students responding to changing wages, previous research suggests that major choice is relatively inelastic to changing wages (Beffy et al. 2012; Wiswall and Zafar 2015). In practice, enrollment is responsive to employment levels.

[18] I construct regions at the Census Division level because this is the level of regional variation that produces the strongest first-stage. Contemporaneous work by Conzelmann et al. (2023) uses a similar instrument to study how students and universities respond to changing demand for college graduates in the labor market.

than university actions, employment shifts provide a plausibly exogenous source of variation in student demand. The IV estimates therefore recover a policy-relevant but local object: how universities adjust course and section supply when labor market shocks shift student enrollment, holding fixed institutional adjustment technologies.

I estimate course quantity elasticities over a single eight-year window spanning 2009-10 to 2018-19, the period between the Great Recession and the Covid-19 pandemic. Course quantity changes from 2010-11 to 2018-19 are regressed on enrollment changes from 2009-10 to 2017-18, instrumented by projected employment growth constructed from the 2009 and 2017 American Community Surveys (ACS). The instrument fixes baseline major-to-occupation shares and projects employment growth for workers aged 30-65, ensuring that measured labor market shifts reflect pre-existing workforce trends rather than contemporaneous course supply decisions.

Formally, the instrument is constructed as:

$$\Delta E_{s,r,t} = \sum_{j=1}^{J} \phi_{s,j,r,t_0} \left(lnE_{j,r,t_1} - lnE_{j,r,t_0} \right) \tag{3}$$

$$z_{s,r,t} = \Delta E_{s,r,t} - \overline{\Delta E_{r,t}} \tag{4}$$

where ϕ_{s,j,r,t_0} denotes baseline major-to-occupation shares and $\overline{\Delta E_{r,t}}$ is the regional average employment growth rate. Subtracting the regional mean isolates differential employment growth across fields within a region. Because each university is small relative to its Census division — comprising 3-8 states and tens of millions of people — its direct influence on regional employment trends is negligible.

The shift-share instrument exploits two sources of variation: differences in occupational growth across fields and differential exposure to those growth rates across local labor markets. The first source arises because fields differ in the occupations their graduates enter. For example, across the US, graduates from Computer Science disproportionately enter software development and engineering occupations, while graduates from Education disproportionately enter teaching. These occupations experienced starkly different growth rates between

While their study measures the direct effect of changing job demand on completed majors, my analysis focuses primarily on how changing labor market conditions impact course quantity through their effects on students' demand. Conzelmann et al. use job postings data to measure changing demand in local labor markets for students from different majors, then measure the exposure of each institution in their sample to these changes using shares of graduates from the institution in each labor market (using data from LinkedIn). Using the same data, I confirm that on average, more than 80% of the graduates from the schools in my sample work in the same Census division where their respective institutions are located (Conzelmann et al. 2022).

2009-17; employment in computing occupations grew rapidly, while teaching grew slowly. This difference in major-to-occupation shares generates a positive demand shock for Computer Science relative to Education at a given university, even holding the local labor market fixed.

The second source of variation arises because labor market conditions differ across locations. Consider two otherwise similar universities with comparable Computer Science programs: one in a region containing a technology hub and another located in a region with slower growth in tech employment.[19] Even with similar baseline major-to-occupation shares, graduates from the first university face stronger growth in relevant occupations, generating a larger demand shock for Computer Science at that institution. As a result, student demand for the same field can shift differentially across universities solely due to local labor market conditions.

Formally, the instrument assigns each institution-field pair weighted average employment growth, where the weights are fixed major-to-occupation shares measured in the base year. Subtracting the average employment growth faced by the institution yields a relative demand shifter that varies both across fields within a university and across universities within a field. This construction isolates a portion of changes in student enrollment driven by labor market conditions, rather than by universities' own course supply decisions.

I estimate the model using two-stage least squares. The first-stage relates de-meaned enrollment growth to the instrument:

$$\Delta x^{(\text{field})}_{i,s,r,t} = \phi \Delta x^{(\text{avg})}_{i,r,t} + \kappa z_{s,r,t} + \eta_{i,s,r,t} \tag{5}$$

In the second-stage, I use the fitted values from the first-stage to instrument for students' changing demand. I then estimate a regression of the percentage change in the number of courses in field s at college i between 2010-11 and 2018-19 on this instrumented enrollment change:

$$\Delta y_{i,s,r,t'} = \alpha \Delta x^{(\text{avg})}_{i,r,t} + \beta \widehat{\Delta x^{(\text{field})}_{i,s,r,t}} + \epsilon_{i,s,r,t} \tag{6}$$

The second-stage regression produces an estimate of the causal effect of changes in demand on changes in course quantity. I cluster standard errors at the field-by-Census division level

[19] For example, in the Pacific Division, containing the Bay Area, growth in Computer Science-related jobs was 13.7 percentage points higher than the regional average. In a more typical region, such as the South Atlantic Division, employment growth for Computer Science-related occupations was 8.1 percentage points faster than the regional average.

to address the potential serial correlation within a field-region.

The IV strategy allows me to estimate demand when enrollment is either rationed by capacity constraints or inflated by institutional steering. The approach uses the relationship between employment and enrollment growth in cases where enrollment accurately reflects demand to project demand shifts in cases where enrollment is constrained or distorted.

If rationing or inflation were pervasive, the first-stage relationship would be attenuated and the IV would lose power. As long as many fields experience demand-driven enrollment changes without binding supply constraints, however, the estimated relationship between employment growth and enrollment remains informative, allowing demand shifts to be projected in constrained cases.

For identification, the instrument must satisfy monotonicity, independence, relevance, and the exclusion restriction. Monotonicity requires that improvements in labor market conditions for a field weakly increase student demand for that field at all institutions. While monotonicity is inherently untestable in this setting, a violation would require the counterintuitive pattern that improved job prospects systematically reduce demand for a field. Appendix Figure A-6 shows a positive relationship between employment growth and enrollment changes, with little evidence of systematic defiers. Independence requires that variation in employment growth be orthogonal to unobserved determinants of course supply. This assumption is plausible if labor market growth reflects macroeconomic forces rather than endogenous university actions. Several features of the design mitigate concerns about endogeneity. First, employment growth is measured at the Census division level, where individual universities are small relative to the regional labor market. Second, the analysis period begins with the Great Recession — a major labor market disruption that limits universities' ability to forecast subsequent trends. Third, the instrument is constructed using employment shifts and occupational shares for workers aged 30-65, ensuring that measured labor market changes predate contemporaneous course supply decisions. I demonstrate relevance through a strong first-stage: the cluster-robust first-stage F-statistic exceeds conventional thresholds (Table 2).[20]

The exclusion restriction requires that labor market conditions affect course quantity only through student demand. This assumption is strong and warrants careful scrutiny. I consider three potential violations and provide supporting evidence, summarized here and detailed in Appendix D. First, universities may anticipate labor market trends and adjust supply in advance of enrollment changes. Such anticipation would bias elasticity estimates downward, as course supply adjustments have already occurred by the time enrollment de-

[20]As a validation exercise, Appendix Table A-2 shows that completed majors — measured using IPEDS data — are similarly responsive to employment growth, consistent with enrollment capturing demand shifts.

mand materializes. This concern is mitigated by the timing of the analysis and by dynamic reduced form evidence: Appendix Figure A-7 shows no differential pre-trends in enrollment or course supply, with adjustments occurring only after enrollment responds to labor market shocks. Appendix Figure A-8 further shows no evidence of pre-emptive capacity expansion in the fastest-growing fields.

Second, labor market growth could affect faculty hiring and thereby influence course supply directly. Several patterns argue against this channel as a primary driver. Inelasticity is most pronounced in declining fields, where outside options for instructors are weakest, and institutions with greater reliance on specialized faculty exhibit higher elasticities in growing fields. Consistent with this interpretation, IV estimates are robust to excluding field-regions with extreme labor market changes, and institutions with graduate programs, which may serve as a more elastic internal labor supply margin, do not respond more elastically to demand shocks (Appendix D.2).[21]

Third, labor market growth could attract targeted funding or industry partnerships that directly expand course offerings. If present, this channel would bias elasticities upward. I test this possibility by examining correlations between changes in institutional funding and effective supply elasticities. Growth in federal, state, local, or private funding is uncorrelated with baseline exposure to high-growth fields and with estimated elasticities (Appendix D.1).

Finally, recent work formalizes the identifying assumptions underlying shift-share instruments (e.g., Goldsmith-Pinkham et al. 2020; Borusyak et al. 2022). In my setting, the "shares" are baseline major-to-occupation shares rather than employment shares. Identification would be compromised if these shares correlated with unobserved determinants of course supply. Three design features mitigate this concern: shares are fixed to a pre-period, shifts and shares are measured for older workers, and regions are defined at a level where individual institutions represent a negligible share of the labor force. A robustness test using shares from all other Census divisions yields similar estimates (Appendix D).

Taken together, these considerations support the validity of the instrument. To the extent that remaining violations exist, they are more likely to attenuate than to inflate estimated elasticities, implying that the results may understate the degree of inelasticity in university supply responses.

[21] Even if the faculty labor market channel is quantitatively important, it reinforces rather than undermines the paper's central finding. If rising outside options in high-growth fields make it more costly for universities to recruit instructors, then some portion of the estimated inelasticity reflects hiring constraints that operate alongside, and compound, the organizational frictions emphasized in the conceptual framework. In either case, labor market signals fail to translate fully into instructional capacity. If the faculty labor market channel is operative, the estimated elasticities correctly measure how much course supply responds to demand shocks, but the mechanism operates partly through factor markets rather than purely through governance and organizational structure.

4.3 Results

Table 2 reports OLS and IV estimates for the elasticity of course (Columns 1-5) and section (Columns 6-10) quantity with respect to enrollment. Columns 1-4 and 6-9 present OLS estimates from Equation 1, measured over windows ranging from two to eight years. In Columns 1-3 and 6-8, I estimate regressions using overlapping institution-field-period log differences across the full sample (e.g., 2010-14, 2011-15). The first row of each panel summarizes changes in course quantity associated with overall enrollment growth or decline at the university; the second row — of primary interest — shows changes associated with a field's relative enrollment growth within the university.

The OLS estimates indicate that course quantity responds substantially less than one-for-one to changes in enrollment at both short and long horizons. The two-year elasticity is roughly 0.21, rising modestly to 0.39 over eight years, suggesting that universities are more responsive to sustained trends than to temporary fluctuations. Section quantity is more elastic than course quantity, implying that institutions accommodate changing demand more by altering the frequency of existing offerings rather than by creating or eliminating courses.[22]

As discussed in Section 4.2.2, enrollment changes may not reflect shifts in student demand. Columns 5 and 10 of Table 2, therefore, present IV estimates of course and section elasticities in cases of rationing or diversion.[23] The IV specification measures changes between 2009-10 and 2018-19; Columns 4 and 9 report comparable OLS estimates for this same period. The IV estimates imply that a 10% increase in demand leads to a 2.1% increase in course quantity. Section quantity adjusts more elastically: fields expand sections by 5.3% for a 10% demand increase.

OLS estimates exceed the corresponding IV estimates, consistent with the fact that enrollment is an equilibrium outcome shaped by both demand and supply. Changes in enrollment may reflect rationing constraints (e.g., students unable to enroll in desired courses) or administrative policies that artificially boost enrollment in some fields (e.g., distribution requirements). Ignoring these factors makes supply appear more responsive than it is; the OLS-IV gap directly quantifies the share of realized enrollment that reflects supply-side distortions rather than student preferences, how much of what enrollment conflates as "de-

[22]For example, a field may begin offering a popular course in both the Fall and Spring semesters, or increase the number of sections in a given term. Such adjustments are more common at large universities with broad elective catalogs and at less-selective institutions where enrollment caps are tighter.

[23]Reduced form estimates appear in Appendix Table A-4: a 10% change in relative employment growth for a field within a region corresponds to a 9.4% change in course quantity and a 23.4% change in section quantity. The reduced form coefficients should not be interpreted as elasticities with a natural unit benchmark; they capture the sensitivity of university-level outcomes to regional labor market changes, where the denominator operates at vastly larger scale than the numerator.

mand" is actually a result of rationing. Accordingly, the IV estimates likely provide a more accurate measure of universities' elasticity of course supply to student demand.

A series of robustness exercises confirm that the estimated course quantity elasticities are not driven by measurement error, spurious trends, or influential fields. Appendix D demonstrates robustness of the estimates to alternative constructions of the instrument and the exclusion of fields with extremely high/low values of the instrument. Appendix Figure A-7 tests for leads in enrollment or course quantity adjustments prior to the start of the employment growth trends. The figure confirms stability in enrollment and course quantity trends for fields that would subsequently experience high employment growth prior to the start of this growth. Appendix Figures A-10 and A-11 test the influence of individual fields or institutions in a leave-one-out strategy and re-estimating the IV specification; the elasticities remain stable across these exclusions.

4.4 Asymmetry in course quantity elasticity

The baseline specification in Equation 1 imposes symmetry in course quantity responses to enrollment changes, implicitly assuming that comparable increases and decreases in demand elicit equal and opposite adjustments. In practice, expansion and contraction face different institutional constraints. Because many faculty are employed on long-term contracts and fields must maintain a minimum set of core offerings, universities may find it easier to accommodate growth than to contract declining fields. Figure 1 provides descriptive evidence consistent with such asymmetric responses.

To capture this asymmetry, I estimate a specification that allows course quantity elasticities to differ for fields growing faster versus slower than the institutional average enrollment change, $\Delta x_i^{(\text{avg})}$.[24] The estimating equation is:

$$\Delta y_{i,s} = \alpha \Delta x_i^{(\text{avg})} + \beta_1 \Delta x_{i,s}^{(\text{field})} \mathbb{I}(\Delta x_{i,s}^{(\text{field})} < 0) + \beta_2 \Delta x_{i,s}^{(\text{field})} \mathbb{I}(\Delta x_{i,s}^{(\text{field})} > 0) + \epsilon_{i,s} \tag{7}$$

where β_1 and β_2 capture elasticities for shrinking and growing fields, respectively. I extend the IV framework in Equation 6 analogously, allowing both the first-stage and second-stage to differ by the sign of the demand shock.

$$\widehat{\Delta x_{i,s}^{(\text{field})}} = \Delta x_{i,r}^{(\text{avg})} + \kappa_1 z_{s,r} \mathbb{I}(z_{s,r} < 0) + \kappa_2 z_{s,r} \mathbb{I}(z_{s,r} > 0) + \xi_{i,s,r} \tag{8}$$

$$\Delta y_{i,s} = \alpha \Delta x_i^{(\text{avg})} + \beta_1 \widehat{\Delta x_{i,s}^{(\text{field})}} \mathbb{I}(\widehat{\Delta x_{i,s}^{(\text{field})}} < 0) + \beta_2 \widehat{\Delta x_{i,s}^{(\text{field})}} \mathbb{I}(\widehat{\Delta x_{i,s}^{(\text{field})}} > 0) + \epsilon_{i,s} \tag{9}$$

[24]For simplicity, I omit time subscripts, which I use identically to the base model in Equation 1.

Table 3 reports OLS and IV estimates from these asymmetric specifications for both courses and sections. The table distinguishes elasticities for fields growing faster versus slower than the institutional average and presents results over short-run and long-run horizons. Columns 5 and 10 report the IV estimates for the eight-year period used in the main analysis.

Over short horizons, course and section quantities respond similarly to rising and falling enrollment. Over longer horizons, elasticities increase overall, but a widening gap emerges between growing and shrinking fields, particularly for course quantity. Columns 5 and 10 present IV estimates from the asymmetric specification.[25] The IV results reveal asymmetry: course quantity rises by 3.4% in response to a field growing 10% faster than the institutional average, but falls by only 1.0% for a field growing 10% more slowly. Section quantity rises by 5.4% under the same positive shock and falls by 5.1% under a negative one.[26]

As in the linear specification, OLS estimates exceed IV estimates for course quantity, but the upward bias is far more pronounced for shrinking fields. Shrinking fields are precisely where diversion is most severe: students rationed out of growing fields inflate enrollment in declining ones, making it look like those fields face less demand pressure to contract than they actually do. An OLS elasticity of 0.35 for shrinking fields, compared to an IV elasticity near zero, implies that nearly all of the observed enrollment-course quantity comovement in declining fields reflects artificial demand sustained by spillovers from constrained fields rather than genuine student interest. The pattern is less pronounced for sections, where OLS and IV estimates for shrinking fields are closer (0.58 and 0.51, respectively). This is consistent with sections being the flexible margin: when diverted students arrive in a low-demand field, departments can absorb them by running scheduled sections at higher enrollment, generating correlated movements in both enrollment and section counts. Course quantity, by contrast, is anchored by the core curriculum floor, so diverted enrollment produces comovement with an outcome that would not have contracted even absent the diversion.

These patterns are consistent with institutional commitments that limit contraction more than expansion. Fields must maintain a minimum set of core offerings to preserve curricular coherence (e.g., British Literature in English or Linear Algebra in Math), which limit their capacity to reduce course offerings in response to declining demand more than their capacity to expand offerings in response to increasing demand. The average upper-level course is offered 1.5 times per year (either once per semester or once per year); the smaller gap between section elasticities suggests that adjusting the cadence of a course's offering between annual and per-semester schedules is a substantially more flexible margin than creating or,

[25] Because the first-stage involves nonlinear transformations, I compute bootstrapped standard errors with 1,000 repetitions, resampling region-field clusters in each iteration.

[26] In the reduced form (Appendix Table A-4), a 10% increase in employment growth for a field is associated with a 17.3% rise in course quantity, while a 10% decline corresponds to a 4.1% reduction.

particularly, eliminating courses altogether.

This distinction also helps explain why the OLS-IV gap is larger for course quantity, particularly in shrinking fields. Where the IV predicts latent declines in enrollment demand for fields, institutions appear to prioritize maintaining curricular breadth while consolidating the number of times courses are offered. OLS therefore overstates responsiveness more sharply for courses than for sections, especially on the downside, because enrollment reallocations mask latent contraction pressure at the course level but less so at the section level.

4.5 Heterogeneity

Universities differ in governance, resources, and instructional capacity, shaping how they adjust to changes in student demand. Figure 2 documents heterogeneity in course and section elasticities across institutional mission, control, selectivity, size, and tenure structure by augmenting the analyses in the preceding sections with interactions of field-level enrollment changes with indicators for institutional type.[27] These patterns are descriptive, but nevertheless informative about the margins through which different institutions accommodate enrollment shocks.

Across institutional characteristics, a dichotomy emerges between institutions that adjust by expanding breadth — through new course creation — and those that adjust by expanding capacity — through additional sections of existing courses. I focus on the expansion margin, as these responses are most policy-relevant for alignment between human capital development and emerging areas in the labor market. Research-intensive (R1), selective, and private universities respond to rising enrollment primarily by introducing new courses, while less selective and public universities rely more heavily on section expansion in existing courses. When enrollment declines, teaching-focused and less selective institutions contract both courses and sections sharply, while research-intensive and selective institutions maintain course breadth and adjust, if at all, by reducing section frequency.

This heterogeneity appears across institutional cuts. R1 universities are the most elastic on the course margin when enrollment rises, while teaching-focused institutions display the strongest contraction on both margins when enrollment falls. Private universities expand largely through course creation, whereas public universities expand more through sections, consistent with differences in governance and approval constraints. Highly selective institutions preserve curricular breadth even during enrollment declines, while medium- and non-selective institutions retrench more aggressively.[28] Smaller institutions, with limited slack in

[27]The analysis uses eight-year course quantity elasticities with a one-year offset and estimates OLS specifications to maximize institutional coverage.

[28]Conzelmann et al. (2023) find the opposite pattern: *degree* production is more elastic at less selective

course offerings, are comparatively inelastic to declining enrollment, while greater downward elasticity for the largest institutions does not translate to higher upward elasticity.

Tenure, an obvious impediment to reducing course offerings, is associated with interesting and offsetting responses. Institutions with higher tenure shares are less elastic to declining enrollment but more elastic when enrollment rises. Thus, while tenure limits an institution's capacity to reallocate away from low-enrollment fields, it may also promote innovation by offsetting the upfront costs of new course creation with certainty that courses can be taught repeatedly.

Taken together, these heterogeneity patterns point to institutional structure as a central determinant of how enrollment shocks translate into instructional supply. Institutions with greater resources expand access to growing fields by increasing curricular breadth, while more constrained institutions adjust primarily by reallocating seats or contracting offerings in declining fields. As a result, student enrollment shocks do not generate uniform instructional responses across higher education, but instead reinforce existing differences in where and how students can access emerging skills.

4.6 Discussion

The IV estimates imply that a 10% increase in labor market-driven demand raises upper-level course quantity by 2.1% and section quantity by 5.3%. Interpreted through the back-of-the-envelope calculations in Appendix E, these elasticities correspond to roughly 1.9% additional Computer Science majors and 1.4% additional Engineering majors between 2009 and 2018 in a counterfactual world without binding capacity constraints, with offsetting reductions in completions in low-demand fields. These magnitudes suggest that inelastic instructional supply shapes not only class sizes and rationing in high-demand fields, but also the composition of the skilled workforce.

The elasticities estimated here should be interpreted as adjustment elasticities, not price elasticities. Instruction is not priced at the margin, and demand is rationed through non-price mechanisms such as enrollment caps, prerequisites, and course availability. The estimates therefore capture how instructional capacity responds to demand pressure in the presence

and teaching institutions and nearly unresponsive at research-intensive ones. Their outcome is degree completions, rather than course or section supply, though the two outcomes are clearly related. A likely source of this discrepancy is that their specification does not control for overall institutional enrollment growth, so the estimated degree elasticity captures both reallocation across fields within a university and changes in cohort size. Less selective and teaching-focused institutions are more elastic along this margin (e.g., Barr and Turner 2013). By contrast, my specification controls for institution-average enrollment growth, isolating how universities reallocate instructional capacity across fields conditional on overall enrollment shifts. R1 universities may be more elastic on this margin because they have greater resources and faculty expertise to create new courses in growing fields, even as they maintain offerings in declining ones.

of adjustments costs, such as faculty hiring, course preparation, curricular approval, and instructor reallocation. Several structural features of higher education make one-for-one adjustment neither feasible nor necessarily desirable. Faculty labor is quasi-fixed: training a PhD takes 5-7 years, and even hiring laterally into a field is slow and lumpy. Moreover, demand shocks may be partly transitory, as illustrated by boom-bust cycles in fields such as Computer Science. Finally, maintaining curricular breadth constrains responsiveness; institutions commit to offering foundational courses (e.g., Linear Algebra, American History) and to sustaining fields with limited short-run labor market demand but perceived long-run value for students or society.[29]

Consistent with these constraints, adjustment occurs along multiple margins. When demand rises sharply, fields often accommodate it by enlarging existing sections, repeating sections of existing courses, and introducing a limited number of new courses. Appendix Figure A-5 shows that upper-level Computer Science sections are roughly 40% larger than a decade ago, while Humanities and Education sections are about 15% smaller. By contrast, contraction is more gradual: tenured and long-contract faculty can continue to offer small courses at relatively low marginal cost, so course offerings adjust slowly even when enrollment declines. The asymmetric elasticities estimated in Section 4.4 are consistent with convex adjustment costs: expanding instruction in growing fields is easier along the section margin, while contraction requires eliminating courses or reallocating faculty, which is more costly and institutionally constrained.

Heterogeneity across institution types reinforces this interpretation. Research-intensive and selective universities exhibit higher course elasticities on the expansion margin, consistent with greater slack resources and broader faculty expertise. Teaching-focused and less selective institutions rely more heavily on section adjustments and contract more sharply in declining fields, consistent with tighter budget constraints and fewer margins for reallocation. Tenure plays an offsetting role: institutions with higher tenure shares contract less in shrinking fields but expand more in growing ones, indicating that tenure both slows retrenchment and supports investment in new course development. Rather than pointing to a single optimal level of responsiveness, these patterns highlight how institutional missions, governance structures, and resources shape trade-offs between stability, breadth, and flexibility.

Taken together, the extensive margin results depict a system in which universities re-

[29] Comparing responses to demand shifts in upper-level to course supply responses for lower-level courses, summarized in the Appendix, reinforces this point. IV estimates in Appendix Table A-7 indicate that lower-level course quantity is essentially inelastic to student demand and that section elasticity is substantially smaller than for upper-level electives. Because introductory courses anchor general education and prerequisite requirements, these lower elasticities reinforce curricular breadth as a binding constraint on universities' responsiveness to demand shocks.

spond to labor market-induced shifts in student demand gradually and asymmetrically, with responsiveness concentrated on particular margins and among particular institutions. The estimated elasticities are best understood as empirical summaries of how existing institutional constraints and objectives translate demand shocks into changes in instructional scale, rather than as deviations from a single normative benchmark.

5 Intensive margin: adaptation through course content

The extensive margin analysis identifies course creation as the primary channel through which universities accommodate labor market-driven demand shocks. But all courses do not equally accommodate these shocks: a new upper-level elective in cybersecurity differs fundamentally from a new seminar in postcolonial literature, even though both register identically on the extensive margin.[30] Whether the courses universities create systematically reflect the labor market signals that drive enrollment demand, or whether entry is largely orthogonal to labor market trends, determines how much of the extensive margin adjustment documented in the previous section actually translates into skills aligned with the changing economy.

This section investigates this question directly. I develop a text-based measure of labor market alignment that links course content to the skill profiles of expanding occupations and use it to track how curricula evolve over time. The analysis is descriptive rather than causal — the alignment score cannot be cleanly instrumented in the same framework used for course quantity — but it serves a distinct and complementary purpose: it characterizes the content of the entry margin that Section 4 identifies as the dominant channel of adjustment. In particular, the decomposition of alignment changes into entry, exit, and within-course components provides direct evidence on whether the new courses universities create move curricula toward or away from the labor market frontier.

5.1 Measuring and validating course content through course descriptions

To characterize the content of university instruction, I analyze the short text descriptions that accompany most course catalog entries.[31] These descriptions — typically fewer than 50 words — summarize a course's topics, learning objectives, and intended skills, providing a concise record of what students are expected to learn. Because I observe the course catalog

[30] Moreover, an institution can accommodate rising demand for particular skills — such as the technical skills emphasized in Computer Science — by updating existing courses or introducing new ones that incorporate those skills, even in fields where those skills are not traditionally taught.

[31] See Appendix Figure A-1.

longitudinally, these descriptions allow me to compare curricular content both across fields and within institutions over time.[32]

Course descriptions provide an informative, though incomplete, measure of instructional content. While instructors may update descriptions infrequently and some changes in classroom practice may not be immediately reflected, most substantive curricular adjustments occur through the introduction of new courses or the retirement of old ones — both of which are directly observed in the data.[33] To mitigate concerns about short-run measurement error, I focus on changes measured over relatively long horizons.[34] Moreover, course descriptions are the primary information students use when selecting courses. If a course incorporates new skills or methods but does not convey this in its description, students cannot act on that information when making enrollment decisions. In this sense, the description defines the course's effective content from the perspective of student demand, even if it understates the breadth of what is taught.

I represent each course description as a numerical vector summarizing the salience of different words and phrases, following standard methods from natural language processing. I represent each course c offered in field s at institution i in year t as a vector of tokens $v_{c,i,s,t}$, where values reflect the Term Frequency-Inverse Document Frequency (TF-IDF) weight of each token.[35] This weighting emphasizes words that are frequent within a course description but uncommon across all course description, highlighting the distinctive concepts that define a course's content. For example, "regression" and "equilibrium" are tokens distinctive of Economics courses, while "poetry" and "composition" are distinctive of English courses. The resulting representation captures how courses differ in the concepts and skills they emphasize.

To validate that these text-based representations capture meaningful variation in course content, I conduct a series of descriptive exercises summarized here and shown in Appendix Figures A-14 and A-15. The tokens most distinctive of each field are closely linked with the disciplinary focus of that field. For example, literature and writing are distinctive of English versus programming and data analysis for Computer Science. Comparing discontinued and

[32] The analysis focuses on regularly offered courses. Some universities include flexible "special topics" or seminar courses whose official descriptions rarely update to match the current course on offer. Not consistently observing the content of these courses is a limitation of the dataset. These courses represent less than 1% of enrollment for schools in the sample.

[33] In my data, roughly 62% of courses are modified or discontinued within a ten-year period (Appendix Figure A-13).

[34] Differential propensity to update course descriptions across fields or institution types might also introduce bias. I see no evidence of systematic differences of these types in the data.

[35] Full details of the text processing and TF-IDF construction appear in Appendix F. Typically, tokens are single words; common multi-word phrases (e.g., "climate change," "machine learning") are treated as single tokens.

newly introduced courses also reveals substantive shifts over time: recent Economics courses emphasize data analysis and applied topics, while Computer Science has moved toward data science and machine learning. Together, these patterns demonstrate that course descriptions capture economically meaningful changes in what universities teach, supporting their use as measures of curricular content in the analysis that follows.

5.2 Relating curriculum changes to the labor market

I develop a measure of the extent to which course content aligns with employment growth in the labor market. The score captures whether the topics and skills emphasized in course descriptions are associated with occupations that are expanding more rapidly. The measure is designed to capture directional curricular updating rather than the full magnitude of skill acquisition and is used to document systematic, interpretable changes in curricula across fields and institutions.

To construct the score, I link words and phrases from course descriptions to occupations using job posting data from Lightcast (formerly Burning Glass Technologies). For each token, I compute the distribution of occupations in which it appears and weight that distribution by national employment growth rates.[36] Tokens associated with faster-growing occupations receive higher weights, while those associated with slower-growing occupations receive lower weights.

Tokens distinctive of fast-growing occupations (e.g., software) receive higher weights, while those associated with slower-growing jobs (e.g., journalism) receive lower weights.[37] Generic terms (e.g., project, employee) lie near zero. An appealing feature of applying these weights to the TF-IDF representation is that words or phrases with similar meanings contribute similarly to a course's labor market alignment if they exhibit comparable distributions across occupations in the job posting data.[38]

Each course's labor market alignment score is defined as the TF-IDF-weighted average of these token weights across its description. Intuitively, the score captures whether a course emphasizes terminology associated with faster- versus slower-growing occupations. Courses in Computer Science and Statistics/Data Science, for example, tend to have higher alignment

[36] Lightcast postings closely track the occupational composition of employment (Hershbein and Kahn 2018). Here, I use them solely to measure token-occupation co-occurrence, not to estimate employment changes. Level differences between job postings and employment counts do not affect comparisons across tokens or institutions.

[37] Appendix Figure A-16 summarizes the distribution of token weights.

[38] Appendix G.3 validates this property by comparing alignment weights for 50 pairs of synonymous or closely related words (e.g., lawyer and attorney; salary and wage; data and information) against 5,000 randomly drawn pairs. The average absolute difference in weights for the meaningful pairs is substantially smaller than for any random pair set (Appendix Figure A-18), confirming that the weighting scheme preserves semantic proximity across related tokens.

scores compared to courses in English and Anthropology. Among Economics courses, courses emphasizing topics in data science and health economics have among the highest alignment scores. Appendix G.2 provides a worked example of the calculation.

Two validation exercises confirm that the measure captures meaningful alignment. First, field-level average alignment tracks realized employment growth in corresponding occupations (correlation = 0.57).[39] Second, an LLM-based validation exercise yields consistent results: when asked to judge which of two courses is more aligned with expanding occupations, the model's choices agree with the alignment ranking in a substantial majority of cases, with agreement increasing as alignment differences grow.[40]

With this measure in hand, I first document how curricular alignment evolves over time, before decomposing the sources of that change. I estimate descriptive course-level regressions of labor market alignment on year dummies, running specifications that weight either by enrollment (where the estimand captures how the typical course a student takes has evolved in its labor market alignment) and course quantity (where the estimand captures how the typical course an institution offers has evolved in its labor market alignment). For each weighting scheme, I estimate two types of models: one with institution fixed effects, where the time trend captures both within-field changes and reallocation across fields, and one with institution-field fixed effects, which isolate changes within fields to study how course offerings change within fields themselves.

Figure 3 plots trends in course- and enrollment-weighted alignment, both of which rise steadily, beginning in the early 2010s. Between 2010-11 and 2022-23, enrollment-weighted alignment increased by 0.092 standard deviations[41] (SDs) and course-weighted alignment by 0.046 SD. Roughly half of this increase reflects shifts in course offerings across fields, but adaptations also occur within institutions and fields. The corresponding within-field rises in enrollment-weighted and course-weighted alignment are 0.032 and 0.021 SD, respectively. As a benchmark, the total increase corresponds to roughly one-quarter of the alignment gap between a Statistics Principles course and a Data Science course. Shifts controlling for field composition are about 8% percent of the same gap. Enrollment has shifted even more rapidly toward higher-alignment courses, implying that student demand reinforces institutional adaptation. The increase is led by fields with initially high alignment, such as Computer Science, Statistics/Data Science, and Skilled Trades. However, average alignment

[39] Employment growth rates based on the same shift-share constructed in Section 4. Importantly, this relationship is not mechanical: alignment is derived from course text, while employment growth is measured independently using ACS data.

[40] Appendix G.3.3 presents additional robustness checks, including sensitivity to excluding extreme tokens and evidence that alignment varies with instructor specialization across fields.

[41] Standard deviations relative to the 2010-11 distribution of labor market alignment.

has risen modestly in most fields.

These magnitudes should be interpreted in light of what the alignment score can and cannot capture. The score measures directional shifts in curricular emphasis relative to the labor market — whether universities are moving toward or away from skills in growing demand — rather than the full magnitude of skill acquisition. That the score registers systematic, positive movement even within narrowly defined fields is notable precisely because most of what universities teach within a field is foundational and appropriately stable: Intermediate Microeconomics and Organic Chemistry do not and should not change substantially from year to year. The finding is not that universities have dramatically reoriented their curricula, but that the margin of adjustment they do exercise, new course creation, is systematically directed toward the labor market frontier.

To assess the sources of rising alignment, I decompose total growth in labor market alignment between 2010-11 and 2022-23 into components due to within-course description updates, shifts in enrollment across continuing courses (between), course exits, and new course, following Foster et al. (2001). Table 4 summarizes the decomposition results.

The decomposition reveals that rising alignment is overwhelmingly driven by new course entry, which accounts for more than 85% of the total change. Shifts in enrollment across continuing courses contribute modestly but decline in importance over time, as continuing courses represent a shrinking share of course offerings. Newly introduced courses exhibit substantially higher alignment than incumbent courses, while updates to existing course descriptions contribute little.[42] Although infrequent description revisions may attenuate the within-course component, the magnitude is small even relative to the alignment gap between new and continuing courses, indicating that curricular updating occurs primarily through entry rather than revision.

Discontinued courses tend to be more labor market-aligned at baseline than those that persist. One interpretation is that durable, upper-level core courses (e.g., Intermediate Microeconomics) are less tied to current labor market trends but are more likely to remain in the catalog, while shorter-lived electives more closely follow the frontier of emerging skills yet are retired sooner. Alternatively, courses oriented toward new technologies or specialized skills may simply be more “fad-driven,” leading to higher exit rates despite initially strong alignment. Both interpretations underscore that responsiveness is concentrated at the entry margin: durable courses are stable but slow to evolve, while innovative courses may be more

[42] The intuition is that a course’s core focus typically remains stable when its description changes: Labor Economics remains Labor Economics, even if specific topics evolve. The alignment measure captures this core orientation rather than incremental topic shifts. To reflect a major reorientation — for example, transforming Labor Economics into a course focused on health sector labor demand — an instructor would likely create a new course altogether.

transient.

Course descriptions may understate true adaptation if content changes precede catalog updates, potentially biasing short-run within-course estimates downward.[43] Studying trends over a long time horizon mitigates this concern but does not eliminate it if course descriptions are never updated. Two robustness exercises address the concern that infrequent updating of course descriptions understates within-course adaptation. First, I construct an upper bound on the within-course component of alignment growth by imputing alignment gains to all continuously offered courses that did not update their descriptions, assuming each changed by as much as the average course that did update. Under this assumption, the within-course component rises from approximately 1% to 10% of total alignment growth, while the total change increases by only 7% (Appendix Table A-15). Even under the most generous assumptions about unmeasured within-course adaptation, entry accounts for the vast majority of alignment growth. Second, I split institutions by the share of continuously offered courses whose descriptions changed between 2010-11 and 2022-23 and re-estimate alignment trends separately for high- and low-update institutions.[44] Alignment trends are similar across the two groups (Appendix Figure A-19). These results indicate that description staleness neither drives the aggregate trends nor confounds the cross-institutional comparisons.

Taken together, these results indicate that universities meet students' demand for courses oriented towards areas of growth in the labor market not only in the scale of their offerings but also in the content of what they teach. The centrality of course entry in driving alignment underscores the importance of curricular innovation: institutions respond to labor market changes primarily by creating new courses that reflect emerging skills rather than by revising existing ones.

5.3 Heterogeneity

Having established that rising labor market alignment is driven primarily by new course entry, I next analyze how this adaptation varies across institutions. Figure 4 shows heterogeneity in the growth of labor market alignment across universities grouped by research intensity, institutional control, selectivity, size, and tenure share. For each characteristic, I estimate course-level regressions of alignment on a linear time trend interacted with indicators for institutional type, controlling for institution-by-field fixed effects to isolate within-field curricular updating. The interpretation of each point is the difference in average annual

[43] Descriptions are also brief and stylized, capturing the framing of a course; if instructors adapt more flexibly in practice, the estimates again understate responsiveness. While this limits examination of the course's full content, the description is nevertheless valuable as the information students use to select courses.

[44] The propensity to update descriptions is uncorrelated with the institutional characteristics used in the heterogeneity analysis.

increases in labor market alignment for courses offered at institutions sharing a given characteristic, relative to universities sharing the reference characteristic, shown at the left of each panel.

The most pronounced differences emerge by research intensity and selectivity. Courses offered at R1 universities exhibit the fastest growth in labor market alignment, while alignment rises more slowly at R2 institutions and liberal arts colleges. Private and selective universities also update course content more rapidly than public and less selective institutions. By contrast, alignment grows most slowly at the largest institutions in the sample.

These patterns closely mirror the extensive margin heterogeneity documented in Section 4.5. Institutions that expand course offerings most elastically in response to growing enrollment — research-intensive, private, and selective universities — are also those whose curricula shift most toward skills associated with growing occupations. By contrast, institutions that adjust primarily through section quantity rather than course creation exhibit slower growth in alignment, consistent with within-course changes and consolidation being weaker mechanisms for curricular adaptation than entry.

The concentration of curricular innovation at research-intensive and selective institutions offers insight into the education production process itself. These institutions combine stronger student preparation with faculty who are more likely to be engaged with the research frontier, suggesting complementarities between advanced students and research-active instructors whose scholarship connects them to the frontier of their fields. Universities with both stronger student preparation and faculty engaged in current research appear best positioned to translate labor market shifts into course content, linking evolving conditions in the economy to classroom instruction more than institutions with fewer such resources. Together with the extensive margin results, these findings suggest that institutional capacity and governance shape not only how much universities teach, but also to what extent they update what they teach in response to a changing economy.

5.4 Discussion

The intensive margin results reinforce and deepen the extensive margin findings. Section 4 establishes that course creation is the primary adjustment channel; this section shows that the courses created disproportionately incorporate skills associated with expanding occupations. Together, the two analyses reveal that when universities do adjust, gradually and inelastically, the adjustment is directionally aligned with the labor market.

A striking additional feature is that the same institutional characteristics predict responsiveness along both margins. Figure 2 documents that research-intensive, selective, and private universities exhibit the highest course elasticities when enrollment is rising. Figure

4 shows that these same institutions exhibit the fastest growth in labor market alignment of course content. This convergence — the institutions that create the most new courses in growing fields also create courses whose content is most closely aligned with expanding occupations — suggests that a common set of institutional characteristics drives responsiveness along both the scale and content margins.

Several features plausibly explain this pattern. Research-intensive universities employ faculty whose scholarship connects them to the academic frontier, reducing the preparation costs of creating courses that incorporate emerging methods and topics. Selective institutions enroll students with stronger baseline preparation, expanding the set of advanced courses that are pedagogically viable and that students can productively absorb. Private institutions face fewer layers of curricular governance and may respond more nimbly to market signals. In each case, the same institutional characteristic that lowers the cost of expanding the number of courses — faculty expertise, student preparation, governance flexibility — also lowers the cost of ensuring that new courses reflect current labor market demand.

The converse is equally informative. Public, teaching-focused, and less selective institutions — those that adjust primarily through section expansion and contract most sharply when demand falls — also exhibit the slowest growth in curricular alignment. At these institutions, adjustment operates through a narrower set of channels: repeating or enlarging existing courses rather than introducing new ones. Because content adaptation occurs primarily through course entry rather than revision of continuing courses (Table 4), institutions that rely on section-level adjustment rather than course creation mechanically limit their capacity for curricular updating. The result is a divergence not only in the quantity of instruction across institution types, but in the rate at which instructional content tracks the evolving labor market, with implications for the distribution of access to emerging skills across students who attend different types of institutions.

6 Conclusion

This paper studies how universities adjust the scale and content of instruction in response to changing student demand. Using a new dataset that tracks course offerings and enrollments at U.S. universities over more than two decades, I document responsiveness along two margins: the extensive margin, through changes in the number of courses and sections, and the intensive margin, through changes in course content linked to labor market trends. Across both margins, adjustment is gradual and heterogeneous. Universities expand offerings and update curricula when demand rises, but contract far less when demand falls. New course creation, rather than revisions to existing courses, is the primary channel of curricular change, and responsiveness varies systematically across institutions. Research-intensive, selective, and private universities expand course offerings more elastically, while public and teaching-focused institutions rely primarily on smaller adjustments in section quantity.

These patterns reveal how institutional structure shapes the economy's capacity to generate and diffuse new skills. Course supply responds positively but less than one-for-one to demand, so students' ability to reallocate across fields exceeds universities' willingness or capacity to reallocate instructional capacity. As a result, demand shocks only partially translate into new instructional offerings. Because curricular updating occurs primarily through new course entry, adaptation depends on institutions' ability to invest in faculty expertise, curricular development, and students prepared for advanced coursework. These requirements help explain why responsiveness is highest where resources and discretion are greatest, and lowest where governance constraints, regulation, or tight budgets limit adjustment.

Interpreting these elasticities normatively requires caution. Inelastic supply imposes costs when students are rationed out of high-demand fields or taught content that lags behind labor market demand. At the same time, one-for-one adjustment would likely be inefficient: stability in course offerings preserves disciplinary continuity, mitigates overreaction to transitory shocks, and reflects frictions in the production of instructors and new courses that require upfront investments and time to amortize. The socially optimal elasticity of instructional supply likely lies between these extremes. Back-of-the-envelope calculations suggest that rationing in high-demand fields modestly reduced completions in Computer Science and Engineering while substantially increasing class sizes, illustrating that these frictions have meaningful consequences for the production of skilled labor.

From a policy perspective, the results underscore that higher education's responsiveness to economic change is mediated by institutional structure. Public and teaching-intensive universities — those that contract more sharply and expand less — face different constraints than research universities, implying that uniform policy interventions are unlikely to be effective. Funding incentives or accountability systems that encourage curricular innovation in fast-growing fields may accelerate adjustment, but must account for institutional heterogeneity. For university administrators, estimates of course supply elasticity provide a diagnostic tool for identifying where capacity constraints bind and where investments in new courses yield the greatest returns. More broadly, the evidence reframes universities not as passive transmitters of student demand, but as active, and sometimes constrained, producers of the economy's adaptive capacity. Their frictions and asymmetries shape how quickly new skills diffuse through the workforce, with implications for both technological adoption and the distribution of opportunity across institutions.

Works cited

Acton, Riley K (2021). "Community college program choices in the wake of local job losses". In: *Journal of Labor Economics* 39.4, pp. 1129–1154.

Ahn, Thomas et al. (2019). *Equilibrium grade inflation with implications for female interest in stem majors*. Tech. rep. National Bureau of Economic Research.

Altonji, Joseph G, Peter Arcidiacono, and Arnaud Maurel (2016). "The analysis of field choice in college and graduate school: Determinants and wage effects". In: *Handbook of the Economics of Education*. Vol. 5. Elsevier, pp. 305–396.

Altonji, Joseph G, Erica Blom, and Costas Meghir (2012). "Heterogeneity in human capital investments: High school curriculum, college major, and careers". In.

Andrews, Michael and Yiling Zhao (2024). "Home Economics and Women's Gateway to Science". In: *Available at SSRN 4708155*.

Autor, David and Neil Thompson (2025). "Expertise". In: *Journal of the European Economic Association*, jvaf023.

Autor, David H, Frank Levy, and Richard J Murnane (2003). "The skill content of recent technological change: An empirical exploration". In: *The Quarterly journal of economics* 118.4, pp. 1279–1333.

Bald, Anthony (2025). *The Birth of an Occupation: Professional Nursing in the Era of Public Health*. Tech. rep. Center for Open Science.

Barr, Andrew and Sarah E Turner (2013). "Expanding enrollments and contracting state budgets: The effect of the Great Recession on higher education". In: *The ANNALS of the American Academy of Political and Social Science* 650.1, pp. 168–193.

Beffy, Magali, Denis Fougere, and Arnaud Maurel (2012). "Choosing the field of study in postsecondary education: Do expected earnings matter?" In: *Review of Economics and Statistics* 94.1, pp. 334–347.

Biasi, Barbara and Song Ma (2025). *Frontier knowledge in college student success*. Tech. rep. National Bureau of Economic Research.

Bleemer, Zachary and Aashish Mehta (2021). "College Major Restrictions and Student Stratification. Research & Occasional Paper Series: CSHE. 14.2021." In: *Center for Studies in Higher Education*.

— (2022). "Will studying economics make you rich? A regression discontinuity analysis of the returns to college major". In: *American Economic Journal: Applied Economics* 14.2, pp. 1–22.

Blom, Erica, Brian C Cadena, and Benjamin J Keys (2021). "Investment over the business cycle: Insights from college major choice". In: *Journal of Labor Economics* 39.4, pp. 1043–1082.

Borusyak, Kirill, Peter Hull, and Xavier Jaravel (2022). "Quasi-experimental shift-share research designs". In: *The Review of Economic Studies* 89.1, pp. 181–213.

Bound, John, Michael F Lovenheim, and Sarah Turner (2010). "Why have college completion rates declined? An analysis of changing student preparation and collegiate resources". In: *American Economic Journal: Applied Economics* 2.3, pp. 129–57.

Bound, John and Sarah Turner (2007). "Cohort crowding: How resources affect collegiate attainment". In: *Journal of public Economics* 91.5-6, pp. 877–899.

Chau, Hung et al. (2023). "Connecting higher education to workplace activities and earnings". In: *Plos one* 18.3, e0282323.
Conzelmann, Johnathan G et al. (2022). *Grads on the go: Measuring college-specific labor markets for graduates*. Tech. rep. National Bureau of Economic Research.
— (2023). *Skills, Majors, and Jobs: Does Higher Education Respond?* Tech. rep. National Bureau of Economic Research.
Courant, Paul N and Sarah Turner (2017). *Faculty deployment in research universities*. Tech. rep. National Bureau of Economic Research.
Deming, David J, Claudia Goldin, and Lawrence F Katz (2012). "The for-profit postsecondary school sector: Nimble critters or agile predators?" In: *Journal of Economic Perspectives* 26.1, pp. 139–164.
Deming, David J and Christopher R Walters (2017). *The impact of price caps and spending cuts on US postsecondary attainment*. Tech. rep. National Bureau of Economic Research.
Denning, Jeffrey T et al. (2022). "Why have college completion rates increased?" In: *American Economic Journal: Applied Economics* 14.3, pp. 1–29.
Eggenberger, Christian, Miriam Rinawi, and Uschi Backes-Gellner (2018). "Occupational specificity: A new measurement based on training curricula and its effect on labor market outcomes". In: *Labour Economics* 51, pp. 97–107.
Ehrenberg, Ronald G (2009). "Tuition rising: Why college costs so much, with a new preface". In: *Tuition Rising*. Harvard University Press.
Foster, Lucia, John C Haltiwanger, and Cornell John Krizan (2001). "Aggregate productivity growth: lessons from microeconomic evidence". In: *New developments in productivity analysis*. University of Chicago Press, pp. 303–372.
Freeman, Richard B (1976). "A cobweb model of the supply and starting salary of new engineers". In: *ILR Review* 29.2, pp. 236–248.
Gentzkow, Matthew, Bryan Kelly, and Matt Taddy (2019). "Text as data". In: *Journal of Economic Literature* 57.3, pp. 535–574.
Gilpin, Gregory A, Joseph Saunders, and Christiana Stoddard (2015). "Why has for-profit colleges' share of higher education expanded so rapidly? Estimating the responsiveness to labor market changes". In: *Economics of Education Review* 45, pp. 53–63.
Goldsmith-Pinkham, Paul, Isaac Sorkin, and Henry Swift (2020). "Bartik instruments: What, when, why, and how". In: *American Economic Review* 110.8, pp. 2586–2624.
Hamermesh, Daniel S and Gerard A Pfann (1996). "Adjustment costs in factor demand". In: *Journal of Economic literature* 34.3, pp. 1264–1292.
Hemelt, Steven W et al. (2021). "Why is math cheaper than English? Understanding cost differences in higher education". In: *Journal of Labor Economics* 39.2, pp. 397–435.
Hershbein, Brad and Lisa B Kahn (2018). "Do recessions accelerate routine-biased technological change? Evidence from vacancy postings". In: *American Economic Review* 108.7, pp. 1737–72.
Hoxby, Caroline M (2012). *Endowment management based on a positive model of the university*. Tech. rep. National Bureau of Economic Research.
Johnson, William R and Sarah Turner (2009). "Faculty without students: Resource allocation in higher education". In: *Journal of Economic Perspectives* 23.2, pp. 169–189.
Long, Mark C, Dan Goldhaber, and Nick Huntington-Klein (2015). "Do completed college majors respond to changes in wages?" In: *Economics of Education Review* 49, pp. 1–14.

Mumford, Kevin J, Richard Patterson, and Anthony Yim (2024). *College Course Shutouts*. Tech. rep. IZA Discussion Papers.

Patnaik, Arpita, Matthew Wiswall, and Basit Zafar (2021). "College majors 1". In: *The Routledge handbook of the economics of education*, pp. 415–457.

Romer, Paul M (1990). "Endogenous technological change". In: *Journal of political Economy* 98.5, Part 2, S71–S102.

Ruggles, Steven et al. (2023). "IPUMS USA: Version 13.0 [dataset]." In: URL: https://doi.org/10.18128/D010.V13.0.

Stinebrickner, Ralph and Todd R Stinebrickner (2014). "A major in science? Initial beliefs and final outcomes for college major and dropout". In: *Review of Economic Studies* 81.1, pp. 426–472.

Thomas, James (2024). "What do course offerings imply about university preferences?" In: *Journal of Labor Economics* 42.1, pp. 53–83.

Truffa, Francesca and Ashley Wong (2024). "Undergraduate Gender Diversity and the Direction of Scientific Research". In.

Weinstein, Russell (2020). "Local labor markets and human capital investments". In: *Journal of Human Resources*, 1119–10566R2.

Wiswall, Matthew and Basit Zafar (2015). "Determinants of college major choice: Identification using an information experiment". In: *The Review of Economic Studies* 82.2, pp. 791–824.

Zafar, Basit (2011). "How do college students form expectations?" In: *Journal of Labor Economics* 29.2, pp. 301–348.

Table 1. Characteristics of course catalog sample

4 year institutions

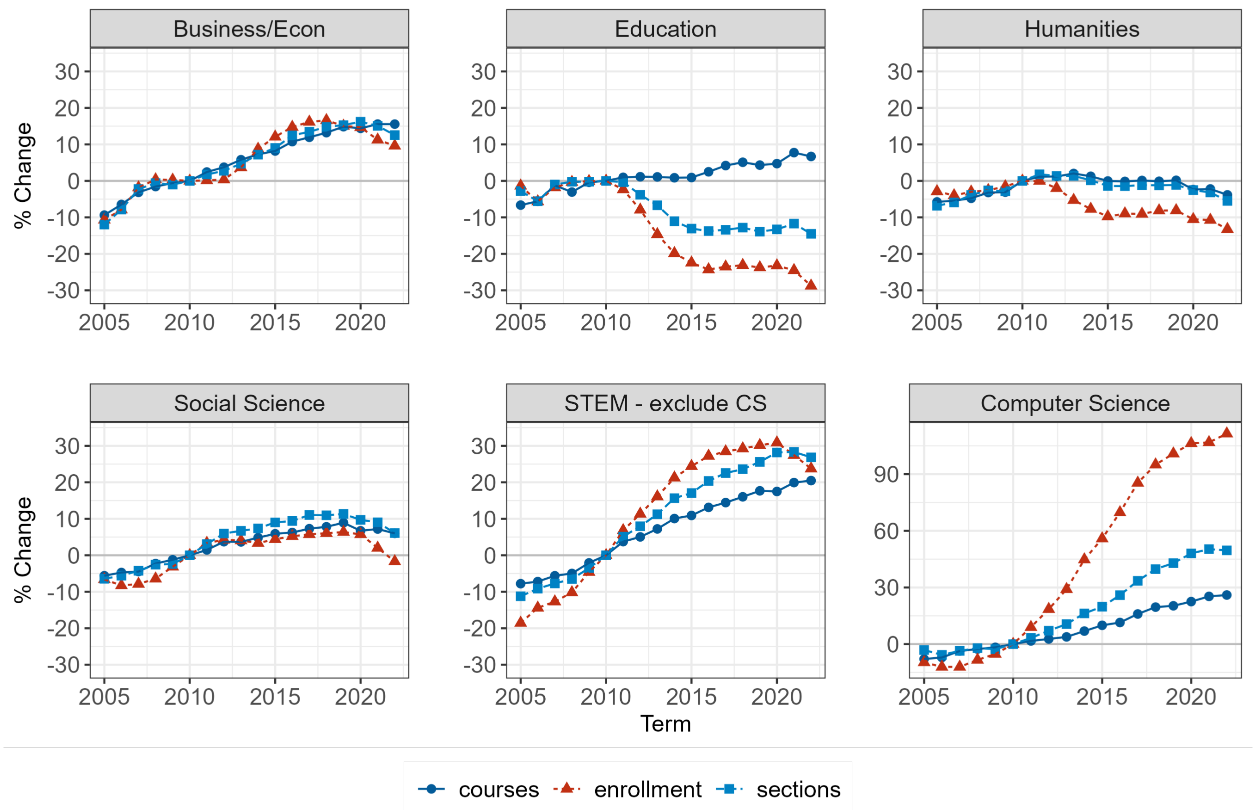
	Population		Catalog Sample		Enrollment Sample	
	mean	sd	mean	sd	mean	sd
Enrollment	4,912	20,330	8,686	20,337	8,505	21,716
Public share	72.48	44.66	79.48	40.39	79.97	40.03
Average tuition	16,774	15,370	15,985	15,029	15,776	15,135
Average price	16,786	8,455	16,778	7,860	16,755	7,742
Admit rate	71.99	22.54	72.27	23.44	73.20	23.36
Tenure share	51.45	19.29	53.14	16.17	52.83	17.40
Student-faculty ratio	17.43	5.40	17.69	4.70	17.51	4.46
6-year graduation rate	59.54	19.62	60.96	19.11	59.63	19.89
Endowment per student	58,785	215,681	73,156	276,765	67,427	254,968
Tuition % of revenue	34.12	19.83	32.33	17.50	32.13	17.57
Research % of spending	8.77	11.96	10.47	13.18	10.54	13.58
N	1,972		620		481	

2 year institutions

	Population		Catalog Sample		Enrollment Sample	
	mean	sd	mean	sd	mean	sd
Enrollment	5,194	16,543	6,730	18,211	6,047	7,945
Public share	99.34	8.11	100	0.00	100	0.00
Average tuition	3,495	1,978	3,273	1,573	3,204	1,584
Average price	7,973	3,079	7,819	2,745	7,831	2,917
Student-faculty ratio	19.29	5.38	19.31	4.80	19.25	5.11
N	933		398		369	

Notes: Institution characteristics from IPEDS for the 2022-23 academic year. Only non-profit, Title IV-eligible, degree-granting institutions are included. Values except for undergraduate enrollment are weighted by enrollment. Averages exclude missing values. The "Catalog Sample" includes all institutions in the sample. The "Enrollment Sample" includes those with course-level enrollment data.

Figure 1. Trends in course enrollment and quantity: comparison to 2010-11



Notes: This figure plots the relative growth trends in course enrollment, course quantity, and section quantity across six aggregated field categories. Enrollment and course quantity for each institution and field category are indexed to their respective levels in the academic year 2010-11. The plotted points represent the average of these indexed values, averaged across all institutions in the sample. The figure restricts to upper-level courses offered at institutions with that first appear in the catalog data in 2010-11 or earlier.

Table 2. Course and section quantity elasticity estimates

	% change courses					% change sections				
	Rolling differences			Single period (2010-18)		Rolling differences			Single period (2010-18)	
	2-year	4-year	8-year	OLS	IV	2-year	4-year	8-year	OLS	IV
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
% enrollment change										
overall	0.199	0.291	0.350	0.292	0.293	0.369	0.560	0.666	0.611	0.612
	(0.029)	(0.019)	(0.018)	(0.051)	(0.048)	(0.036)	(0.028)	(0.021)	(0.059)	(0.037)
field	0.206	0.318	0.393	0.385	0.211	0.305	0.489	0.593	0.588	0.526
	(0.010)	(0.010)	(0.009)	(0.022)	(0.052)	(0.012)	(0.013)	(0.010)	(0.022)	(0.036)
First Stage F-stat					108.5					108.5
Observations	94,291	78,570	50,825	4,014	4,014	94,291	78,570	50,825	4,014	4,014
R^2	0.067	0.182	0.318	0.320	0.265	0.129	0.341	0.544	0.558	0.553

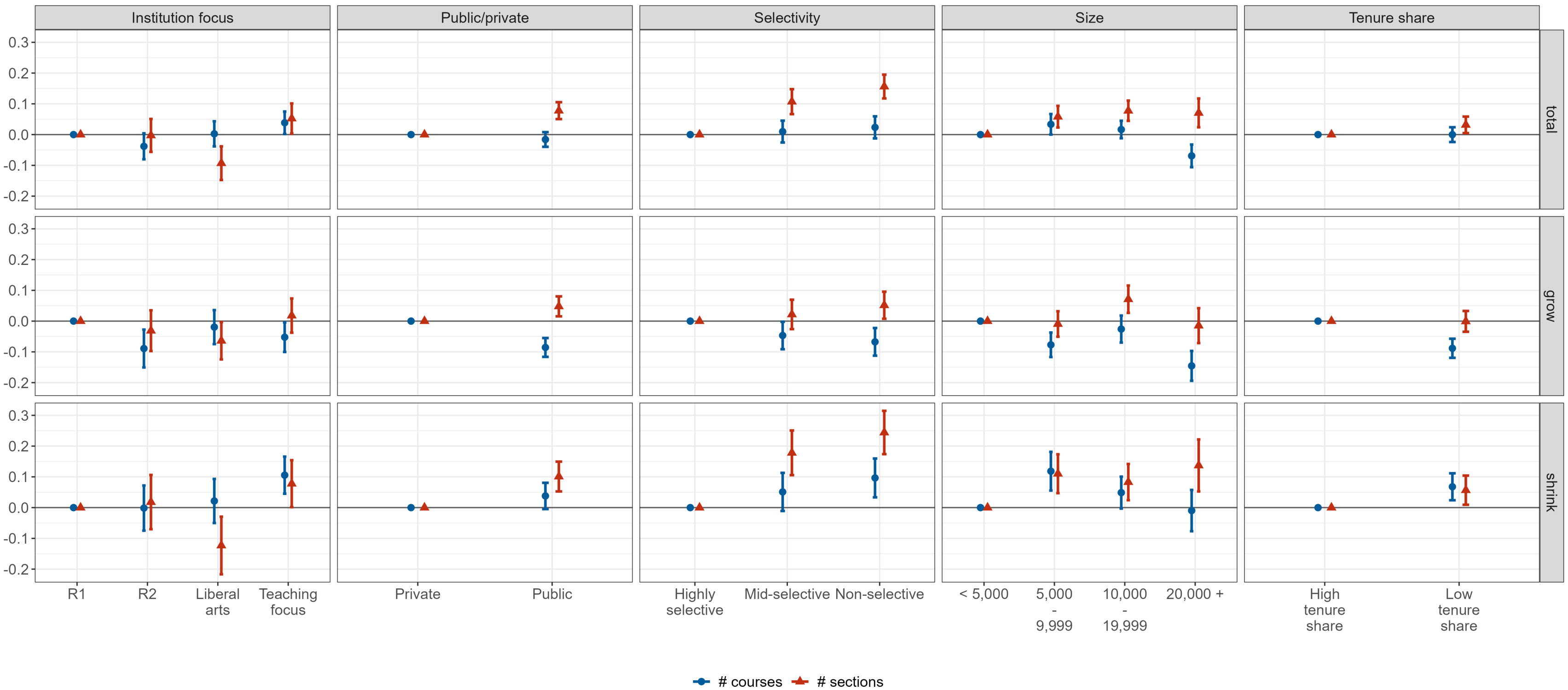
Notes: Observations are at the institution-field-period level, where a period is a pair of comparison years differenced to measure percent changes. The analysis regresses change in upper-level course or section quantity on change in enrollment, each represented as long log differences. Quantity and enrollment are credit-hour weighted. Each institution receives equal weight; within each institution, fields are weighted by start-of-period enrollment. Columns 1-5 estimate course quantity elasticities; Columns 6-10 estimate section quantity elasticities. Columns 1-3 and 6-8 measure changes in course/section quantity and enrollment using long log differences for course enrollment and sections from all years in the course catalog dataset. Observations in these columns use overlapping periods (e.g. 2010-2014, 2011-2015). Standard errors in these columns are clustered at the institution-by-period level. In Columns 4-5 and 9-10, each observation is an eight-year long-log difference at the institution-field level for the 2010-2018 period, which is the focus of the IV analysis. For the IV estimates, standard errors are clustered at the field-by-Census division level, which is the level of variation for the instrument. Significance stars are suppressed because the relevant benchmark is not necessarily zero.

Table 3. Asymmetric course and section quantity elasticity estimates

	% change courses					% change sections				
	Rolling differences			Single period (2010-18)		Rolling differences			Single period (2010-18)	
	2-year	4-year	8-year	OLS	IV	2-year	4-year	8-year	OLS	IV
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
% enrollment change										
overall	0.197	0.290	0.354	0.300	0.295	0.367	0.559	0.669	0.618	0.612
	(0.029)	(0.018)	(0.018)	(0.055)	(0.049)	(0.037)	(0.028)	(0.021)	(0.059)	(0.038)
growing	0.195	0.314	0.409	0.427	0.341	0.297	0.485	0.606	0.627	0.543
	(0.009)	(0.010)	(0.012)	(0.030)	(0.066)	(0.012)	(0.012)	(0.012)	(0.029)	(0.061)
shrinking	0.213	0.321	0.381	0.353	0.098	0.310	0.492	0.582	0.558	0.511
	(0.016)	(0.018)	(0.016)	(0.032)	(0.082)	(0.017)	(0.019)	(0.015)	(0.032)	(0.059)
First stage F-stat					57					57
p-value grow = shrink	0.337	0.737	0.222	0.097	0.022	0.512	0.773	0.225	0.119	0.721
Observations	94,291	78,570	50,825	4,014	4,014	94,291	78,570	50,825	4,014	4,014
R^2	0.067	0.182	0.319	0.322	0.062	0.129	0.341	0.544	0.559	0.177

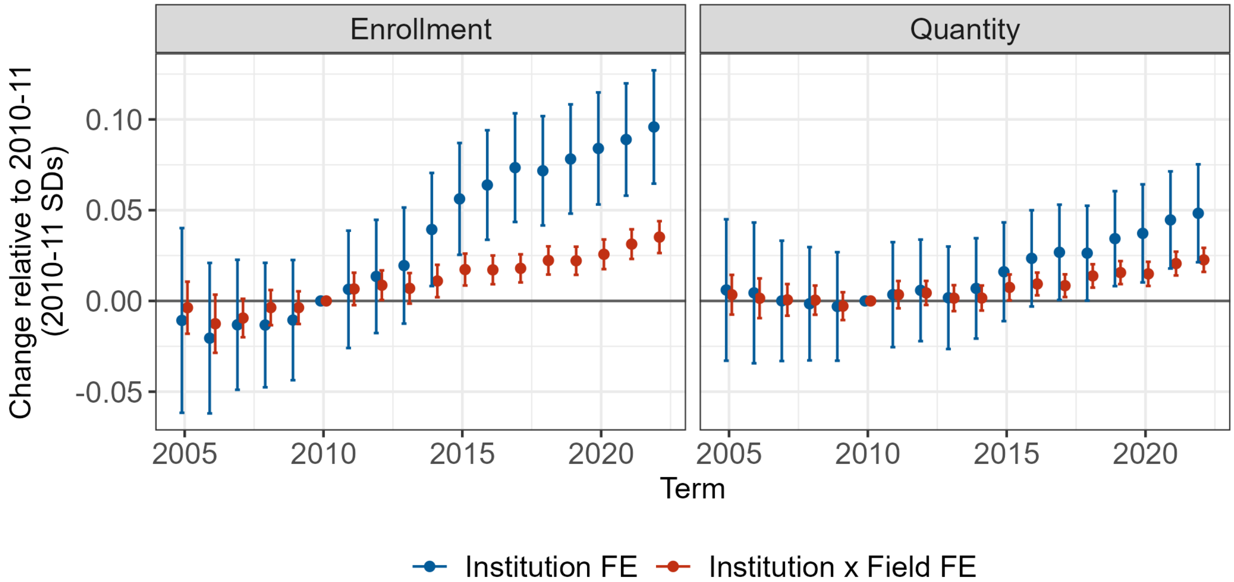
Notes: Observations are at the institution-field-period level, where a period is a pair of comparison years differenced to measure percent changes. The analysis regresses change in upper-level course or section quantity on change in enrollment, each represented as long log differences. Quantity and enrollment are credit-hour weighted. Each institution receives equal weight; within each institution, fields are weighted by start-of-period enrollment. Columns 1-5 estimate course quantity elasticities; Columns 6-10 estimate section quantity elasticities. Columns 1-3 and 6-8 measure changes in course/section quantity and enrollment using long log differences for course enrollment and sections from all years in the course catalog dataset. Observations in these columns use overlapping periods (e.g. 2010-2014, 2011-2015). Standard errors in these columns are clustered at the institution-by-period level. In Columns 4-5 and 9-10, each observation is an eight-year long-log difference at the institution-field level for the 2010-2018 period, which is the focus of the IV analysis. For the IV estimates, bootstrapped standard errors are calculated using $1,000$ repetitions of the estimation, resampling region-by-field clusters in each iteration, and standard errors are clustered at the field-by-Census division level, which is the level of variation for the instrument. Significance stars are suppressed because the relevant benchmark is not necessarily zero.

Figure 2. Heterogeneity in course and section quantity elasticity by institution category



Notes: This figure compares course and section quantity elasticities across institution types. Each panel plots coefficients from regressions interacting relative enrollment changes with institution characteristics; the leftmost category in each panel is the omitted group. Each column plots estimates from two separate regressions. The top row shows estimates from linear interaction models, while the bottom panels report results from a single specification distinguishing fields growing faster or slower than the institution average. Elasticities are estimated over eight-year periods with a one-year offset. Observations are at the institution-field-term level, and standard errors are clustered by institution-term.

Figure 3. Change in labor market alignment



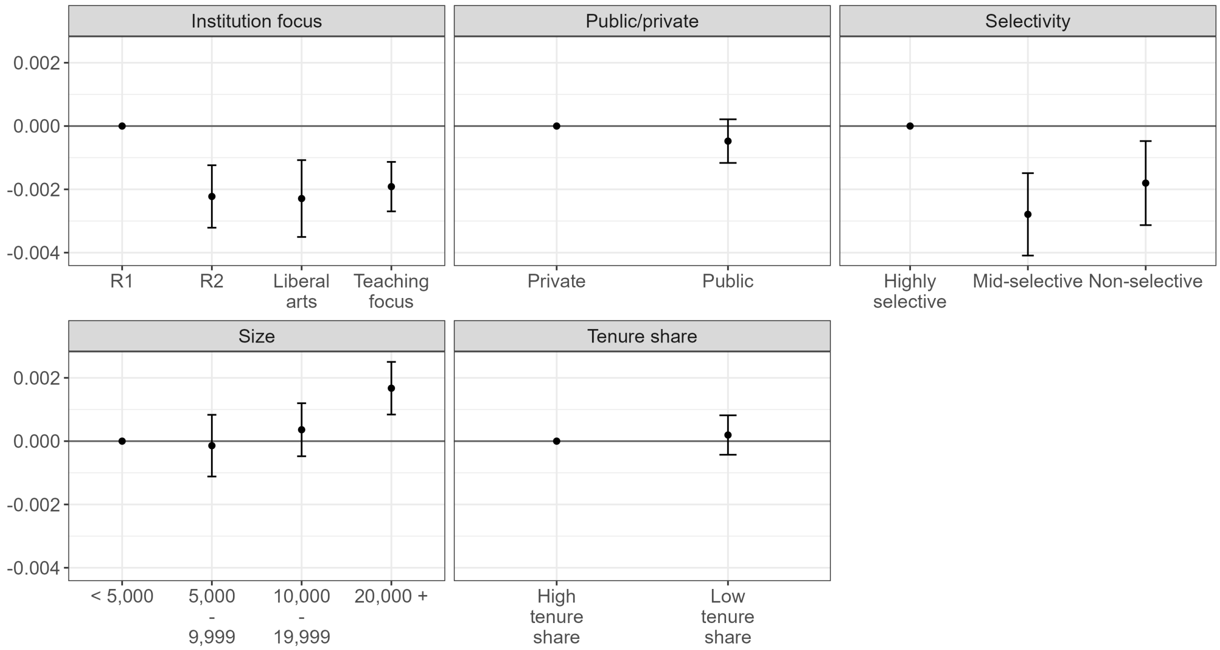
Notes: The figure plots the trend in labor market alignment for courses offered between 2005-06 and 2022-23, measured in standard deviations of the labor market alignment distribution for courses in 2010-11. Estimates come from course-level regressions of labor market alignment on academic-year dummies, controlling for institution (blue) and institution-by-field (red) fixed effects. In each regression, each institution-year receives identical weight; within institution-year, weight is apportioned equally across courses in the right panel and in proportion to enrollment in the left panel. Standard errors are larger in the institution-FE specification because alignment varies much more across fields than within fields; controlling for institution-by-field fixed effects absorbs this cross-field variation that comes primarily from shifts in the field composition of course offerings and reduces residual dispersion. Standard errors are clustered at the institution-field-year level. Analysis restricts to upper-level courses.

Table 4. Labor market alignment change decomposition

Year (1)	Within (2)	Between (3)	Exit (4)	Entry (5)	Total (6)
2011-2012	-0.0015	0.0029	-0.0025	0.0069	0.0058
2012-2013	-0.0001	0.0050	-0.0016	0.0052	0.0085
2013-2014	-0.0021	0.0070	-0.0007	0.0069	0.0111
2014-2015	-0.0017	0.0084	-0.0017	0.0106	0.0156
2015-2016	0.0002	0.0065	-0.0008	0.0135	0.0194
2016-2017	-0.0006	0.0085	0.0001	0.0129	0.0209
2017-2018	-0.0035	0.0068	-0.0010	0.0140	0.0163
2018-2019	-0.0028	0.0078	-0.0008	0.0154	0.0197
2019-2020	-0.0035	0.0044	-0.0004	0.0160	0.0165
2020-2021	-0.0003	0.0032	-0.0026	0.0126	0.0130
2021-2022	-0.0007	0.0079	-0.0035	0.0205	0.0242
2022-2023	0.0002	0.0070	-0.0042	0.0196	0.0225

Notes: The table decomposes the overall average change in labor market alignment (Column 6) using a Foster et al. (2001) decomposition. "Within" captures changes arising from changing course descriptions for continuously offered courses; "between" captures changes from enrollment shifts between continuously offered courses; "exit" captures changes from courses offered in 2010-11 but not offered in the referenced year; and "entry" captures changes from courses not offered in 2010-11 but offered in the referenced year. The decomposition is calculated at the institution-reference year level for each institution. Totals in this table are a simple average across institutions within each year. Restrict to upper-level courses and institutions with course descriptions and enrollments covering the full period 2010-11 to 2022-23.

Figure 4. Heterogeneity in labor market alignment by institution type



Notes: Each panel estimates a course-level regression of labor market alignment on a linear academic year term and academic year-characteristic interaction terms, omitting the leftmost category, controlling for institution-by-field fixed effects. Estimates capture the difference in annual average change in labor market alignment compared to the omitted category. Observations at the course level. Each institution-year receives equal weight in the regression; within institution-year, each course receives equal weight. Restrict to upper-level courses. Standard errors clustered at the institution-field-term level.

For online appendix

A Model of course supply in higher education

This appendix formalizes the interpretation of the supply elasticities described in Section 2 and estimated in Section 4, and derives predictions about margin ordering, asymmetry, and the mapping between estimated elasticities and underlying institutional parameters.

A.1 Setup and notation

Universities $i \in \mathcal{I}$ supply instruction in fields $s \in \mathcal{S}$ over discrete periods t. The supply of seats in field s at institution i in period t can be decomposed as:

$$S_{i,s,t} = C_{i,s,t} \cdot Sec_{i,s,t} \cdot q_{i,s,t} \tag{10}$$

where $C_{i,s,t}$ is the number of distinct courses, $Sec_{i,s,t}$ is the average number of sections per course, and $q_{i,s,t}$ is the average number of seats per section.

Students have latent demand $D_{i,s,t}$ for seats in field s. Latent demand for courses is influenced by the expected return on course characteristics in the labor market (e.g., wages, employment growth), tastes that are unrelated to the labor market (e.g., preferences for topics tied to the political or cultural zeitgeist, pure consumption value of courses), and institution-level policies (e.g., distribution requirements).[1]

Observed enrollment satisfies $E_{i,s,t} \leq \min\{D_{i,s,t}, S_{i,s,t}\}$, with enrollment falling below latent demand when capacity constraints bind.[2]

Each instructional margin has a frictionless optimum $m^*_{i,s,t}(D_{i,s,t})$ for $m \in \{C, Sec, q\}$ that the university would choose absent adjustment costs, given its objective over enrollment, curricular breadth, and instructional costs. I do not specify the university's objective function in full; rather, I take as given that such an optimum exists and that it is weakly increasing in latent demand.[3]

[1]In principle, the model presented in this section could apply to characterize university responses to any of these components of latent demand. The parameter $\beta^m_{i,s}$, which captures the university's frictionless optimal adjustment to some change in student demand, may vary by the type of demand shock. For example, universities may prefer to respond more to labor market-driven demand shocks than demand shocks arising from cultural fads.

[2]In practice, rationing is not all-or-nothing: students may be partially accommodated through waitlists, substitution across sections, or enrollment in related fields. The inequality captures the key economic content — that enrollment understates demand in constrained fields — without imposing a knife-edge equilibrium condition.

[3]The university's objective is not well defined in the sense that universities balance instruction, research, and institutional mission with weights that vary across institutions and are not directly observed. The partial adjustment framework requires only that a desired level of instructional capacity exists for each margin.

A.2 Partial adjustment

In practice, instructional capacity adjusts gradually. Creating or eliminating courses requires faculty expertise, curricular approval, and catalog development; adding or removing sections requires staffing and scheduling changes; adjusting class sizes affects instructional quality. Following the standard partial adjustment framework (e.g., Hamermesh and Pfann 1996), I assume that each margin adjusts toward its frictionless[4] optimum at a rate that reflects the cost of adjustment relative to the cost of being away from the optimum:

$$m_{i,s,t} - m_{i,s,t-1} = \lambda_{i,s}^{m}\left(m_{i,s,t}^{*} - m_{i,s,t-1}\right) \tag{11}$$

where $0 < \lambda_{i,s}^{m} < 1$ is the adjustment speed for margin m. This law of motion can be derived from a dynamic optimization problem with quadratic adjustment costs, where the university maximizes the discounted sum of per-period payoffs net of costs that are quadratic in changes to each margin.[5] When $\lambda_{i,s}^{m} = 1$, the margin adjusts fully each period; when $\lambda_{i,s}^{m}$ is close to zero, the margin is nearly fixed.

Suppose the frictionless optimum satisfies a constant-elasticity relationship with latent demand:

$$\log m_{i,s,t}^{*} = \beta_{i,s}^{m} \log D_{i,s,t} + \mathrm{K} \tag{12}$$

where $\beta_{i,s}^{m}$ is the static elasticity — the responsiveness of the frictionless optimum to demand. Combining (11) and (12) via a first-order log approximation yields:

$$\Delta \log m_{i,s,t} = \eta_{i,s}^{m}\, \Delta \log D_{i,s,t} \tag{13}$$

where

$$\eta_{i,s}^{m} = \lambda_{i,s}^{m}\, \beta_{i,s}^{m} \tag{14}$$

is the demand-mediated elasticity: the observed responsiveness of instructional capacity to exogenous changes in latent demand. This is the object the empirical analysis recovers.

A low estimated η could reflect either low static responsiveness (β is small because universities would not adjust much even without frictions) or high adjustment costs (λ is small

[4]By frictionless, I mean in the absence of adjustment costs. In practice, some frictions (e.g., in instructor labor supply) produce inelasticity but are essential to the operation of the university. Others (e.g., rent-seeking by faculty arising from self-governance) may be genuinely inefficient from both the student and institution's perspectives.

[5]Specifically, if per-period payoffs are approximated as quadratic around the static optimum with curvature $a_{i,s}^{m}$, and adjustment costs are $\kappa_{i,s}^{m}(m_{i,s,t} - m_{i,s,t-1})^2$, then $\lambda_{i,s}^{m} = a_{i,s}^{m}/(a_{i,s}^{m} + 2\kappa_{i,s}^{m})$. Larger adjustment costs $\kappa_{i,s}^{m}$ imply slower adjustment.

because frictions slow the response).

A.3 Implications

The framework generates three implications that the empirical analysis evaluates.

Margin ordering: If course creation involves larger adjustment costs than section changes, and section changes are costlier than seat adjustments ($\kappa_{i,s}^{C} > \kappa_{i,s}^{Sec} > \kappa_{i,s}^{q}$) then, as long as the static elasticities are not ordered in the opposite direction, the demand-mediated elasticities satisfy

$$\eta_{i,s}^{q} \geq \eta_{i,s}^{Sec} \geq \eta_{i,s}^{C}.$$

This ordering is consistent with the institutional cost structure described in Section 2: course creation incurs high fixed costs (faculty hiring, curricular governance), section expansion incurs moderate costs (scheduling, staffing), and seat expansion incurs primarily quality costs.

Asymmetry: If expansion and contraction involve different adjustment costs, the framework predicts asymmetric elasticities. In the quadratic adjustment cost formulation, $\kappa_{i,s}^{m-} > \kappa_{i,s}^{m+}$ implies $\lambda_{i,s}^{m,+} > \lambda_{i,s}^{m,-}$ and therefore larger elasticities for positive demand shocks. Asymmetry may also arise from constraints on the static optimum rather than from adjustment costs: if fields maintain a minimum set of core courses regardless of demand, the frictionless optimum for course quantity has a floor that does not bind when demand rises but constrains contraction when demand falls. Both mechanisms — asymmetric adjustment costs and asymmetric static constraints — predict greater responsiveness to rising than to falling demand.

Institutional heterogeneity: The framework does not predict which institutions should be more responsive, but it clarifies the interpretation of observed heterogeneity. If research-intensive universities exhibit higher course elasticities when demand rises, this may be consistent with either lower adjustment costs for course creation (faculty expertise reduces development costs, lowering κ^{C+}), higher static responsiveness (research-active faculty are better positioned to identify frontier topics, raising β^{C}), or both.

A.4 Adjustments to course content

The preceding framework treats courses as homogeneous units within a field. In practice, courses differ in the skills they convey, and universities can respond to student demand shifts not only by adjusting how much they teach but also by adjusting what they teach. Content adjustment is a distinct margin of supply response that operates even when the total number of courses is unchanged.

Content can adjust through two channels that differ in cost and scope. First, an instructor can revise the topics, methods, or examples covered in an existing course. Revision is low-cost but constrained: a course retains its title, prerequisites, role in the major sequence, and core disciplinary identity. An instructor teaching Labor Economics can introduce material on the gig economy or automation, but the course remains Labor Economics.[6] The feasible set of content changes within a continuing course is bounded by the course's established position in the curriculum. Second, a field can create an entirely new course. Creation incurs the full fixed costs described above — faculty preparation, curricular approval, catalog entry — but faces no constraint on content. A new course in Health Economics or Applied Machine Learning can be designed from the outset around skills associated with expanding occupations in a way that incremental revision of an existing course cannot.

This distinction yields implications for the composition of content adjustment. If revision is cheap but constrained and creation is costly but unconstrained, then the courses that enter the curriculum should be systematically more aligned with expanding occupations than continuing courses, even when the number of new courses is small relative to the stock of existing offerings. The aggregate shift in curricular content should therefore be driven primarily by entry rather than by within-course revision. Moreover, because course creation is the least constrained channel of content adjustment, the institutional characteristics that predict higher course elasticities on the extensive margin — lower κ^C or higher β^C — should also predict faster content updating.

B Dataset construction

I assembled a sample of schools for inclusion in the course catalog by using two strategies. Initially, I selected schools from the IPEDS directory to scrape their course catalogs. I conducted an initial manual search of over 1,000 institutions. For institutions with online course catalogs that were available in a format that could be scraped and had at least a few years of archived data, I scraped the course descriptions for all courses offered in all available years. Subsequently, I searched for institutions that used the most common course schedule templates to scrape course enrollment data, prioritizing those with at least five years of schedule data available.

The current sample comprises data from 1,018 institutions, including 620 4-year schools

[6] The constraints may be especially acute in core classes that must provide foundational knowledge for subsequent elective courses.

and 398 2-year schools. The 4-year schools make up 31% of schools and enroll 56% of the students at all 4-year non-profit, bachelor's degree-granting Title IV-eligible institutions. The 2-year schools make up 43% of schools and enroll 55% of the students at 2-year non-profit, degree-granting Title IV-eligible institutions. Figure A-2 plots a map of the institutions included in the sample. The focus of this paper is on course supply in the sample of 4-year institutions.

The data date back to 1994, with the most dense coverage in the last decade. Figure A-3 plots the number of institutions for which course descriptions or course enrollment data are observed annually. Data availability grows over time. 302 of institutions in my sample have data first available in 2010 or earlier, and 447 have data first available in 2015 or earlier.

Data collection began in February 2020 and is ongoing. For real-time data collection, I scrape course offerings and enrollment data mid-semester, after each school's add-drop deadline, when course offerings and section enrollment have stabilized. Scraping mid-semester ensures that I capture data for schools that remove their course schedules later in the term to replace them with the next semester's schedule. Additionally, for many universities in my sample, I am able to access archived course data from periods before the school entered my sample. In these cases, enrollment and course offerings reflect end-of-semester values. When I have compared scraped data for the same term collected mid-semester and end-of-semester, course quantities and total enrollment are nearly always identical.

To validate the course catalog data, I compare it with publicly available aggregated enrollment statistics from IPEDS, which reports the total number of undergraduate credit hours completed at each institution. I construct a comparable measure from the course catalog data by aggregating course-level enrollment. Figure A-4 compares enrollment growth trends across the two sources. For each institution-term, I index total undergraduate credits in both datasets relative to their 2018-19 levels and plot the resulting values.[7]

The figure demonstrates a strong correlation between undergraduate enrollment hours aggregated using my data and the reference data collected by IPEDS. In the figure, alignment along the 45° line indicates that both datasets reflect similar rates of enrollment growth. The strong correlation between the two series (correlation coefficient = 0.82) confirms that the catalog data reliably replicate benchmark trends in the aggregate.

Substantial processing was required to convert the scraped course catalog and schedule

[7] Validating indexed values, rather than levels, serves two purposes. First, many schools assign course credits (e.g., 1 credit for a full course, 0.25 credits for a mini-course) differently from the instructional hours reported to IPEDS. Normalizing by instructional hours in a base year standardizes these institutional differences. Second, discrepancies between the catalog and IPEDS data may arise for several reasons — for example, from courses that offer a range of credit hours, from mismatches between course numbering and degree level, or from reporting errors in either source. When large discrepancies occur, I conduct institution-by-term quality checks and exclude a small number of schools with clearly anomalous data.

data into a dataset suitable for analysis. The processing of course enrollment data is outlined in this section, while the processing of course description data is detailed in Appendix Section F.

In the analysis estimating course quantity elasticity, I limit the data to the main terms offered by each institution, which typically include a Fall and Spring semester or Fall, Winter, and Spring quarters. I exclude independent study, internship, supervised research, thesis, study abroad, student teaching, private lessons, teaching assistantship courses. Often, "honors" sections of a course are assigned different course numbers (e.g., Econ 101 vs Econ 101H). I treat these instances as multiple sections of the same course. Additionally, I exclude sections with fewer than 5 students enrolled due to uncertainty about whether the course actually ran.[8]

I assign course levels (pre-undergraduate, lower, upper, graduate) according to the institution's numbering convention. For example, at many institutions, courses numbered 100-299 are lower-level courses; courses in the 300-499 range are upper-level electives; and courses numbered 500-999 are graduate-level courses. Occasionally, the course schedule distinguishes between lower/upper/graduate courses, and in these cases, I defer to the course-specific designation.

Cross-listing occurs when a single class is listed under multiple fields or levels, but such instances are not always explicitly identified in the course schedule. I match cross-listed sections using details from the course catalog data. Courses are classified as cross-listed if they share the same instructor, meeting days, times, location, course title, and section number. I credit each associated field and level (e.g., upper-level Economics) with a portion of the cross-listed course. For example, if a course is listed as both Econ 101 and Business 101 with identical cross-listing identifiers, I split quantity "credit" for this course between Economics and Business based on enrollment. When enrollment totals are reported separately for Econ 101 and Business 101, I distributed credit in proportion to the number of students enrolled in each section. When only a single enrollment total is reported for the joint Econ/Business 101, I apportion both enrollment and course credit based on the relative enrollment in other courses within the same field-level cell.[9]

[8]The overwhelming majority of the sections dropped are for courses in the Humanities and Arts; to the extent that I am erroneously dropping some small courses that actually ran, I am, if anything, understating course quantity inelasticity by removing these small sections.

[9]For example, if Econ 101 and Business 101 are lower-level courses and 100 students are enrolled in other lower-level Economics courses while 50 students are enrolled in other lower-level Business courses, I allocate 2/3 of the enrollment and course credit for Econ/Business 101 to the Economics department and 1/3 to the Business department.

C Fields of study

I manually classify the names of more than 48,000 departments into 54 unique fields for the analysis. A given field may be described in a number of ways depending on the institution. For example, Math may be called "Math," "Mathematics," "College Math," etc. I manually classify each department name into one of 170 sub-fields (largely at the level of a 4-digit CIP code), which I then assign to one of 54 fields. The unit of analysis in this paper is typically a field, although some analyses summarize fields at a more aggregate field category level. Table A-1 lists the sub-field to field mapping in my analysis.

For most of my analysis, I exclude fields that do not represent departments in the conventional sense and fields associated with professional degrees or skilled trades. A number of courses are offered by administrative units (e.g. "Learning Communities" or "Office of Academic Affairs") that do not correspond to a single field of study, are often difficult to classify, and likely are not offered through the same decision-making process as courses offered within a conventional department. I exclude such courses from all parts of the analysis.

I exclude courses associated with professional degrees, including those in Medicine, Law, Nursing, Pharmacy, and Architecture. While Medicine and Law courses are rarely offered at the undergraduate level, their course numbering often does not explicitly indicate graduate-level status, so I exclude all courses in departments classified as Medicine or Law. The exclusion of professional degree programs is motivated by the segmentation of these courses within most universities. These programs are often siloed within universities, making it structurally challenging for students to enter or leave these fields in response to shifting demand. Additionally, the regulated nature of careers in these fields means that taking a few courses is unlikely to open job opportunities, unlike fields such as Computer Science or Business. As such, students may not be able to flow as elastically into these professional programs, thereby complicating my instrumental variables strategy. I therefore exclude them from my analysis.[10] Finally, I exclude skilled trade programs, such as Beautician or Mechanic programs. Enrollment in these fields is minimal at the baccalaureate level, and there are often too few observations in the ACS to construct a reliable instrument for employment growth in occupations tied to these majors.

[10]These slios are a form of inelasticity to the extent that they restrict students from entering capacity-constrained fields and from leaving fields when expected returns decrease. In expectation, the exclusion of these fields from analysis would likely inflates IV estimates of course and section elasticity.

D Discussion of the IV assumptions and robustness

Section 4 estimates course quantity responsiveness to changing student demand using an instrumental variables strategy to isolate a demand-driven portion of changing enrollment attributable to changing job growth. In this section, I discuss potential violations of the identification assumptions and summarize tests that address the severity of these concerns.

A potential concern with my identification strategy is that local labor market conditions might induce direct institutional responses, rather than working through students' enrollment decisions. If, for example, a major employer or state government preemptively funds new faculty lines or facilities in a burgeoning field, the expansion in course offerings would be driven by university-level initiatives rather than by increased student demand. Under these circumstances, my shift-share strategy would violate the exclusion restriction, as it would affect course supply directly rather than only shifting student enrollment patterns.

However, there are several reasons to believe this type of violation is unlikely to be widespread in my setting. Universities, particularly in four-year institutions, are constrained in their ability to proactively expand or contract course offerings due to structural features such as budget cycles, tenure constraints, and facility constraints. The descriptive evidence summarized in Figure 1 supports this hypothesis: course offerings often lag behind surges in enrollment — indicating that institutions respond to students' immediate course-taking decisions, rather than lead them — while course offerings remain relatively stable in fields experiencing declining enrollment.

To further strengthen the case for the exclusion restriction, I discuss three potential channels by which it could be violated and provide evidence that none of these factors drive the main findings. First, I test the concern that universities may better anticipate changing labor market conditions and respond to these conditions directly, rather than meeting growing student demand in these areas. If this were happening, we would expect to see instances where course quantity expands before demand for these courses manifests in higher enrollment. I test for this by calculating enrollment as a share of total course capacity in the two highest-growth fields — Computer Science and Engineering — between 2005-06 and 2018-19. In contrast with this story, I find no evidence that universities are preemptively expanding course offerings before the demand surge materializes.

A second violation of the exclusion restriction would be that the growing labor market opportunities associated with certain fields increase the cost of recruiting instructors in those fields, and therefore course quantity responses are constrained by labor market conditions. While plausible, I demonstrate that this does not drive my results by Winsorizing 5% on the value of my instrument, thereby excluding from the estimation some of the region-field pairs that would be most exposed to this possible exclusion restriction violation, and demonstrate that the estimates are not sensitive to these highly-exposed values. I compare the estimates from these regressions to the main results in Tables A-9 and A-10. Comparing Columns 1 and 2, and 4 and 5, the course and section quantity elasticity estimates are nearly identical when I exclude the kinds of fields for which this potential exclusion restriction concern may be most acute.

A third case where the exclusion restriction would be violated would occur when a local employer or donor, recognizing a skill gap in the local labor force, contributes to the creation or expansion of a field to build an employee base that fills this gap. Philanthropic or governmental funding specifically targeted at expanding academic departments is not uniformly distributed across fields and institutions, and tends to be more prevalent in two-year colleges or professional/vocational programs, which are excluded from my analysis. My focus on academic departments in four-year institutions avoids consideration of fields and institutions that may be particularly susceptible to this exclusion restriction violation. Moreover, while universities are exposed to the influence of donors and (in the case of public universities) political leaders, it is not obvious that these influences are systematically correlated with labor market conditions. While this potential exclusion restriction is genuinely of concern and may occur at a small number of schools, there is not strong evidence of systemic violations of this kind among academic disciplines in four-year universities.

Tables A-9 and A-10 present a robustness test addressing potential endogeneity in the instrument. In Columns 3 and 6, I construct an alternative shift-share instrument that assigns each university the major-to-occupation shares from all Census divisions *except* its own. While endogeneity in the main specification is unlikely — given that any single university contributes minimally to a multi-state region — this alternative approach further mitigates concerns by ensuring that a university's course supply cannot meaningfully influence the composition of the national labor force outside its own Census division.

The IV estimates from this exercise closely align with the main results. As in the primary analysis, the IV estimates are generally lower than the OLS estimates, reinforcing the conclusion that universities adjust course offerings at rates well below one-for-one with changes in student demand. Notably, for fields experiencing growing demand, the IV estimates are slightly higher than in the main specification. This likely reflects the fact that the alternative instrument, by excluding local employment conditions, attenuates predicted demand growth for fields with the strongest regional labor market pipelines. Because these are disproportionately fields where local employment growth exceeds the national average, the leave-out instrument compresses the right tail of predicted demand shifts, generating slightly smaller projected enrollment changes in growing fields and, consequently, a somewhat larger estimated supply response per unit of predicted demand.

D.1 Donations and appropriations

Another potential threat to the exclusion restriction is that improvements in a field's labor-market conditions induce targeted investments from governments or donors, thereby enabling institutions to expand teaching capacity for reasons unrelated to student demand. If such resource flows disproportionately support fields experiencing positive shocks, course supply could increase even absent demand-driven adjustments.

Systematic data on individual gifts are not available, but I provide suggestive evidence against differential resource flows as a driver of the heterogeneity in course quantity elasticity by examining whether changes in institutional resources are correlated with course supply responses. I construct three measures of growth in external funding: federal appropriations, state and local appropriations, and private gifts and donations. Using IPEDS Finance data, I compute real per-student funding for each category from 2002-2017. I then calculate long log differences comparing average annual per-student funding during the observation period (2010-2017) to an equivalently long base period (2002-2009). These long differences capture the extent to which an institution received an influx of resources during the analysis period relative to its earlier funding levels.

I correlate these funding shocks with three institution-level measures relevant for course supply elasticity: a "specialization" index capturing an institution's baseline (2009-10) enrollment concentration in fields most exposed to subsequent labor-demand growth,[11] the institution's effective elasticity of course quantity,[12] and the analogous elasticity of section quantity. High correlations between revenue shocks and specialization would suggest that firms or governments preferentially channel resources to institutions with strong existing capacity in high-growth fields; high correlations between revenue shocks and the elasticity measures would indicate that institutions experiencing resource surges also exhibit disproportionately large supply responses. Either pattern would be concerning for the exclusion restriction.

Table A-11 reports the results. Across all three sources of revenue, correlations with specialization range from 0.02 to 0.06, and correlations with course and section elasticities range from -0.07 to 0.13. None are large in magnitude, none display consistent signs, and none approach levels that could meaningfully bias the IV estimates. These findings indicate that institutions specializing in high-growth fields did not receive systematically larger increases

[11] Calculated as the dot product of field enrollment shares in 2009-10 and the shift-share instrument.

[12] Defined as the log change in course quantity divided by the log change in enrollment, using a one-year offset, weighted by field enrollment shares in 2009-10.

in external funding, nor did changes in funding predict greater responsiveness in course supply.

D.2 Labor market tightness

Another concern related to the exclusion restriction is that changes in labor market opportunities for workers in high-demand fields may constrain universities' ability to hire instructors. If rising outside options make it more difficult for institutions to recruit qualified instructors, course supply may adjust inelastically for reasons unrelated to student demand. Addressing this mechanism directly would require detailed information on instructor rank or salaries — data that are not available in the catalog records. In the absence of such data, I provide suggestive evidence on the potential importance of instructor-side tightness by exploiting variation, both within and across universities, in access to an internal labor pool: graduate students.

If instructor tightness were a first-order constraint on institutional adjustment, universities with deeper internal labor pools, such as those offering graduate degrees in a field, should be better able to expand teaching capacity. To assess this possibility, I construct an indicator for whether an institution awarded any graduate degrees in a given field in 2009 and estimate OLS versions of the course and section quantity regressions that interact field-specific enrollment changes with this graduate program indicator. These specifications test whether institutions with graduate programs exhibit systematically different responsiveness to demand shocks.

Table A-12 reports the results. Across all specifications, the interaction terms are small in magnitude, though they are often imprecisely estimated. For course quantity, the interaction coefficients are negative, indicating that institutions with graduate programs do not expand the number of courses more readily than those without such programs. For section quantity, the interaction terms are slightly positive but similarly small and statistically indistinguishable from zero. None of the estimates exhibit the large positive differential responses that would be required for instructor-side labor market tightness to generate meaningful violations of the exclusion restriction.

E Counterfactual major completions without course rationing

I perform a counterfactual exercise using the OLS and IV estimates from Table 2 to project enrollments and completed majors under a scenario in which students are neither rationed out of preferred courses nor diverted into less-preferred alternatives. In this scenario, universities respond to student demand with the elasticity implied by the OLS estimates, which capture both observed and unobserved demand suppressed by rationing and diversion.

To construct the counterfactual, I adjust section quantity upward by the bias implied by the difference between the OLS and IV estimates. I focus on section elasticity because it most directly maps to instructional capacity — the margin determining who gains access to a field — rather than to the breadth of course offerings. I then scale institution-field enrollments by the ratio of additional (or removed) sections to the average upper-level course enrollment in the base year (2009-10). To translate these enrollment changes into completed majors, I multiply the projected enrollments by the ratio of major completions to upper-level enrollments in IPEDS data.

Figure A-12 displays the median and interquartile range of projected changes in major completions across selected fields. The simulation suggests that, if universities responded to student demand as elastically as implied by the OLS estimates but without rationing or diversion U.S. institutions would have produced substantially more majors in Computer Science and Engineering, and fewer in the Humanities and Education. Under this counterfactual, major completions in Computer Science would have been 1.9% higher and in Engineering 1.4% higher, while History majors would have declined by 4.3%. These should be interpreted as upper-bound effects in low-demand fields: tenure constraints and institutional inertia often make reducing faculty positions costly, limiting contraction even when demand falls.

The inelasticity of course supply thus creates both winners and losers within the university. Students in high-demand fields face rationing or overcrowded classes, while those in low-demand fields benefit from smaller courses and a broader set of options that might contract under a more elastic regime. Figure A-5 illustrates this reallocation: since 2010, average upper-level Computer Science sections have grown by roughly 40%, while average section size in the Humanities and Education has fallen by about 15%.

F Text data processing

F.1 Text processing

I apply consistent pre-processing procedures to all the text corpora, including the course descriptions. These procedures involve removing all punctuation and numbers, converting all strings to lowercase, eliminating URLs, and lemmatizing the text (i.e., transforming "regressions" to "regression").

However, my approach incorporates two non-standard pre-processing steps. First, I exclude "boilerplate" language from the text data to prevent the model from over-weighting phrases that occur frequently in standardized or domain-specific contexts, such as legal disclaimers or institutional templates, where their meaning is unrelated to the substantive topic of the text.[13] To handle boilerplate language, I exclude sentences that are identically repeated across numerous documents within a given corpus from my analysis. Specifically, if a particular sentence appears identically more than 10 times across all documents in a specific tranche, it is removed during pre-processing.

Second, I create a dictionary with tokens of varying word length based on the co-occurrence of words in a neutral third corpus: the full scrape of Wikipedia. The objective here is to distinguish common n-grams (e.g., "machine learning" or "regression analysis") from their component words. This procedure essentially allows for all possible n-grams but removes sparse tokens and n-grams that frequently co-occur simply because they are composed of common words rather than because they form a meaningful phrase. I combine any two-word pair into a single token if the two words appear consecutively at least 500 times and if the co-occurrence of the two-word pair occurs for at least 4% of all instances of the less frequent word in the pair. For example, in the Wikipedia corpus, the word "machine" appears 59,799 times, and the word "learning" appears 37,991 times. The words "machine" and "learning" appear consecutively 1,583 times (4.1% of the time "learning" appears in the Wikipedia corpus). Consequently, I consider "machine learning" a token distinct from "machine" and "learning."

This approach allows for tokens of varying word lengths. For example, if the words "university" and "michigan" co-occur frequently enough ("of" is removed as a stopword), and the words "michigan" and "wolverine" co-occur with sufficient frequency, the phrase "university [of] michigan wolverine" would be included in the dictionary.

Enrollment and course description data often come from different sources. In some instances, overlap between the enrollment data and the course description data is imperfect. For example, it is somewhat common for a new course to not have a course description in the course catalog during the first year it is offered. In instances where a course is continuously offered (enrollment is nonzero) but the course description appears inconsistently in the course catalog, I backfill from next term a course description is available.[14] For continuously-offered courses, course descriptions change somewhat infrequently and rarely change substantively (see, for example, Figure A-13).

[13] For example, many job descriptions include nearly identical non-discrimination clauses at the end. Including these texts in my analysis could mistakenly suggest that phrases like "gender," "sexual orientation," and "discrimination" are highly important tokens for job skill demand, even though their usage in job descriptions is unrelated to the skills demanded of the jobs.

[14] I only backfill course descriptions in institution-years where I observe course catalog descriptions for other courses offered at in the institution-year.

F.2 Validating course description data

To validate the effectiveness of course descriptions in assessing course content, it is essential to demonstrate that they provide meaningful insights about courses. Specifically, variation in topics or skills across fields or over time should reflect genuine changes, rather than differences in terminology describing similar concepts. This section aims to show, descriptively, that the text data and methods reveal differences that are both meaningful and intuitive.

Distinctive tokens in course descriptions align closely with the skills and concepts emphasized in each field, demonstrating that these descriptions capture meaningful differences in content. Figure A-14 applies the NLP methods outlined in the previous section to illustrate these differences, displaying the 25 most distinctive tokens for a sample of fields based on course descriptions from the 2022-23 academic year.[15] The results align intuitively with disciplinary focus: for example, English courses emphasize literature, reading, and writing, while Computer Science courses highlight programming and data analysis. These distinctive tokens capture both skills (e.g., reading, programming) and concepts (e.g., markets, theorems), reinforcing the validity of using course descriptions to analyze curricular content.

The effectiveness of the text analysis methods depends on their ability to detect substantive changes in course content over time, rather than merely shifts in terminology. For example, adding "climate change" to a course description where no equivalent concept previously existed signifies a meaningful change. In contrast, replacing "global warming" with "climate change" would represent a terminological update rather than a substantial alteration to the course.

In Figure A-15, I demonstrate that changes in course description text represent meaningful differences in course content. For each field, I list 15 tokens distinctive of courses that have been discontinued over the last decade and 15 tokens distinctive of courses that have been introduced over the last decade. The figure highlights that the text data and methods pick up substantive changes to course content rather than changes in jargon. For example, recently created Economics courses emphasize data analysis, inequality, and topics in applied economics more than discontinued courses, which emphasize topics related to international economics and monetary policy. Similarly, Computer Science has shifted from hardware-oriented courses towards data science, cybersecurity, and machine learning.

[15] I collapse course descriptions into a single document for each institution-field, then represent each document as a TF-IDF vector. I average across institutions to get field-level values, then select the 25 tokens with highest value for each field.

G Additional details on labor market alignment analysis

This section provides additional details on and summarizes validation exercises for measuring the labor market alignment of courses using course descriptions.

G.1 TF-IDF

The TF-IDF of a word w in document $d_{i,s,t}$ is the product of Term Frequency (TF) and Inverse Document Frequency (IDF). The TF for a given token in a given document is equal to the number of times w occurs in $d_{i,s,t}$ ($c_{w,d_{i,s,t}}$), normalized by the token count of $d_{i,s,t}$:

$$TF(w, d_{i,s,t}) = \frac{c_{w,d_{i,s,t}}}{\sum_{w' \in W} c_{w',d_{i,s,t}}}$$

The IDF for a given token w measures the distinctiveness of w across all documents. In other words, $IDF(w)$ reflects how rare w is in the complete corpus (D) of field descriptions. The IDF for a given token w is calculated:

$$IDF(w) = log\left(\frac{||D||}{\sum_{d \in D} \mathbb{I}(w \in d)}\right)$$

The TF-IDF value applied to a token w in document $d_{i,s,t}$ is the product of the two values:

$$v_{i,s,t}(w) = TF\text{-}IDF(w, d_{i,s,t}) = TF(w, d_{i,s,t}) \times IDF(w)$$

G.2 Example labor market alignment calculation

This section illustrates how the labor market alignment score is calculated. To simplify the calculation, I calculate the score for a relatively simple, stylized course description.

Consider the course description "Study statistical and econometric methods." In pre-processing, I lemmatize all words, transform the sentence to lower-case, and remove all punctuation and stopwords. I can then represent the resulting fragment, "study statistical econometric method," as a text vector and calculate its TF-IDF representation. For simplicity of notation, I show only a portion of the vector corresponding to the four words in the fragment; the full representation of the description takes the length of all tokens in the dictionary, where the remaining values are all 0 because the token does not appear in the dictionary. Each token appears once in the course description, so the TF value associated with each word is 1/4. The IDF weight is inversely proportional to how common each token is across all of the course description. IDF puts greater weight on the distinctive words in the course description — econometric and statistical — and down-weights the more common words. I then (L1) normalize the vector such that the weights sum to 1, yielding the following:

$$
\begin{array}{l}
\text{econometric} \\
\text{method} \\
\text{statistical} \\
\text{study}
\end{array}
\quad
\begin{bmatrix} 0.25 \\ 0.25 \\ 0.25 \\ 0.25 \end{bmatrix}_{\text{TF}}
\cdot
\begin{bmatrix} 3.14 \\ 0.32 \\ 1.27 \\ 0.17 \end{bmatrix}_{\text{IDF}}
=
\begin{bmatrix} 0.79 \\ 0.08 \\ 0.32 \\ 0.04 \end{bmatrix}_{\text{TF–IDF}}
\longrightarrow
\begin{bmatrix} 0.64 \\ 0.07 \\ 0.26 \\ 0.04 \end{bmatrix}_{\text{L1 Norm.}}
$$

Thus, in the TF-IDF representation of the course description, almost all of the weight is given to the tokens "econometric" and "statistical," which are the distinctive topics/skills in this course.

Next, I demonstrate how I calculate the labor market alignment weight for a token — in this case, econometric.[16]. The two-digit occupation groups in which "econometric" appears most frequently are The top four occupation codes whose job descriptions contain the token "econometric" are: 13 (Business and Financial Operations Occupations, 38% of instances), 15 (Computer and Mathematical Occupations, 25% of instances), 19 (Life, Physical, and Social Science Occupations, 18% of instances), and 11 (Management Occupations, 11% of instances). From ACS employment counts, these occupations grew by 30, 34, 34, and 9 log points, respectively. The alignment weight for "econometric" is the frequency-weighted average log employment growth rate. I normalize the alignment weights based on the full distribution of token-level alignment weights, giving an alignment weight for "econometric" of 0.36, meaning "econometric" appears in descriptions for jobs that, on average, grew 0.36 standard deviations (0.07 log points) faster than the national average.

The course description's labor market alignment score is the product of the TF-IDF weights and the labor market alignment weights:

$$
\begin{array}{l}
\text{econometric} \\
\text{method} \\
\text{statistical} \\
\text{study}
\end{array}
\quad
\begin{bmatrix} 0.64 \\ 0.07 \\ 0.26 \\ 0.04 \end{bmatrix}_{\text{L1 Norm.}}
\times
\begin{bmatrix} 0.36 \\ -0.03 \\ 0.00 \\ -0.21 \end{bmatrix}_{\text{Alignment weights}}
= \quad 0.22
$$

I normalize these raw scores by subtracting by the mean and dividing by the standard deviation of the labor market alignment distribution for courses offered in 2010-11. This

[16] To simplify this example, I conduct this exercise at the two-digit SOC level. For the actual calculation, I match occupations at the six-digit SOC level. The employment growth rates I show in this example are a weighted average at the two-digit SOC level of employment growth rates at the six-digit level, weighted by the token "econometric"'s frequency within each two-digit group

course would score in the 98th percentile of labor market alignment.[17] Figure A-17 plots the distribution of alignment scores for courses offered in 2022-23.

G.3 Validating the labor market alignment measure

G.3.1 Pair similarity exercise

To validate the labor market alignment measure, I conduct an exercise analogous to how embedding models are evaluated. I compiled a set of 50 word pairs that are closely related in meaning or usage within the context of jobs and skills.[18] If the method is robust to synonyms, words that have similar meaning/usage should have similar alignment weights and, therefore, small absolute difference. For each pair, I calculate the absolute difference in their alignment weights, then take the average across all pairs. I compare this observed average to a benchmark distribution constructed from 5,000 draws of random token pairs. I consider two benchmarks: (i) pairs drawn from the full token dictionary, and (ii) pairs drawn from the restricted set of 100 tokens that appear in the curated pairs.

Figure A-18 compares the average absolute difference in alignment weights for the paired words, plotted as the vertical dashed line, against the distributions of average absolute differences for the 5,000 random draws of 50-pair token lists. The average for the paired tokens is substantially below the smallest value for either random draw distribution. This validation demonstrates that the alignment weights capture semantic and functional relationships between words in ways that are consistent with embeddings. In particular, tokens that are used similarly in job descriptions also map to similar positions in the one-dimensional alignment score, despite the underlying TF-IDF structure that imposes independence between tokens. This exercise builds confidence that the alignment measure is robust and interpretable, and that it meaningfully reflects the economic content of course descriptions.

G.3.2 LLM validation

As an additional validation exercise, I use a large language model (LLM) to assess whether the text-based labor market alignment measure captures economically meaningful variation in course content. The goal of this exercise is not to treat the LLM as a benchmark for "true" alignment, but rather to evaluate whether an external text-based judgment, constructed in-

[17] As an unusually short course description, the outsize influence of a single word contributes to a relatively extreme alignment score.

[18] I compiled this list by prompting ChatGPT to "produce 50 pairs of words/phrases related to jobs or job descriptions with similar meaning, usage, etc." The pairs include occupation titles that refer to similar work (e.g., attorney vs lawyer, manager vs leader), tasks (e.g., negotiate vs bargain, calculate vs compute), and topics (e.g., data vs information, group vs team).

dependently of the alignment algorithm and employment data, exhibits systematic agreement with the measure.

Starting from all course descriptions in the 2018-19 academic year, I draw random samples of approximately 650 pairs of course descriptions. One-third of the pairs are drawn within field (e.g., English-English), one-third are drawn within field category (e.g., Humanities-Humanities), and the final third are drawn without regard for field match. Pairs are separated by at least 20 percentile points in the alignment score. Using the OpenAI API, I present the LLM with raw course descriptions and ask it to select the course that is most aligned with occupations that were expanding in employment during the 2010s (prior to the COVID-19 pandemic). The prompt instructs the model to focus on substantive course content (skills, tasks, and methods taught) and to ignore prerequisites, administrative details, and institutional reputation. Importantly, the model is not provided with any employment growth rates, occupational statistics, or information derived from the American Community Survey.

For each pair, it must select one of the paired courses as having higher labor market alignment. I compare the model's selections to the ordering implied by the alignment scores. Agreement is defined as cases in which the model selects the course with the higher alignment score.

The LLM's judgments exhibit meaningful agreement with the alignment measure. Among course pairs that differ by at least 20 percentiles in the alignment distribution, the model's selections agree with the alignment ranking in 66% of cases. Agreement rises to 74% for pairs that differ by at least 50 percentiles. This increase in agreement with distance in the alignment distribution indicates that the measure captures a latent ordering that becomes increasingly salient as differences in labor market relevance grow. Agreement rates are similar for within-field comparisons, within broad field categories, and across fields, suggesting that the validation does not rely solely on coarse disciplinary differences. Disagreements are concentrated among course pairs that are close in the alignment distribution, where distinctions in labor market relevance are inherently more ambiguous.

G.3.3 Additional validation exercises

I conduct supplemental validation exercises to assess whether the labor market alignment score captures substantive differences in course content rather than mechanical features of text data.

A common concern with TF-IDF-based analyses is that results may be driven by changes in jargon or by the presence of a small number of highly influential tokens. The alignment score is designed to mitigate this concern by projecting the TF-IDF representation of each course description onto token weights derived from occupational employment growth, which assigns similar weight to tokens that are relevant to similar sets of occupations. Nevertheless, if the index were overly sensitive to a narrow set of words, the results could reflect changes in terminology rather than underlying curricular content. To evaluate this possibility, I conduct a robustness exercise in which I exclude from the dictionary all tokens in the top and bottom 5 percent of the labor market weight distribution.[19] If measured alignment were driven primarily by the presence of these extreme tokens, removing them would substantially alter course rankings and aggregate patterns. By contrast, if these tokens reflect broader bundles of skills and topics described throughout course descriptions, the main results should be largely preserved under the reduced dictionary.

The results are robust to this exclusion. Restricting attention to course descriptions that contain at least one excluded token, the correlation between the original alignment score and the reduced-dictionary index is 0.72. Across all courses, the rank-rank correlation between the two measures is 0.66. The headline time trend in average alignment is unchanged and, if anything, slightly larger (though substantively similar) under the reduced dictionary. While the distribution of alignment scores is mechanically compressed when extreme tokens are removed, the ordering of fields by average alignment is nearly identical to that produced by the baseline measure. Taken together, this exercise provides strong evidence that the alignment score is not driven by a small set of jargon words, but instead reflects broader patterns in course content.

A second validation exercise exploits instructor-level variation to assess whether the alignment score captures meaningful within-university diffusion of skills. Some instructors teach across multiple fields within the same institution, creating a natural channel through which tools, methods, and applied skills may be introduced into fields where they are not traditionally emphasized. Using course-instructor-term-level data, I identify instructors who teach courses at least one course in a top-tercile field at their institution over the sample period and compare the alignment of courses they teach in their lower (bottom two terciles)-alignment fields to courses taught by instructors without such cross-field exposure.[20]

I estimate regressions of course-level alignment on an indicator for whether the instructor also teaches in a top-tercile alignment field, including institution $\times$ term $\times$ field fixed effects. This specification compares courses offered in the same field, institution, and term, isolating differences attributable to instructor composition rather than departmental curricula or time-varying institutional trends. Courses taught by instructors with exposure to

[19] Examples of omitted tokens at the low end include archaeology, theology, and clarinet; examples at the high end include programmer, physical therapy, cryptography, and carpentry.

[20] I restrict to courses offered in the bottom two terciles of the field-level alignment distribution to ensure that comparisons are made within fields that are not high-alignment by default.

top-alignment fields exhibit alignment scores that are 0.035 SD higher (p-value < 0.005), corresponding to approximately 5% of the residual standard deviation of alignment (after removing institution-term-field averages). While modest in magnitude, this difference is statistically distinguishable from zero despite the demanding fixed effects structure. The result implies that instructors who span departments — particularly those with exposure to high-alignment fields — teach courses that are measurably closer to the skill profile of growing occupations even when offering instruction in traditionally lower-alignment fields. This pattern is consistent with diffusion of frontier tools and methods through instructors rather than changes in departmental classification or catalog language. Importantly, the magnitude of the effect is small relative to cross-field differences in alignment, suggesting that instructor-level diffusion operates at the margin rather than driving wholesale convergence across fields. As such, the exercise should be interpreted as validating the alignment measure's sensitivity to meaningful within-university variation, not as evidence of large curricular transformation driven by individual instructors.

G.4 Labor market alignment decomposition

This section describes the implementation of the decomposition in Equation (18).

I decompose the total change in average labor market alignment between 2010-11 and each subsequent year t' through 2022-23 into contributions from within-course revision, reallocation across continuing courses, course entry, and course exit. Suppose each course c offered by institution i in field s and period t has a scalar content index $\phi_{i,s,ct}$ (e.g., alignment with skill bundles used in expanding occupations). Let average content in the field be the enrollment-weighted mean

$$\Phi_{i,s,t} = \sum_{c \in \mathcal{C}_{i,s,t}} \omega_{i,s,c,t}\, \phi_{i,s,c,t}, \qquad \sum_{c} \omega_{i,s,c,t} = 1 \tag{15}$$

where $\mathcal{C}_{i,s,t}$ is the set of courses offered and $\omega_{i,s,c,t}$ is the course's enrollment share within the field.

Content can adjust through two channels. First, fields can change the content of continuously offered courses: for $c \in \mathcal{C}_{i,s,t-1} \cap \mathcal{C}_{i,s,t}$,

$$\phi_{i,s,c,t} = \phi_{i,s,c,t-1} + u_{i,s,c,t}$$

where $u_{i,s,c,t}$ denotes updates to topics, tools, or methods. Second, entry and exit change the set of courses $\mathcal{C}_{i,s,t}$.

These two channels imply a natural decomposition of changes in average content in the spirit of Foster et al. (2001):

$$\Delta\Phi_{i,s,t'} = \underbrace{\sum_{c\in\mathcal{S}} \omega_{i,s,c,t-1} \left(\phi_{i,s,c,t'} - \phi_{i,s,c,t-1}\right)}_{\text{within}} \tag{16}$$

$$+ \underbrace{\sum_{c\in\mathcal{S}} \left(\omega_{i,s,c,t'} - \omega_{i,s,c,t-1}\right)\left(\phi_{i,s,c,t-1} - \Phi_{i,s,t-1}\right) + \sum_{c\in\mathcal{S}} \left(\omega_{i,s,c,t'} - \omega_{i,s,c,t-1}\right)\left(\phi_{i,s,c,t'} - \phi_{i,s,c,t-1}\right)}_{\text{between}} \tag{17}$$

$$+ \underbrace{\sum_{c\in\mathcal{E}} \omega_{i,s,c,t'} \left(\phi_{i,s,c,t'} - \Phi_{i,s,t-1}\right)}_{\text{entry}} - \underbrace{\sum_{c\in\mathcal{X}} \omega_{i,s,c,t-1} \left(\phi_{i,s,c,t-1} - \Phi_{i,s,t-1}\right)}_{\text{exit}} \tag{18}$$

where $\mathcal{S} = \mathcal{C}_{i,s,t} \cap \mathcal{C}_{i,s,t-1}$ refers to the set of continuing courses, $\mathcal{E} = \mathcal{C}_{i,s,t} \setminus \mathcal{C}_{i,s,t-1}$ refers to entering courses, and $\mathcal{X} = \mathcal{C}_{i,s,t-1} \setminus \mathcal{C}_{i,s,t}$ refers to exiting courses.

I compute the four components of Equation (18) at the institution-field level for each reference year t'. To aggregate, I first average across fields within each institution to avoid large institutions to dominating the aggregate pattern, weighting each field s by its share of enrollment in the base period. I then average across institutions, weighting each institution equally. Table 4 reports the resulting decomposition.[21]

G.5 Robustness to infrequent updating of course descriptions

A potential concern with the text-based alignment measure is that course descriptions may not be updated when instructors modify course content in practice. If within-course adaptation occurs but is not reflected in catalog descriptions, the analysis would understate the within-course component of alignment growth and overstate the relative importance of course entry. This section presents two exercises that bound the potential impact of description staleness on the main findings.

First, I calculate an upper bound of the within-course component under the plausible assumption that updates to course descriptions for continuously-offered courses whose descriptions change between 2010-11 and 2022-23 are representative of updates to continuously offered courses whose descriptions do not change. Among continuously offered courses, approximately half update their course descriptions; the enrollment-weighted share is smaller because relatively larger core classes are more likely to persist without changes to the course description — consistent with these courses covering more foundational or theoretical mate-

[21] Because the sample is restricted to institutions with continuous course offerings from 2010-11 to 2022-23, and because the regression and decomposition approaches differ in weighting and sample composition, the total changes in Table 4 differ slightly from those plotted in Figure 3.

rial that is durable but less tied to current labor market trends. I impute alignment gains to all non-updating courses by adding to each course's labor market alignment the mean alignment change observed among courses in the same field that did update their descriptions. This assumption is deliberately generous: it supposes that every non-updating course experienced the same content evolution as the average updater but simply failed to revise its catalog entry.

Table A-15 reports the results alongside the baseline decomposition from Table 4. Under this upper bound, the within-course component of alignment growth increases from 0.0002 to 0.0020, rising from approximately 1% to approximately 8% of the total change. The total change in alignment increases by roughly 7%, from 0.0225 to 0.0241. The entry component, at 0.0196, continues to account for more than 80% of total alignment growth even under the bounding assumption. These magnitudes confirm that importance of entry over within-course revision is not an artifact of stale descriptions: even if all non-updating courses adapted as much as the typical updater, the entry margin would remain the primary driver of rising labor market alignment.

Second, I separate institutions based on their propensity to update course descriptions in continuously offered courses and calculate separate trends in labor market alignment growth. If changes to course descriptions are less reflective of content changes and moreso reflective of institution norms, interpretation of both the overall trends and cross-institution heterogeneity may be confounded. For example, if research-intensive universities update descriptions more often, their faster alignment growth could partly reflect measurement rather than substantive curricular change. To assess this possibility, I split institutions at the median share of continuously offered courses whose descriptions changed between 2010-11 and 2022-23. I then re-estimate the alignment trend regressions from Figure 3 separately for each group, controlling for institution-by-field fixed effects. Figure A-19 plots the results. I plot estimates under the specification with controls for institution-by-field fixed effects; insights are identical when I control only for institution fixed effects.

Alignment trends are similar across high- and low-update institutions on both enrollment-weighted and course-weighted bases. While high-change institutions exhibit slightly faster enrollment-weighted alignment growth in the middle of the period, the confidence intervals overlap throughout and the trends converge by the end of the sample. Course-weighted alignment trends are nearly indistinguishable across the two groups. To further rule out confounding with the heterogeneity analysis, I test whether the propensity to update course descriptions is correlated with the institutional characteristics used in Section 5.3: research intensity, control, selectivity, size, and tenure share. Update propensity is not significantly related to any of these characteristics at conventional levels. These results indicate that differential description maintenance across institution types does not drive the cross-institutional patterns documented in Figure 4.

H Supplemental figures and tables

Figure A-1. Sample entry in the course catalog dataset

ECON 101
Lecture: 01
Units: 5
Class#: 7559

Winter 2026
Open

Economic Policy Seminar

Department of Economics

Lecture, Discussion
1/5/26 - 3/13/26

Mon, Wed
1:30 PM - 3:20 PM
Econ 140

Instructor: Light, J.

Enrollment Status

Open Seats: 7
Enrolled: 17 Waitlist: 0
Capacity: 24 Waitlist Max: No waitlist

Course Description

Capstone and writing in the major course open to Econ majors only. Economic policy analysis, writing and oral presentations will be large components of this course. Students may also complete group projects that include empirical economic analysis focused on a specific topic. The goal of this course is to enable students to utilize the skills they have acquired throughout their time in the major. Section topics vary by instructor. Enrollment limited to application at the start of each school year with student placement notifications before the term starts. Permission numbers will be provided to students. Limited to students applying to graduate in 2025-26. Enrollment by application: https://economics.stanford.edu/forms.

Grading basis

Letter (ABCD/NP)

Class level

Undergraduate

Instructional mode

In Person

Final exam

Wed, March 18th
3:30 PM - 6:30 PM
Econ 140

Gen Ed Requirement(s)

WAYS - Social Inquiry (SI)

Source: Stanford University.

Figure A-2. Geographic coverage of the course catalog dataset

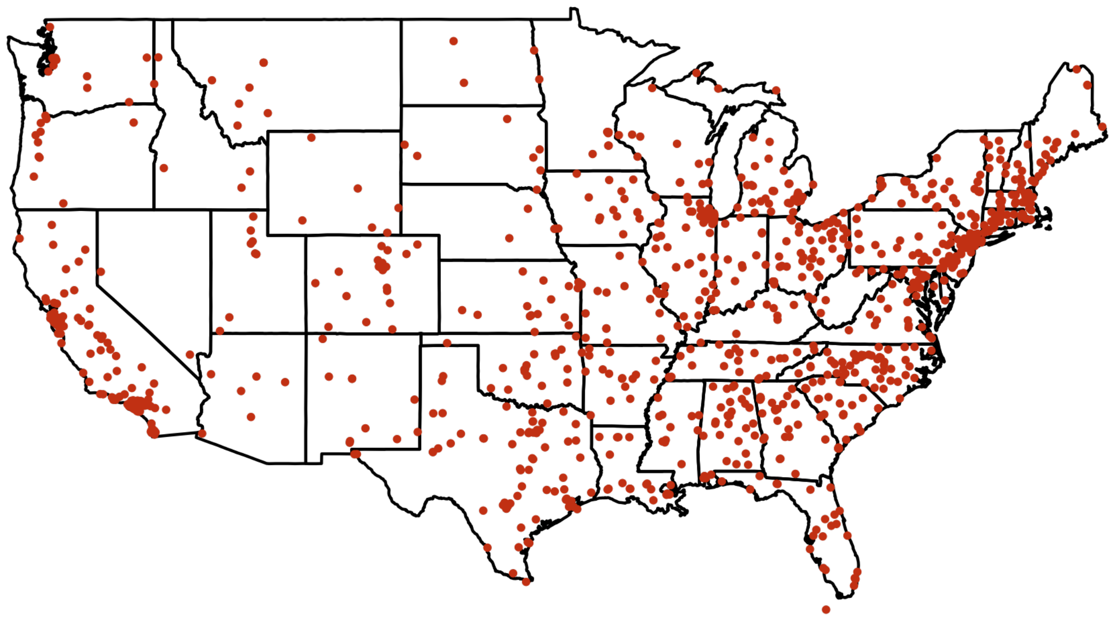
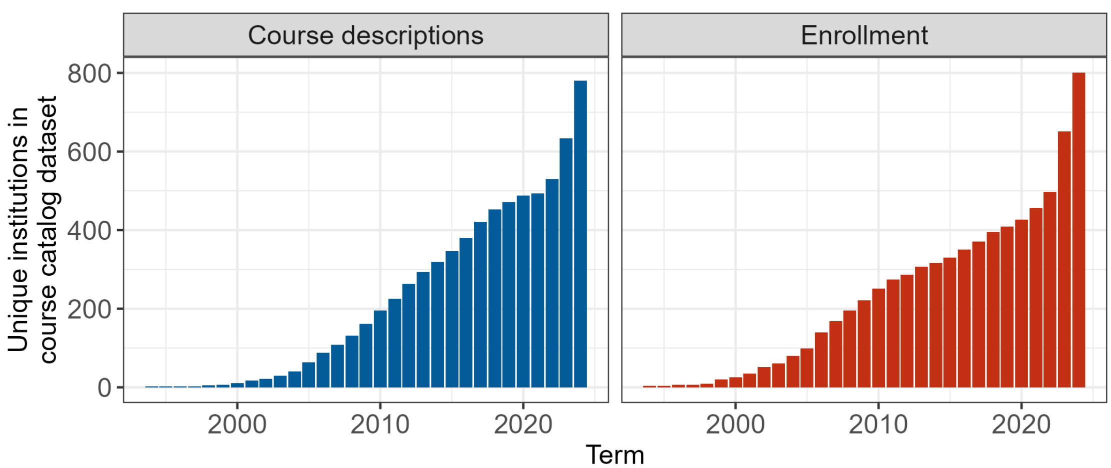
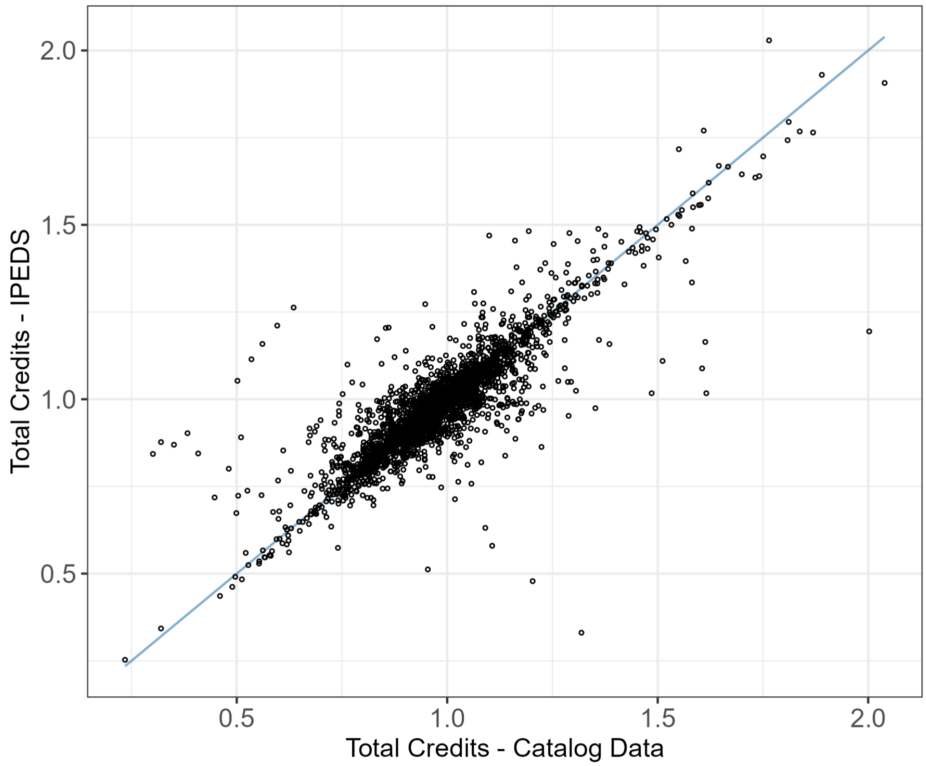


Figure A-3. Annual coverage of course catalog data



Notes: The figure counts the number of institutions in the course catalog dataset by year. The left panel counts the number of institutions with course description data; the right panel counts the number of institutions with enrollment data. For many institutions, the data record both enrollment and course descriptions. Institutions enter and exit the dataset during the period; thus, the max total in any given year may not reflect the total number of institutions that ever appear in the dataset.

Figure A-4. Compare indexed credit growth rates in catalog data to IPEDS

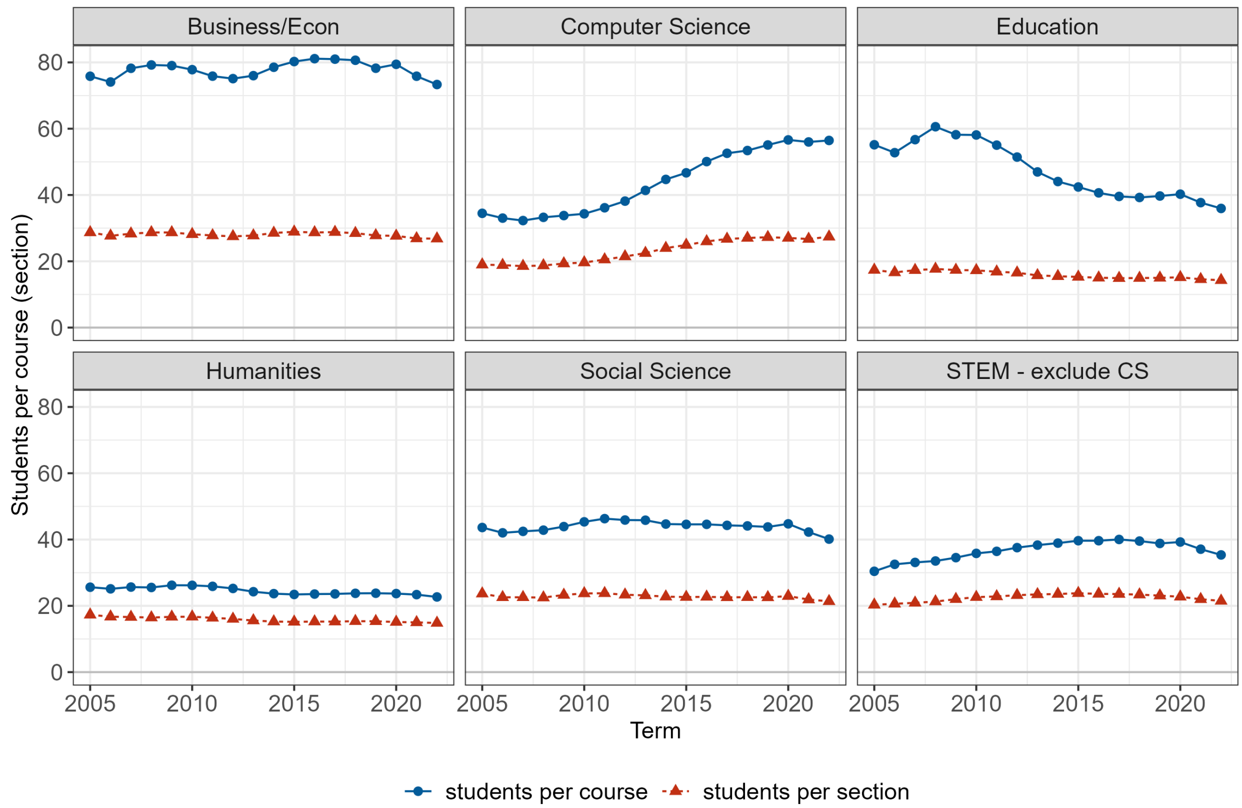


Notes: The figure compares the growth in total credits for enrollment in undergraduate courses in the course catalog data to the growth in total undergraduate credits reported in IPEDS. Observations are at the institution-year level. Catalog credits are indexed as the percent change relative to undergraduate credits completed in 2018-19; IPEDS credits are indexed as the percent change relative to undergraduate credits completed in 2018-19 in IPEDS. Because it is used as the index, enrollment in 2018-19 is omitted from the plot. The plotted line is the 45° line. The correlation coefficient between the two series is 0.82.

Table A-1. Field classification

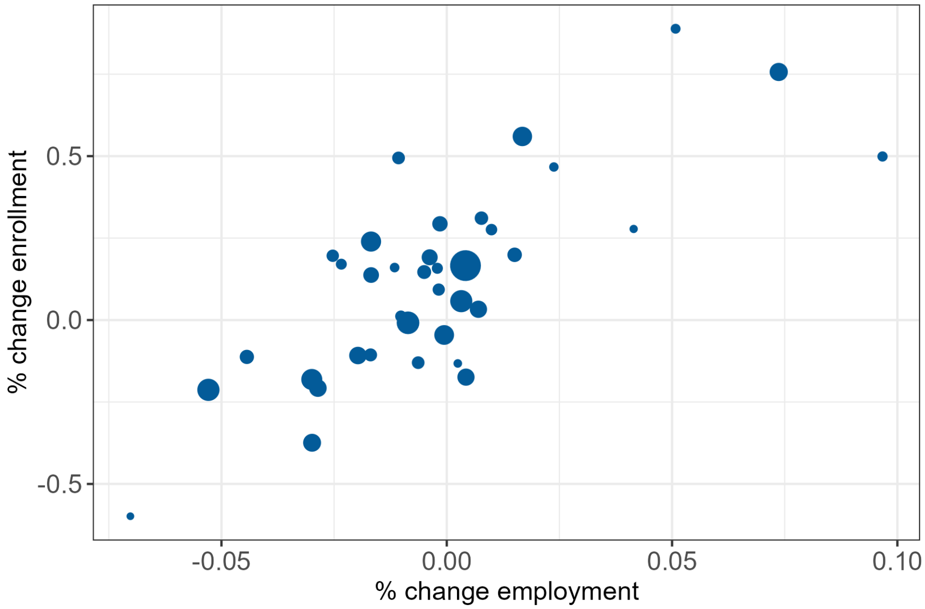
Field category	Field	Sub-field	Field category	Field	Sub-field	Field category	Field	Sub-field	Field category	Field	Sub-field
Business	Business	Accounting	**Social Science**	Communication	Advertising	**STEM - exclude CS**	Agriculture	Agriculture	**Skilled Trade**	Architecture	Architecture
		Business Administration			Communication			Agriculture Economics		Arts	Animation/Game Design
		Business Math			Journalism			Animal Science			Graphic Design
		Finance			Media Studies			Botany		Hospitality	Hospitality
		Leadership		Community Studies	Community Studies			Food Science		Medicine	EMT
		Management		Consumer Science	Consumer Studies			Horticulture		Other	CAD
		Marketing		Criminal Justice	Criminal Justice			Plant Science		Physical Education	Kinesiology
		Operations		Ethnic/Cultural Studies	American Studies		Biology	Biochemistry		Rehabilitation	Rehabilitation
		Organization Studies			Ethnic/Cultural Studies			Biology		Security Studies	Security Studies
		Real Estate			Gender Studies			Cognitive Science		Skilled Trade	Automotives
		Statistics - Business		International Studies	International Studies			Neuroscience			Aviation
	Consumer Science	Decision Science		Law	Law		Chemistry	Chemistry			Construction
	Economics	Economics		Political Science	Political Science		Engineering	Aerospace			HVAC
	Human Resources	Human Resources		Psychology	Counseling			Bioengineering			Manufacturing
	Math	Risk Management			Psychology			Chemical Engineering			Skilled Trade
	Other	Admin		Public Policy	Public Administration			Civil Engineering			Tax
Humanities	Anthropology	Anthropology			Public Policy			Engineering			Vocational
		Archeology		Security Studies	Peace Studies			Industrial Engineering	**Other**	Audiology	Audiology
	Arts	Art		Social Science	Social Science			Mechanical Engineering		ESL	ESL
		Art History			Social Science - Other			Nuclear Engineering		Other	Adult Learning
		Dance			Social Studies			Systems Engineering			Apprenticeship
		Film		Social Work	Social Work			Technology - Other			Cannabis
		Music		Sociology	Sociology		Environmental Studies	Energy Science			General Studies
		Theater			Urban Studies			Environmental Engineering			Graduate
	Consumer Science	Fashion		Urban Planning	Urban Planning			Environmental Studies			Military
		Human Development	**Education**	Education	Early Childhood Education			Forestry			Other
	English	English			Education			Natural Resources			Professional Development
		Literature			Elementary Education			Naval Studies			Remedial
		Writing			Higher Education		Health	Health			Student Affairs
	History	History			Secondary Education			Nutrition			Study Abroad
	Humanities	Classics			Special Education		Math	Math			Univeristy
		Humanities			Teaching		Medicine	Allied Health			University
	Language	Asian Languages	**STEM - CS**	Computer Science	Computer Science			Dentistry			University - Other
		Asian Studies			Computer Science - Other			Medicine			Wine
		Germanic Languages			Electrical Engineering			Optometry		Physical Education	Physical Education
		Language - Other			Informatics			Physiology			Recreation
		Mideast Languages			IT		Nursing	Nursing			Sports
		Romance Languages			Statistics - CS		Other	Mining		Rehabilitation	Occupational Therapy
		Slavic Languages						Oil and Gas			
	Library	Library					Pharmacy	Pharmacy			
		Library Science					Physics	Physics			
	Linguistics	Linguistics					Public Health	Public Health			
	Other	Museum Studies					Science - Other	Astronomy			
	Philosophy	Philosophy						Earth Science			
	Religion	Religion						Science - Other			
	Social Science	Geography					Stats/Data Science	Data Science			
								Statistics			

Figure A-5. Change in average course size



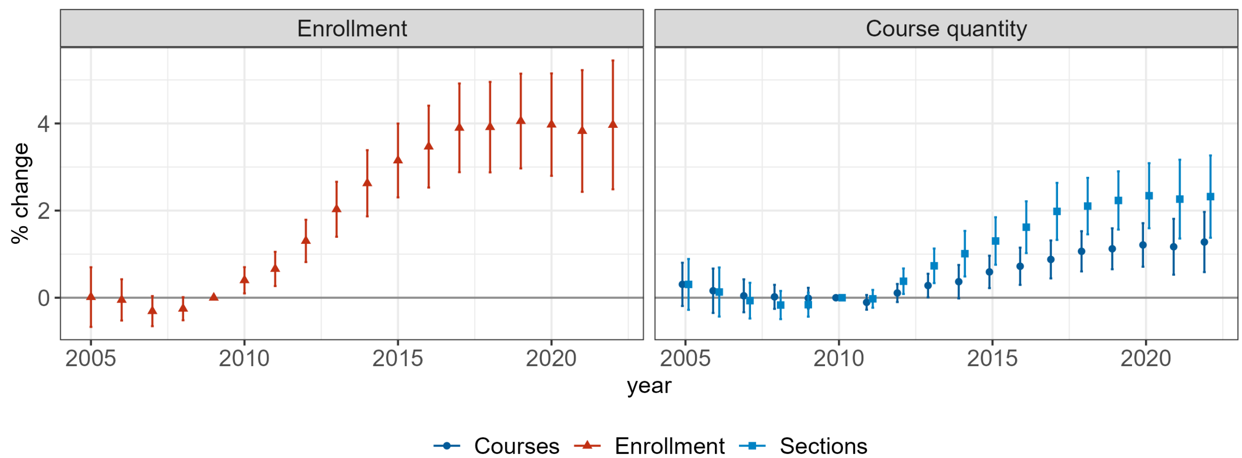
Notes: This figure plots the trend in average number of students per course and section between for six aggregated field categories. For each institution, I calculate the average number of students per course and section in each of the field categories by year. The figure plots the average of these values across institutions.

Figure A-6. Relationship between enrollment and employment change



Notes: This figure compares relative enrollment growth by field against the shift-share instrument capturing region-by-field employment growth. Points are at the field level. For each institution and field, I calculate the relative enrollment growth from 2009-10 to 2017-18, relative to the overall enrollment growth at the institution. For each field, I then calculate the average relative enrollment growth and plot it against the average value of the shift-share instrument. Each point in the figure is proportional in size to the sum of the weight each field receives in the regression analysis, where weights are allocated by field within each institution in proportion to 2010-11 enrollment and each institution receives total weight equal to 1.

Figure A-7. Test for quantity and enrollment anticipation of labor market changes



Notes: The figure plots point estimates from separate regressions of log enrollment, course quantity, and section quantity on the value of the shift-share instrument. Observations are at the institution-field-year level. Regression controls for institution-by-year fixed effects. Because of the one-year offset imposed to break the mechanical link between course offerings and contemporaneous enrollment, enrollment trend estimates are plotted relative to 2009-10 and course and section quantity trend estimates are plotted relative to 2010-11 — the corresponding reference years in the IV analysis. Standard errors are clustered at the institution level.

Table A-2. First-stage estimates

	Catalog data		IPEDS
	All undergraduate	Upper-level	Completed degrees
	(1)	(2)	(3)
% enrollment change - overall	-0.013	-0.017	-0.048
	(0.033)	(0.060)	(0.053)
Employment change	2.494***	4.440***	4.501***
	(0.304)	(0.426)	(0.533)
F-stat	67	108	71
Observations	4,530	4,014	4,015
R^2	0.059	0.101	0.077

Notes: Observations are at the institution-by-field level. I regress the log change in enrollment on the shift-share instrument reflecting major-typical employment growth in the Census division where the institution is located. Columns 1-2 measure changing enrollment using the course catalog data; Column 3 measures changing enrollment using completed degrees data from IPEDS for the same institutions in Columns 1-2. In the regression, each institution is uniformly weighted. Within an institution, subjects receive weights proportional to the start-of-period enrollment. In all columns, standard errors are clustered at the institution and Census division-by-field level.

Table A-3. F-stats for alternative instruments

	Lag length							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
All periods	9.32	9.40	12.25	19.08	36.40	47.35	64.89	73.54
Only period ending 2018-19	2.45	13.52	15.69	26.35	28.86	42.24	45.03	108.49

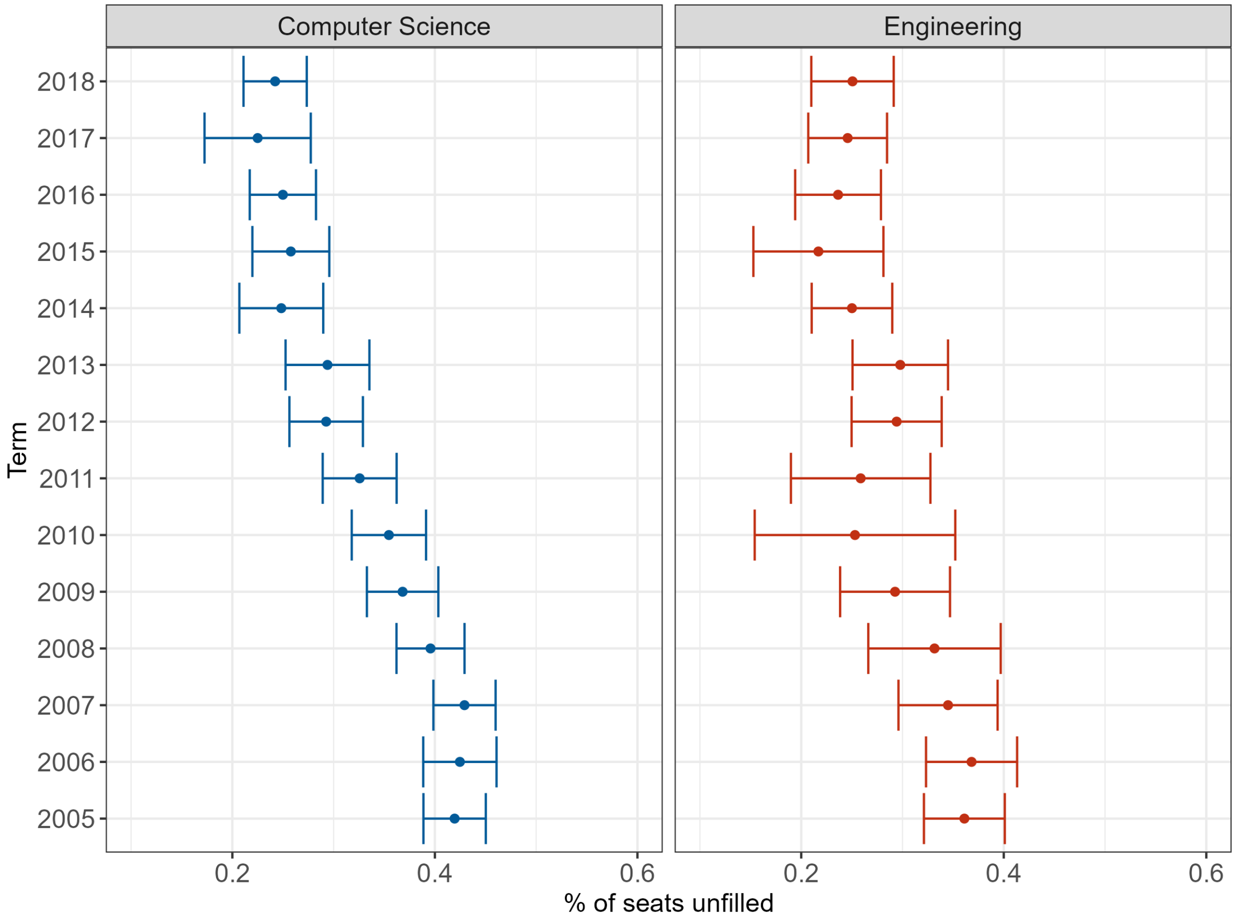
Notes: This table summarizes the first-stage F-statistics of log enrollment changes on the employment growth instrument calculated over various periods. "Lag length" refers to the duration (in years) over which these changes are calculated. The table includes F-statistics using data from all overlapping periods from 2009 to 2022 (e.g., a 4-year lag would cover intervals like 2009-2013, 2010-2014, etc.) and for a single period ending in the 2017-18 school year (to align with the period used for the IV analysis).

Table A-4. Reduced form estimates

	# of Courses		# of Sections	
	(1)	(2)	(3)	(4)
% enrollment change - overall	0.290	0.292	0.602	0.603
	(0.053)	(0.053)	(0.051)	(0.051)
Employment change	0.936		2.34	
	(0.254)		(0.280)	
Employment change - growing		1.73		2.78
		(0.329)		(0.405)
Employment change - shrinking		0.411		2.05
		(0.314)		(0.387)
Observations	4,014	4,014	4,014	4,014
R^2	0.04	0.05	0.17	0.17

Notes: Observations are at the institution-by-field level. The analysis regresses change in upper-level course quantity on the institution average change in enrollment, represented as log differences from 2009-10 to 2017-18, and the shift-share instrument capturing region-by-field variation in changing occupation growth from 2009 to 2017. Quantity and enrollment are credit hour-weighted. Each institution receives equal weight; within each institution, fields are weighted by start-of-period enrollment.

Figure A-8. Testing for leads in Computer Science course quantity change



Notes: The figure plots the distributions of the share of Computer Science and Engineering seats unfilled by year. For each school, I calculate the share of seats unfilled based on total enrollment in Computer Science and Engineering courses and the listed capacity for these courses.

Table A-5. Alternative course elasticity specification - no controls

	% change courses					% change sections				
	Rolling differences			Single period (2010-18)		Rolling differences			Single period (2010-18)	
	2-year	4-year	8-year	OLS	IV	2-year	4-year	8-year	OLS	IV
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
% enrollment change										
% enrollment change	0.206	0.318	0.393	0.386	0.235	0.305	0.489	0.592	0.590	0.576
	(0.010)	(0.010)	(0.009)	(0.022)	(0.051)	(0.012)	(0.013)	(0.010)	(0.022)	(0.047)
First Stage F-stat					106					106
Observations	94,291	78,570	50,825	4,014	4,014	94,291	78,570	50,825	4,014	4,014
R^2	0.052	0.138	0.239	0.271	0.229	0.088	0.227	0.356	0.417	0.417

Notes: Observations are at the institution-field-period level, where a period is a pair of comparison years differenced to measure percent changes. The analysis regresses change in upper-level course or section quantity on change in enrollment, each represented as long log differences. Quantity and enrollment are credit-hour weighted. Each institution receives equal weight; within each institution, fields are weighted by start-of-period enrollment. Columns 1-5 estimate course quantity elasticities; Columns 6-10 estimate section quantity elasticities. Columns 1-3 and 6-8 measure changes in course/section quantity and enrollment using long log differences for course enrollment and sections from all years in the course catalog dataset. Observations in these columns use overlapping periods (e.g. 2010-2014, 2011-2015). Standard errors in these columns are clustered at the institution-by-period level. In Columns 4-5 and 9-10, observations are at the institution-field level covering a single long log difference. For the IV estimates, standard errors are clustered at the field-by-Census division level, which is the level of variation for the instrument. Significance stars are suppressed because the relevant benchmark is not necessarily zero.

Table A-6. Course and section quantity elasticity regression, all undergraduate courses

	% change courses					% change sections				
	Rolling differences			Single period (2010-18)		Rolling differences			Single period (2010-18)	
	2-year (1)	4-year (2)	8-year (3)	OLS (4)	IV (5)	2-year (6)	4-year (7)	8-year (8)	OLS (9)	IV (10)
% enrollment change										
overall	0.199	0.251	0.310	0.358	0.358	0.445	0.604	0.709	0.712	0.712
	(0.022)	(0.018)	(0.018)	(0.040)	(0.023)	(0.027)	(0.027)	(0.016)	(0.059)	(0.023)
field	0.201	0.317	0.390	0.372	0.268	0.344	0.545	0.649	0.633	0.494
	(0.011)	(0.013)	(0.013)	(0.019)	(0.065)	(0.012)	(0.012)	(0.010)	(0.022)	(0.048)
First Stage F-stat					67.2					67.2
Observations	106,307	88,677	57,559	4,530	4,530	106,307	88,677	57,559	4,530	4,530
R^2	0.055	0.146	0.251	0.275	0.260	0.150	0.365	0.566	0.565	0.548

Notes: Observations are at the institution-field-period level, where a period is a pair of comparison years differenced to measure percent changes. The analysis regresses change in upper-level course or section quantity on change in enrollment, each represented as long log differences. Quantity and enrollment are credit-hour weighted. Each institution receives equal weight; within each institution, fields are weighted by start-of-period enrollment. Columns 1-5 estimate course quantity elasticities; Columns 6-10 estimate section quantity elasticities. Columns 1-3 and 6-8 measure changes in course/section quantity and enrollment using long log differences for course enrollment and sections from all years in the course catalog dataset. Observations in these columns use overlapping periods (e.g. 2010-2014, 2011-2015). Standard errors in these columns are clustered at the institution-by-period level. In Columns 4-5 and 9-10, observations are at the institution-field level covering a single long log difference. For the IV estimates, standard errors are clustered at the field-by-Census division level, which is the level of variation for the instrument. Significance stars are suppressed because the relevant benchmark is not necessarily zero.

Table A-7. Course and section quantity elasticity regression, lower-level courses

	% change courses					% change sections				
	Rolling differences			Single period (2010-18)		Rolling differences			Single period (2010-18)	
	2-year	4-year	8-year	OLS	IV	2-year	4-year	8-year	OLS	IV
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
% enrollment change										
overall	0.126	0.174	0.203	0.259	0.259	0.432	0.601	0.699	0.762	0.762
	(0.015)	(0.016)	(0.020)	(0.055)	(0.028)	(0.024)	(0.025)	(0.021)	(0.060)	(0.025)
field	0.143	0.245	0.304	0.309	0.010	0.310	0.516	0.631	0.655	0.307
	(0.007)	(0.011)	(0.014)	(0.023)	(0.114)	(0.011)	(0.016)	(0.018)	(0.027)	(0.104)
First Stage F-stat					35.2					35.2
Observations	101,301	84,546	54,819	4,325	4,325	101,301	84,546	54,819	4,325	4,325
R^2	0.025	0.077	0.126	0.141	0.045	0.125	0.314	0.482	0.505	0.422

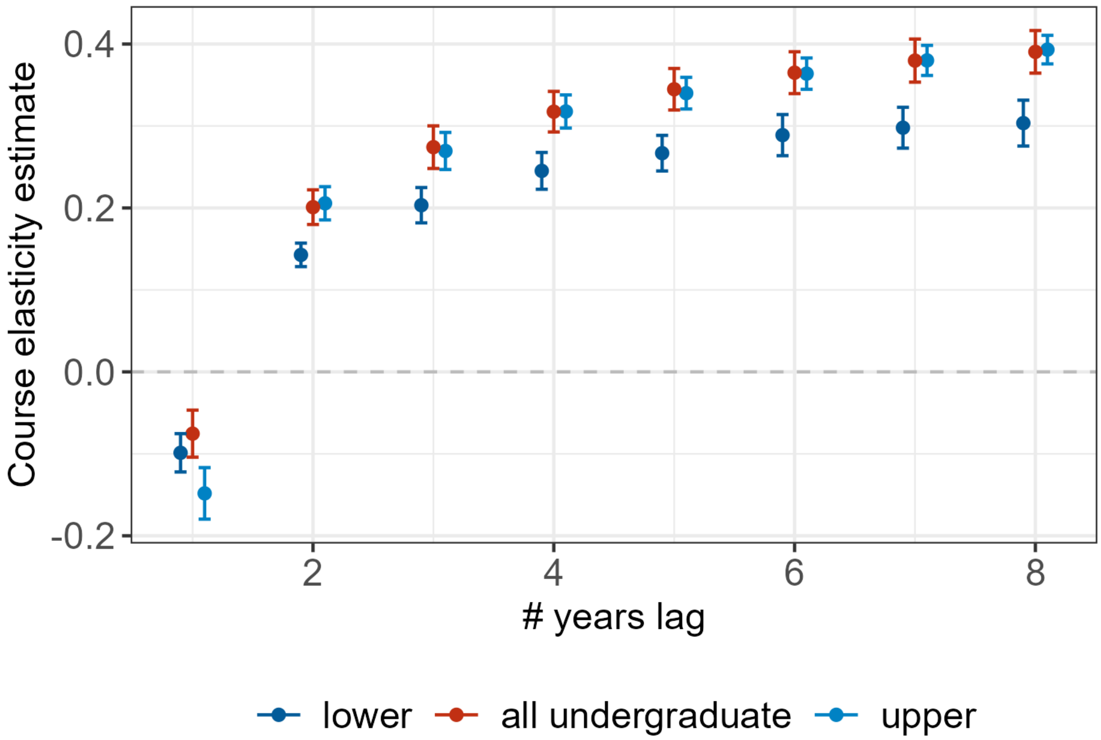
Notes: Observations are at the institution-field-period level, where a period is a pair of comparison years differenced to measure percent changes. The analysis regresses change in upper-level course or section quantity on change in enrollment, each represented as long log differences. Quantity and enrollment are credit-hour weighted. Each institution receives equal weight; within each institution, fields are weighted by start-of-period enrollment. Columns 1-5 estimate course quantity elasticities; Columns 6-10 estimate section quantity elasticities. Columns 1-3 and 6-8 measure changes in course/section quantity and enrollment using long log differences for course enrollment and sections from all years in the course catalog dataset. Observations in these columns use overlapping periods (e.g. 2010-2014, 2011-2015). Standard errors in these columns are clustered at the institution-by-period level. In Columns 4-5 and 9-10, observations are at the institution-field level covering a single long log difference. For the IV estimates, standard errors are clustered at the field-by-Census division level, which is the level of variation for the instrument. Significance stars are suppressed because the relevant benchmark is not necessarily zero.

Table A-8. Robustness on course quantity elasticities using different offsets and lags

	Lag length							
offset	1	2	3	4	5	6	7	8
0	0.55	0.51	0.50	0.49	0.49	0.49	0.49	0.50
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
1	-0.15	0.21	0.27	0.32	0.34	0.36	0.38	0.39
	(0.02)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
2	0.04	-0.06	0.18	0.23	0.28	0.30	0.33	0.34
	(0.01)	(0.02)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
3	-0.01	0.02	-0.03	0.14	0.19	0.24	0.27	0.29
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
4	0.02	0.01	0.03	-0.01	0.13	0.18	0.22	0.24
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)

Notes: This table summarizes OLS estimates of course quantity elasticity using different lag lengths and offsets. Lag length refers to the length of time in years over which percent changes in enrollment and course quantity are calculated. Offset refers to the lag imposed when regressing changes in course quantity on earlier changes in enrollment. Estimates come from regressions of change in course quantity on change in enrollment, each represented as long log differences. Quantity and enrollment are credit-hour weighted. Each institution receives equal weight; within each institution, fields are weighted by start-of-period enrollment. Standard errors are clustered at the institution-by-year level.

Figure A-9. Growth in course quantity elasticity with longer lags



Notes: The figure plots OLS estimates of course quantity elasticity estimated using different "lag lengths" of change in course quantity and enrollment. Lag length refers to the number of years over which changes in enrollment and course quantity are calculated. Enrollment and course quantity changes are offset by 1 year. Estimates are plotted separately for lower-level courses, upper-level courses, and all undergraduate courses. Standard errors are clustered at the institution-year level.

Table A-9. Course quantity IV robustness to alternative specifications

	Base (1)	Winsorized (2)	Alternative IV (3)	Base (4)	Winsorized (5)	Alternative IV (6)
% enrollment change						
overall	0.293	0.290	0.292	0.295	0.293	0.296
	(0.048)	(0.049)	(0.046)	(0.049)	(0.051)	(0.048)
field	0.211	0.197	0.336			
	(0.052)	(0.066)	(0.054)			
growing				0.341	0.364	0.456
				(0.066)	(0.099)	(0.082)
shrinking				0.098	0.084	0.164
				(0.082)	(0.095)	(0.073)
First stage F-stat	108.5	75.5	110.8	57	39.1	66.4
p-value grow = shrink				0.022	0.047	0.007
Observations	4,014	3,821	4,014	4,014	3,821	4,014
R^2	0.265	0.254	0.315	0.062	0.060	0.074

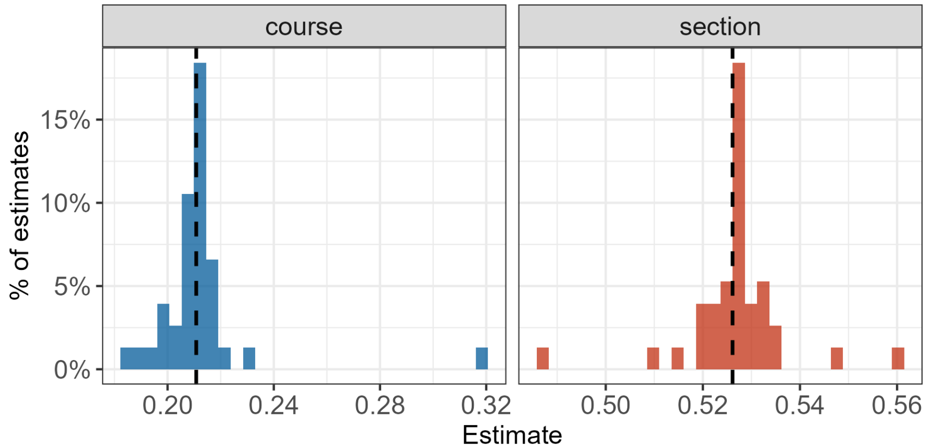
Notes: Columns 1 and 4 contain estimates from the main IV specification presented in the paper. Columns 2 and 5 drop the 2.5% of region-fields with the highest and lowest relative employment growth. Columns 3 and 6 estimate the IV with an alternative instrument based on field-level employment occupation growth in all Census divisions excluding the Census division in which the university is located. For all regressions, standard errors are clustered at the region-by-field level. For the estimates in Columns 4-6, bootstrapped standard errors are calculated using $1,000$ repetitions of the estimation, resampling region-by-field clusters in each iteration. Significance stars are suppressed because the relevant benchmark is not necessarily zero.

Table A-10. Section quantity IV robustness to alternative specifications

	Base (1)	Winsorized (2)	Alternative IV (3)	Base (4)	Winsorized (5)	Alternative IV (6)
% enrollment change						
overall	0.612	0.608	0.611	0.612	0.608	0.612
	(0.037)	(0.040)	(0.037)	(0.038)	(0.041)	(0.038)
field	0.526	0.519	0.591			
	(0.036)	(0.047)	(0.047)			
growing				0.543	0.543	0.625
				(0.061)	(0.091)	(0.082)
shrinking				0.511	0.502	0.544
				(0.059)	(0.079)	(0.052)
First stage F-stat	108.5	75.5	110.8	57	39.1	66.4
p-value grow = shrink				0.721	0.742	0.433
Observations	4,014	3,821	4,014	4,014	3,821	4,014
R^2	0.553	0.550	0.558	0.177	0.171	0.190

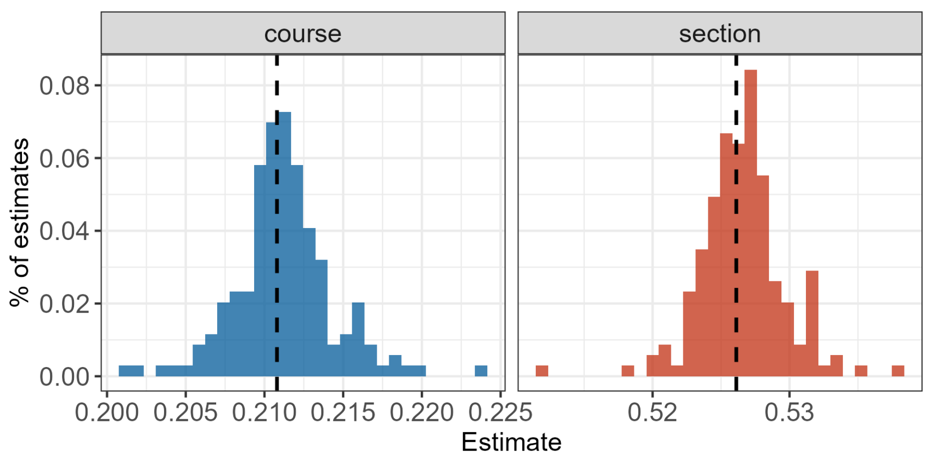
Notes: Columns 1 and 4 contain estimates from the main IV specification presented in the paper. Columns 2 and 5 drop the 2.5% of region-fields with the highest and lowest relative employment growth. Columns 3 and 6 estimate the IV with an alternative instrument based on field-level employment occupation growth in all Census divisions excluding the Census division in which the university is located. For all regressions, standard errors are clustered at the region-by-field level. For the estimates in Columns 4-6, bootstrapped standard errors are calculated using $1,000$ repetitions of the estimation, resampling region-by-field clusters in each iteration. Significance stars are suppressed because the relevant benchmark is not necessarily zero.

Figure A-10. Elasticity estimates from field leave-one-out IV



Notes: The figure plots the distribution of estimated course supply elasticities obtained by iteratively re-estimating the baseline IV specification while excluding one field at a time. Each histogram reflects the sampling distribution of elasticity estimates across leave-one-field-out replications. The baseline IV estimate is indicated by a vertical line.

Figure A-11. Elasticity estimates from institution leave-one-out IV



Notes: The figure plots the distribution of estimated course supply elasticities obtained by iteratively re-estimating the baseline IV specification while excluding one institution at a time. Each histogram reflects the sampling distribution of elasticity estimates across leave-one-field-out replications. The baseline IV estimate is indicated by a vertical line.

Table A-11. Correlations between institutional funding shocks, specialization, and course quantity elasticities

	Correlation		
Funding source	Specialization	Course elasticity	Section elasticity
Federal appropriations	0.043	0.072	0.129
State & local appropriations	0.058	-0.066	0.037
Gifts and donations	0.022	0.090	0.127

Notes: The table reports pairwise correlations between long-run changes in institutional funding and measures of specialization and course supply responsiveness. Funding shocks are measured as log differences in average real per-student funding between a base period (2002-2009) and an observation period (2010-2017), using IPEDS Finance data. Funding categories include federal appropriations, state and local appropriations, and private gifts and donations. Specialization is defined as the dot product of baseline (2009-10) field enrollment shares and the shift-share instrument, capturing exposure to subsequent labor demand growth. Course elasticity and section elasticity are defined at the institution level, calculated as the weighted average of field-level ratios of the log change in course or section quantity to the log change in enrollment, averaged using baseline field enrollment share weights and calculated using a one-year offset between course enrollment and quantity.

Table A-12. Graduate programs and the elasticity of course and section quantity

	# of Courses		# of Sections	
	(1)	(2)	(3)	(4)
Has graduate program	0.043	0.027	0.013	-0.001
	(0.010)	(0.016)	(0.008)	(0.016)
% enrollment change - overall	0.288	0.289	0.609	0.616
	(0.046)	(0.046)	(0.038)	(0.039)
% enrollment change - field	0.414		0.575	
	(0.028)		(0.026)	
Has graduate program × % enrollment change - field	-0.075		0.033	
	(0.044)		(0.042)	
% enrollment change - growing		0.405		0.603
		(0.026)		(0.025)
% enrollment change - shrinking		0.420		0.555
		(0.043)		(0.041)
Has graduate program × % enrollment change - growing		-0.004		0.060
		(0.071)		(0.062)
Has graduate program × % enrollment change - shrinking		-0.137		0.005
		(0.070)		(0.072)
Observations	4,014	4,014	4,014	4,014
R^2	0.325	0.326	0.558	0.559

Notes: The table reports OLS estimates from regressions of log changes in course or section quantity on log changes in enrollment, interacted with an indicator for whether the institution awarded any graduate degrees in the field in 2009. The "has graduate program" indicator equals one if the institution awarded at least one post-baccalaureate degree in the field and zero otherwise, based on IPEDS completions data. Enrollment changes are measured with a one-year offset relative to course and section quantities. Specifications (1) and (3) include overall and field-specific enrollment changes; specifications (2) and (4) allow for asymmetric responses in growing and shrinking fields. Standard errors are clustered at the field-by-region level.

Table A-13. Asymmetric course and section quantity elasticity estimates, all undergraduate courses

	% change courses					% change sections				
	Rolling differences			Single period (2010-18)		Rolling differences			Single period (2010-18)	
	2-year (1)	4-year (2)	8-year (3)	OLS (4)	IV (5)	2-year (6)	4-year (7)	8-year (8)	OLS (9)	IV (10)
% enrollment change										
overall	0.200	0.254	0.315	0.366	0.356	0.447	0.606	0.712	0.717	0.711
	(0.022)	(0.019)	(0.018)	(0.039)	(0.023)	(0.027)	(0.027)	(0.016)	(0.058)	(0.024)
growing	0.208	0.335	0.431	0.459	0.488	0.357	0.556	0.673	0.690	0.594
	(0.009)	(0.011)	(0.017)	(0.031)	(0.095)	(0.010)	(0.011)	(0.014)	(0.032)	(0.079)
shrinking	0.195	0.303	0.357	0.295	0.018	0.334	0.537	0.629	0.583	0.378
	(0.019)	(0.024)	(0.026)	(0.024)	(0.124)	(0.019)	(0.020)	(0.018)	(0.037)	(0.114)
First stage F-stat					36.7					36.7
p-value grow = shrink	0.561	0.268	0.036	0.000	0.003	0.278	0.439	0.075	0.056	0.127
Observations	106,307	88,677	57,559	4,530	4,530	106,307	88,677	57,559	4,530	4,530
R^2	0.055	0.146	0.253	0.284	0.099	0.150	0.365	0.566	0.567	0.231

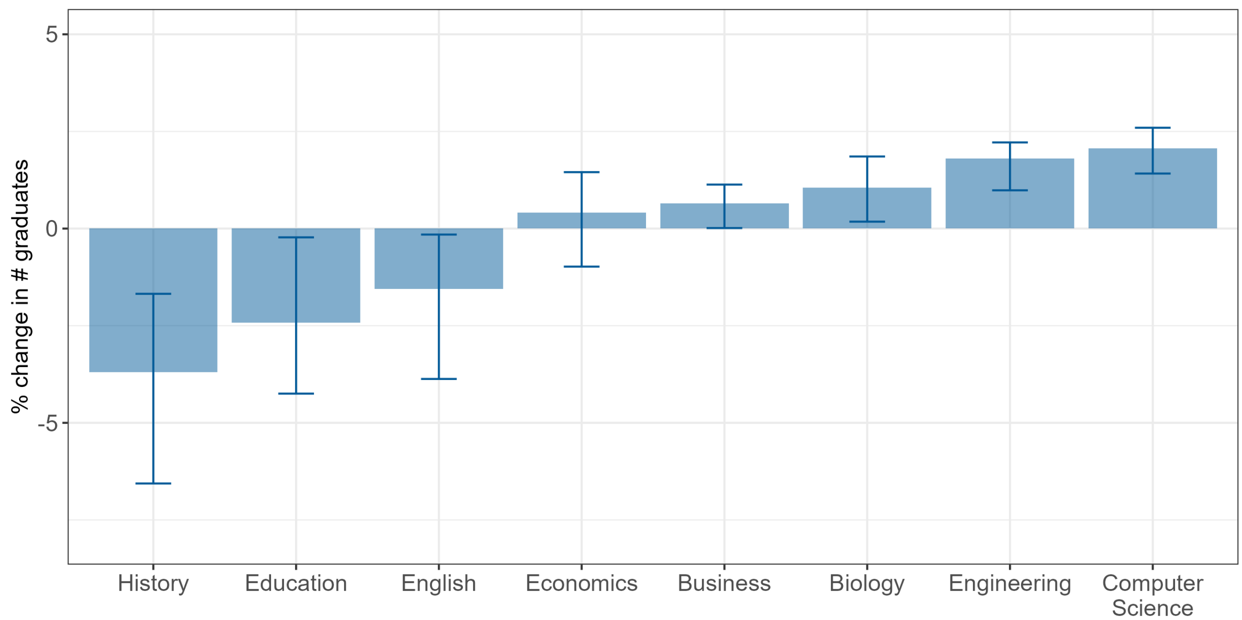
Notes: Observations are at the institution-field-period level, where a period is a pair of comparison years differenced to measure percent changes. The analysis regresses change in upper-level course or section quantity on change in enrollment, each represented as long log differences. Quantity and enrollment are credit-hour weighted. Each institution receives equal weight; within each institution, fields are weighted by start-of-period enrollment. Columns 1-5 estimate course quantity elasticities; Columns 6-10 estimate section quantity elasticities. Columns 1-3 and 6-8 measure changes in course/section quantity and enrollment using long log differences for course enrollment and sections from all years in the course catalog dataset. Observations in these columns use overlapping periods (e.g. 2010-2014, 2011-2015). Standard errors in these columns are clustered at the institution-by-period level. In Columns 4-5 and 9-10, observations are at the institution-field level covering a single long log difference. For the IV estimates, bootstrapped standard errors are calculated using $1,000$ repetitions of the estimation, resampling region-by-field clusters in each iteration, and standard errors are clustered at the field-by-Census division level, which is the level of variation for the instrument. Significance stars are suppressed because the relevant benchmark is not necessarily zero.

Table A-14. Asymmetric course and section quantity elasticity estimates, lower-level courses

	% change courses					% change sections				
	Rolling differences			Single period (2010-18)		Rolling differences			Single period (2010-18)	
	2-year (1)	4-year (2)	8-year (3)	OLS (4)	IV (5)	2-year (6)	4-year (7)	8-year (8)	OLS (9)	IV (10)
% enrollment change										
overall	0.132	0.186	0.221	0.270	0.261	0.440	0.612	0.713	0.770	0.764
	(0.015)	(0.016)	(0.019)	(0.057)	(0.033)	(0.024)	(0.026)	(0.020)	(0.060)	(0.029)
growing	0.176	0.304	0.389	0.394	0.390	0.347	0.571	0.702	0.713	0.620
	(0.009)	(0.013)	(0.019)	(0.030)	(0.123)	(0.011)	(0.012)	(0.016)	(0.040)	(0.145)
shrinking	0.117	0.200	0.234	0.230	−0.530	0.281	0.473	0.573	0.601	−0.146
	(0.013)	(0.019)	(0.023)	(0.041)	(0.382)	(0.017)	(0.025)	(0.028)	(0.044)	(0.388)
First stage F-stat					18.5					18.5
p-value grow = shrink	0.001	0.000	0.000	0.003	0.021	0.000	0.000	0.000	0.082	0.063
Observations	101,301	84,546	54,819	4,325	4,325	101,301	84,546	54,819	4,325	4,325
R^2	0.026	0.080	0.132	0.148	0.044	0.126	0.315	0.485	0.507	0.217

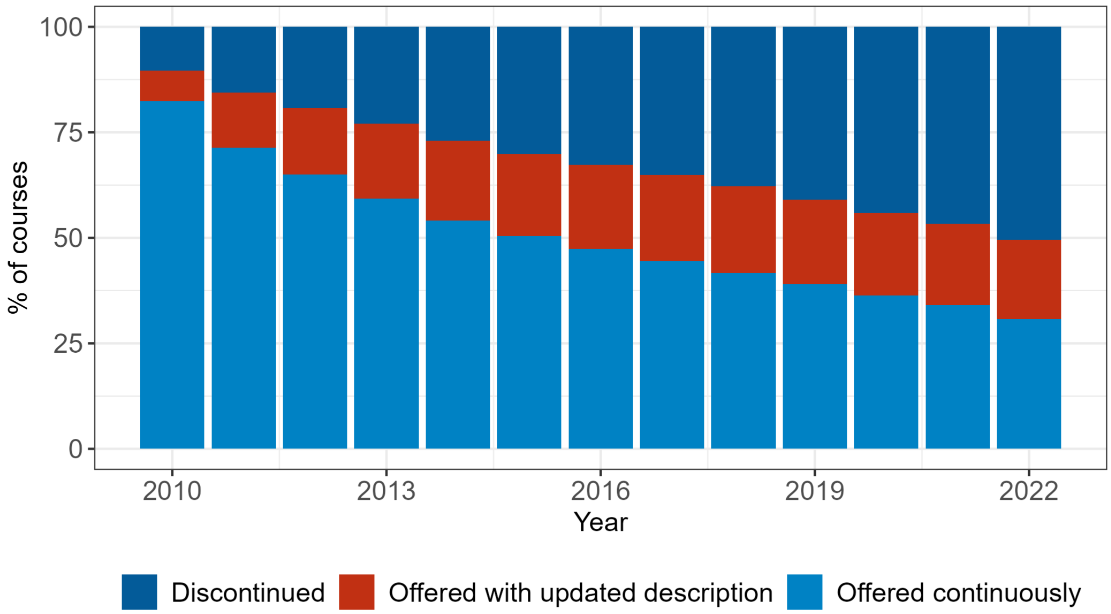
Notes: Observations are at the institution-field-period level, where a period is a pair of comparison years differenced to measure percent changes. The analysis regresses change in upper-level course or section quantity on change in enrollment, each represented as long log differences. Quantity and enrollment are credit-hour weighted. Each institution receives equal weight; within each institution, fields are weighted by start-of-period enrollment. Columns 1-5 estimate course quantity elasticities; Columns 6-10 estimate section quantity elasticities. Columns 1-3 and 6-8 measure changes in course/section quantity and enrollment using long log differences for course enrollment and sections from all years in the course catalog dataset. Observations in these columns use overlapping periods (e.g. 2010-2014, 2011-2015). Standard errors in these columns are clustered at the institution-by-period level. In Columns 4-5 and 9-10, observations are at the institution-field level covering a single long log difference. For the IV estimates, bootstrapped standard errors are calculated using $1,000$ repetitions of the estimation, resampling region-by-field clusters in each iteration, and standard errors are clustered at the field-by-Census division level, which is the level of variation for the instrument. Significance stars are suppressed because the relevant benchmark is not necessarily zero.

Figure A-12. Counterfactual major completions without course rationing



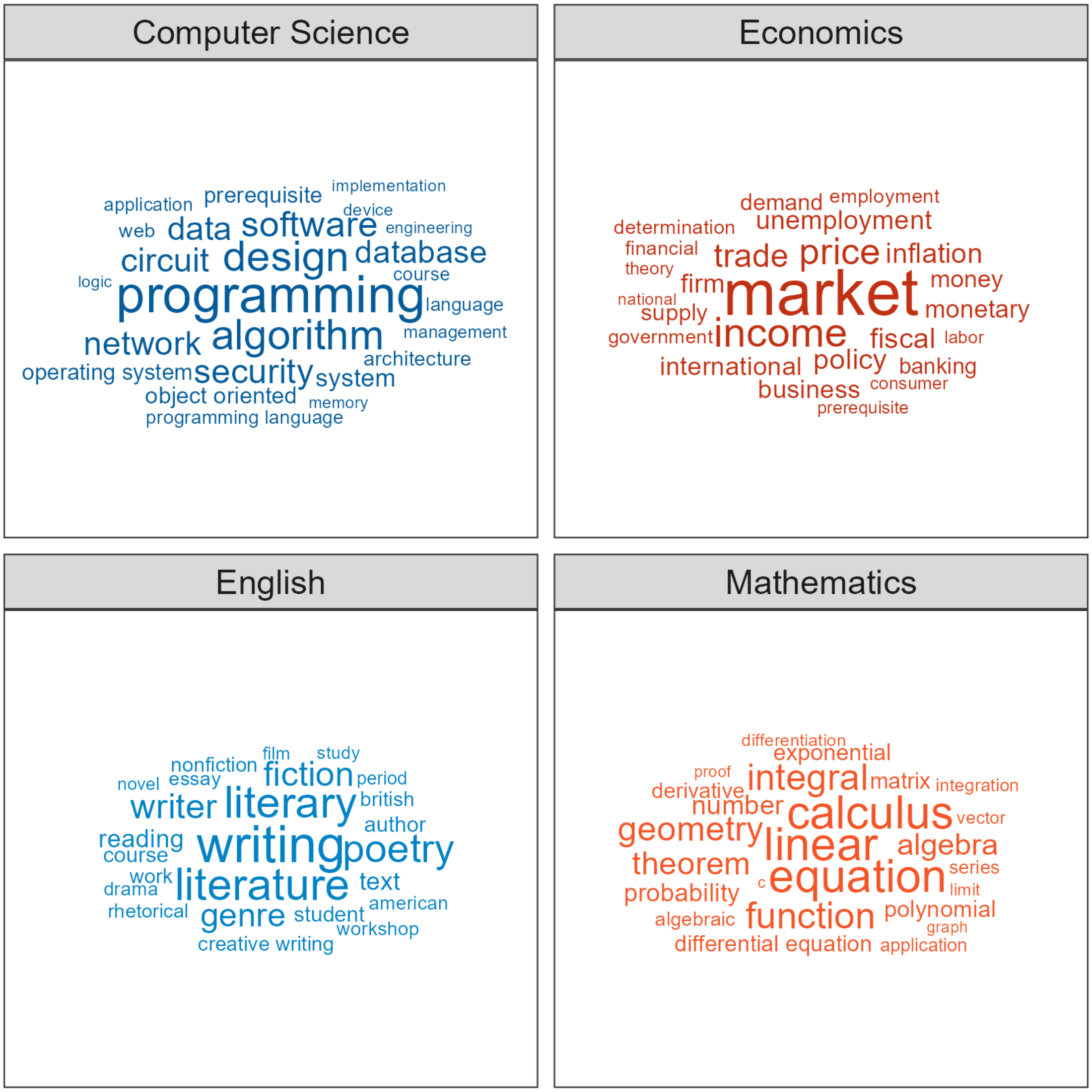
Notes: Figure plots estimates of counterfactual change in completed majors in the absence of rationing of seats in high demand sections. Values are estimated by estimating the unobserved percent change in demand for each institution-field pair between 2010-11 and 2018-19, using the difference in the section quantity point estimates between the IV and OLS specifications in Table 2. I translate the percentage change in demand into credit hours, then estimate the corresponding change in majors by multiplying by the 2010-11 ratio of number of completed majors (from IPEDS) per credit hour. The figure plots the average and inter-quartile range of estimated change in completed majors, calculated within field and across institutions, for a sample of fields.

Figure A-13. Survival of courses offered in 2010-11



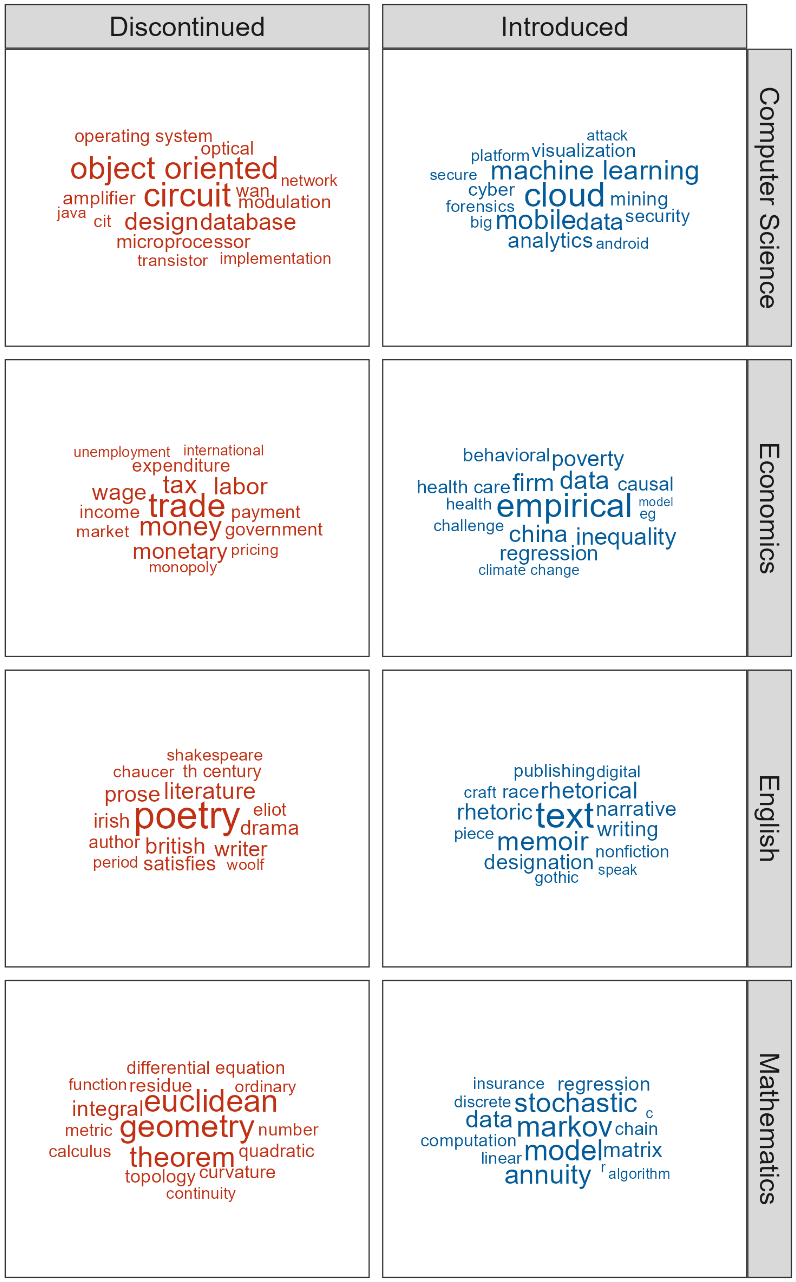
Notes: Figure plots the survival path of courses offered in 2010-11. In each year, the course can enter one of three states; a course is "Discontinued" if it is offered in a given year but never offered subsequently, a course is "Offered with updated description" if the course is offered in a given year but with a course description that does not match its description in 2010-11. A course is "Offered continuously" if it is not discontinued or offered with updated description. Each course receives equal weight in this analysis. States plotted represent the state into which a course transitions after the given year.

Figure A-14. Prominent words/phrases in selected fields (2022-23)



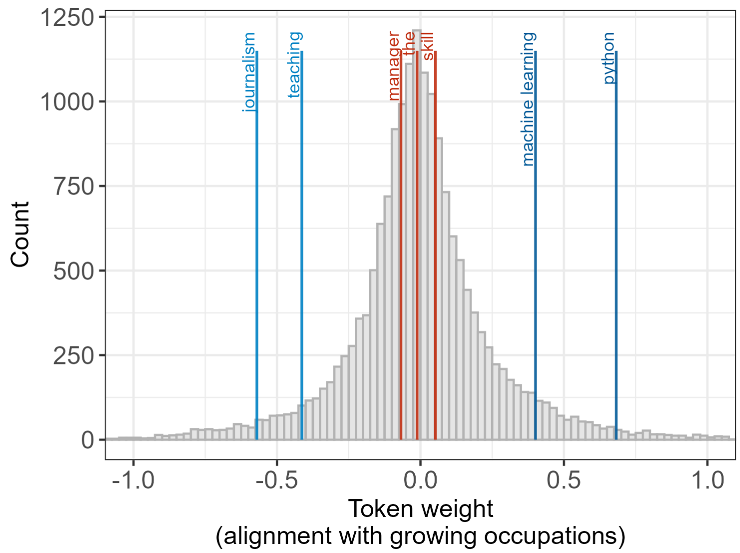
Notes: This figure showcases the top 25 tokens (words or phrases) for selected fields based on their average TF-IDF weight. For each field, courses from 2022-23 are aggregated into an institution-field document. The TF-IDF weight for each token is computed per document and then averaged within its field. Tokens containing the field's full name or common abbreviation (e.g., "Econ" for Economics) are excluded.

Figure A-15. Evolution of token significance in discontinued vs introduced courses



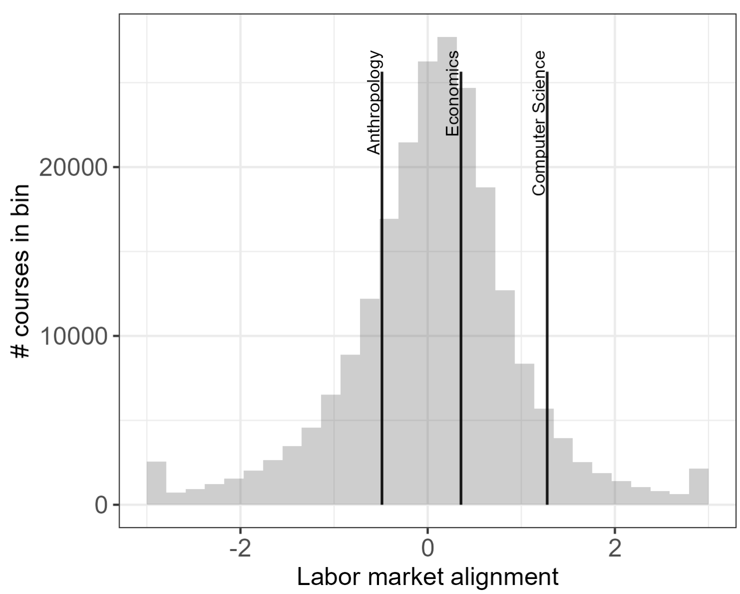
Notes: This figure contrasts the distinctive words of courses from 2012-13 to those of 2022-23. "Discontinued" courses are those offered in 2012-13 but no longer offered by 2022-23. "Introduced" courses are those not offered before 2012-13 but offered in 2022-23. Descriptions are grouped by field and course category (discontinued vs introduced). The figure shows the top 15 tokens with the highest TF-IDF values from both course groups. Tokens with the field's full name or common abbreviation (e.g., "Econ" for Economics) are excluded.

Figure A-16. Distribution of token weights



Notes: The figure plots the distribution of token-level labor market alignment weights, with selected tokens highlighted. Weights are calculated at the token level as the product of token-to-occupation frequency shares from job description text and log difference in occupation-level employment between 2010-2018.

Figure A-17. Distribution of labor market alignment scores



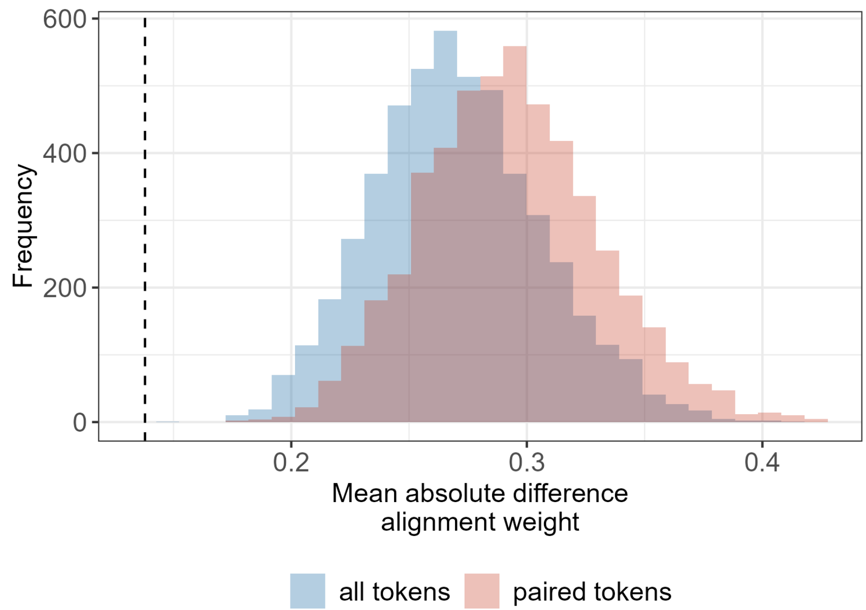
Notes: The figure plots the distribution of labor market alignment scores for courses offered in 2022-23. The figure plots average labor market alignment scores for selected fields as vertical lines. Values are censored above 2.5 SD and below -2.5 SD from the 2010-11 mean for readability.

Table A-15. Bounding within-course alignment growth

Specification	Within	Between	Entry	Exit	Total change
Base	0.0002	0.0070	0.0196	-0.0042	0.0225
Update all continuously offered courses	0.0020	0.0068	0.0196	-0.0042	0.0241

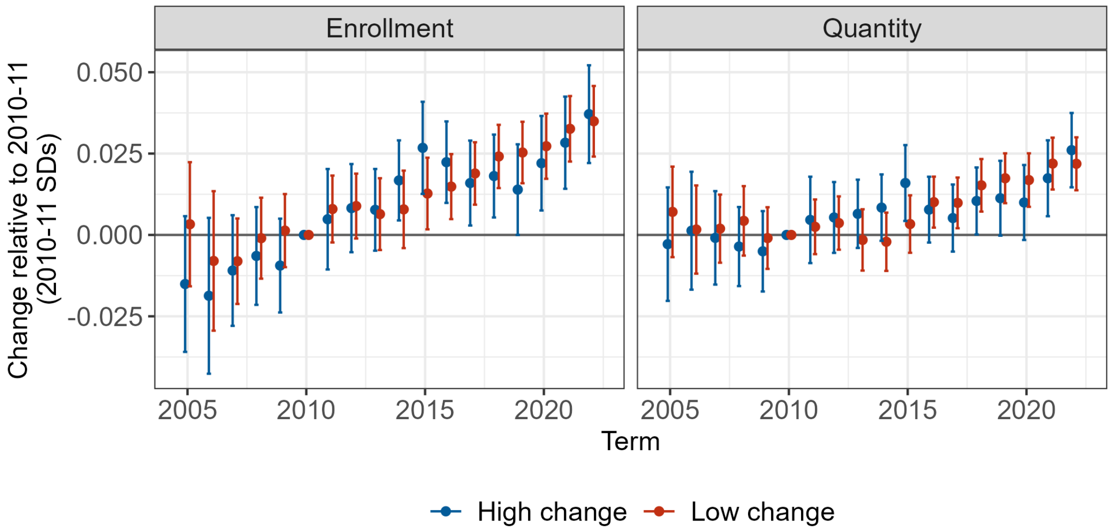
Notes: The table reports Foster et al. (2001) decompositions of the change in labor market alignment between 2010-11 and 2022-23. The top row reports values from the baseline specification in Table 4. The second row reports values from a bounding exercise where the "adaptation" of continuously offered courses whose descriptions are not updated — approximately half of continuously offered courses — is imputed as the average 2010-11 to 2022-23 change in curriculum alignment for continuously offered courses whose course descriptions are updated. By construction, entry and exit are unchanged across specifications.

Figure A-18. Labor market alignment weights capture semantic similarity



Notes: The figure compares the average absolute difference in alignment weights for curated word pairs with similar meanings (vertical dashed line) against the distribution of average differences for random word pairs. Blue histograms show random pairs drawn from the full token dictionary; red histograms show random pairs restricted to the 100 tokens used in the curated pairs. Each observation in the figure is the average difference in absolute labor market alignment weight for a list of 50 token pairs. The histograms each contain 5,000 50-pair lists.

Figure A-19. Labor market alignment trends by institution description update frequency



Notes: The figure plots the trend in labor market alignment for courses offered between 2005-06 and 2022-23, measured in standard deviations of the labor market alignment distribution for courses in 2010-11. The figure splits institutions at the median based on the share of continuously offered courses with description updates between 2010-11 and 2022-23. Regressions include controls for institution-by-field fixed effects. In each regression, each institution-year receives identical weight; within institution-year, weight is apportioned equally across courses in the right panel and in proportion to enrollment in the left panel. Standard errors are clustered at the institution-field-year level. Analysis restricts to upper-level courses.