Student Demand and the Supply of College Courses *

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Abstract

In an era of rapid technological and social change, do universities adapt enough to play their important role in creating knowledge? To examine university adaptation, I extracted the information contained in the course catalogs of over 450 US universities spanning two decades (2000-2023). When there are changes in student demand, universities respond inelastically, both in terms of course quantity and content. Supply inelasticity is especially pronounced in fields experiencing declining demand and is more pronounced at public universities. Using Natural Language Processing, I further show that while the content of existing courses remains largely unchanged, newly-created courses incorporate topics related to current events and job skills. Notably, at selective institutions, new content focuses on societal issues, while at less selective institutions, new content emphasizes job-relevant skills. This study contributes uniquely to our understanding of the supply-side factors that affect how universities adapt to the rapidly evolving landscape.

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1 Introduction

Universities have long been instrumental in developing a skilled workforce, creating knowledge, and fostering innovation in the United States. Their continued relevance, even amid changing economic and societal demands, underscores their capacity for adaptation. Take, for example, the evolution of Harvard College. Originally established in 1636 to train Puritan clergymen, Harvard has transformed over the centuries into a world-class research institution — demonstrating an adaptability central to the evolution of many of today's elite universities (MacLeod and Urquiola (2021)).[1] Arguably, however, today's technological, economic, and social environment is changing at a faster pace than universities have faced in previous centuries. The accelerating pace of technological change increases the rate of change in human capital required for an individual's success in the labor market (e.g., Autor et al. (2003)). How universities adapt is important not only for individual student outcomes but also for the development of a skilled workforce and for the continued relevance of these institutions.

Whether universities are, in fact, adaptable and nimble in response to changing demands is a question widely debated in higher education, yet lacking in systematic empirical evidence. I aim to bridge this gap by producing evidence of two main types. First, I show how responsive universities are to changes in student demand for skills and knowledge. I consider multiple margins along which universities could respond to changing demand, including the quantity and content of college courses, and find that they respond inelastically along both of these margins. Second, after demonstrating this inelasticity, I explore the features that distinguish more adaptable universities from less responsive ones.

To measure course supply and student demand, I constructed a novel dataset containing granular course-level information for a large and nationally representative sample of US universities. The dataset includes the complete set of courses offered by more than 450 universities, which collectively enroll over 37% of all US baccalaureate-level undergraduate students, amounting to over 24 million course sections offered since 1998. I collected the data by scraping information from online course catalogs. I recorded details such as the instructor(s), course enrollment, number of sections, instructional format (e.g., in-person or online), and a brief text description of the course content.

Using this new dataset, I analyze how universities adjust their supply of courses in response to changes in student demand. I consider two margins of course supply adjustment.

[1] Harvard's transformation, especially its elevation to a premier research institution, was significantly influenced by Charles Eliot's leadership in the late 19th Century. Drawing inspiration from eminent European universities of his time, Eliot implemented sweeping reforms, expanding research initiatives, diversifying graduate programs, and introducing a versatile course selection system, paving the way for enhanced curriculum in sciences, history, languages, and social sciences.

Along the extensive margin, universities meet changing demand for courses in a field of study (hereafter, "field") by adjusting the number of courses or sections.[2] Along the intensive margin, fields within universities might meet changing demand by modifying the content of the courses they offer.

I document inelasticity on the extensive margin by estimating the elasticity of the number of courses a field offers in response to changes in demand for that field. Such estimation is complicated because course enrollment, which I use as a proxy for demand, is influenced by both demand and supply factors. Students cannot enroll in courses that do not exist or that are rationed.[3] These forms of non-supply may obscure the measurement of demand changes as reflected in changing enrollment. I address this issue by using an instrumental variables (IV) strategy. I construct a shift-share instrument[4] that captures field-specific variation in employment growth and use this instrument to isolate the portion of changing student enrollment that is attributable to changing labor market conditions. This instrument allows me to focus on student demand for fields or skills rather than universities' supply of courses that reflect those fields or skills.

My estimates suggest that while students are responsive to changing conditions in the labor market, course supply is inelastic to this changing demand. On average, a field that experiences a 10% change in demand leads to a 2.7% change in the number of courses and 6.0% change in the number of course sections it offers. The elasticity varies across fields. Course supply is relatively more elastic when demand for a field is growing and less elastic when demand is decreasing. The results suggest that the constraints that an institution faces when it seeks to grow a field may differ from the constraints it faces when it seeks to shrink a declining field.

Universities can adapt to evolving student demand not just by offering more or fewer courses in a particular field, but also by modifying the content of pre-existing courses. For example, an Economics course might incorporate programming concepts to cater to surging demand for Computer Science skills. This adaptation, occurring within the content of courses rather than through the sheer number of courses supplied, represents a response on the university's intensive margin. To the extent that fields also respond to students' changing demand on the intensive margin, the extensive margin elasticities described above may

[2]For example, a large lecture course in the Principles of Economics might be offered at multiple times, in multiple semesters, with multiple instructors. In this example, Principles of Economics is a single course and each instance of Principles of Economics during a term counts as a single section.

[3]For example, suppose that the underlying demand for Economics courses quintupled but the university only expanded course offerings to add a few more seats. We might naively think that demand for Economics courses was tepid when, in fact, it was surging. In public universities especially, fields may impose a ceiling on enrollment (see, for example, Bleemer and Mehta (2021)).

[4]Also commonly known as a Bartik instrument, after Bartik (1991).

understate the university's responsiveness to changing demand.

I apply Natural Language Processing (NLP) techniques to course descriptions to measure course content changes in response to students' changing demand. The central challenge in this analysis is the lack of a direct measure of students' preferences for specific topics or skills. To overcome this, I develop a method that assesses course content in relation to broader themes that students might consider when selecting courses.[5]

The text analysis proceeds in two steps. In the first step, I employ Term Frequency-Inverse Document Frequency (TF-IDF), a widely-used method for representing text documents as vectors. In the second step, I assess each course description's "alignment" to the selected themes by scoring words in the description based on their frequency in representative documents of each theme. For instance, a word's prevalence in New York Times articles helps gauge a course's alignment with current events, while its appearance in job descriptions indicates its relevance to job market demands. To my knowledge, the approach I describe is a novel extension of NLP methods and is particularly appealing for its transparency and interpretability.

In general, the courses a university offers are highly stable: 65% of upper-level courses offered in 2022-23 have existed for a decade or more. After their introduction, the central topics and skills emphasized in these courses change infrequently thereafter. Thus, changes in the topics and skills offered by courses come primarily through the introduction of new courses. Through this channel of new courses, universities gradually incorporate content related to current events, social justice, and job relevance. Between 2013 and 2023, the average course offered at universities in my sample became 0.064 sd more aligned to current events and 0.055 sd more aligned to job relevance. In practical terms, the size of the change over the period of a decade is equivalent to swapping in every field at every institution one course at its 15th percentile of current events relevance with one course at its 85th percentile of current events relevance.

My results collectively indicate that there is inelasticity in the supply of courses, and that the content of these courses remains relatively stable. I use an elasticity of 1 as a benchmark for considering course supply to be inelastic, but we do not know the socially optimal course supply elasticity or orientation of course content. These choices involve trade-offs between students' desire for course access and the costs and challenges universities face in modifying course offerings. The optimal course supply elasticity is likely greater than 0 but also likely less than 1 due to, for example, frictions in the market for instructor supply.

[5] I relate each course to five themes: current events, job relevance, scholarship, social justice, and technology. I chose themes based on three main criteria: first, their general applicability across multiple fields; second, the availability of text data sources that could help identify relevant words/phrases; and third, their relevance to intellectual interests students might possess or cultivate during college.

Understanding why universities do not adjust course supply more rapidly can provide better context for the estimated inelasticity. To develop this insight, I explore three hypotheses that are frequently referenced in policy discussions concerning university responsiveness but lack empirical substantiation. The first, the "institutional rigidities" hypothesis, suggests that universities, especially public ones, may be restricted by entrenched stakeholders, such as tenured faculty, who might resist change and thus impede rapid adaptation to changing demand. The second, the "objective mismatch" hypothesis, posits that universities operate with a longer-term vision than students, balancing the immediate needs of the current student cohort against the broader mission of generating knowledge for the future, making them less responsive to the immediate demands of current students. Finally, the "learning complementarities" hypothesis asserts that universities most likely to incorporate trendy and cutting-edge content are those with high-achieving students, as these students are best positioned to pick up these new skills and stand to gain the most from them. To assess the validity of these hypotheses in explaining the observed inelasticity in course supply, I generate predictions for each and test them empirically.

My findings most strongly support the "institutional rigidities" hypothesis. Universities where individual stakeholders have the ability to extract rents tend to be less responsive to students' changing demand for courses. Specifically, public institutions (relative to private institutions) are significantly more inelastic to changing enrollment, both when enrollment is increasing and declining.[6] Interestingly, this inelasticity does not seem to be driven by tenure; while I find suggestive evidence that institutions with higher shares of tenured faculty are more inelastic when enrollment is declining, these institutions are, if anything, more elastic in creating new courses to accommodate fields experiencing enrollment growth. I also provide some support for the "learning complementarities" hypothesis, particularly with respect to course content. Selective institutions tend to offer newer courses focusing on current societal topics, while less selective institutions offer a more stable curriculum emphasizing skills immediately applicable to skill demand in the labor market.

This paper makes three central contributions. First, I introduce a novel dataset that provides detailed insight into higher education instruction through course-level enrollment, supply, and course description data. This detailed dataset allows for quicker and finer detection of trends in student demand across fields compared to previously used data sources, and can highlight differences in student learning across institutions that might not otherwise be observable at the level of completed majors. Second, the project is unique for analyzing

[6] The scope for "institutional rigidities" is greater at public universities because these institutions are governed by an expansive group of stakeholders: the electorate. This can result in decisions made without comprehensive knowledge of the institution's inner workings. Political influence in board nominations may lead to the appointment of governors whose interests diverge from the university's primary objectives.

supply-side responses to changing student demand. The results complement the comprehensive existing literature on how students adjust to changing returns to college degrees by highlighting the potential influence of imperfect course supply adjustments and the adaptability of course content in shaping students' course preferences.

Third, and perhaps most importantly, my exploration of the mechanisms underlying course supply inelasticity tests hypotheses central to any discussion of universities' objectives, why they make different choices, and their role in training a skilled workforce. Such discussions have high policy relevance but often are not grounded in rigorous evidence. My findings indicate that public universities are less responsive to student demand compared to private universities, highlighting the importance of governance structures and stakeholder influence in the university's ability to adapt to changing needs. Additionally, I show that courses at selective institutions place greater emphasis on current events and societal challenges, while less selective institutions emphasize more vocational training. These differences suggest a divergence in universities' missions: while less selective universities tend to offer a practical education tailored for immediate career needs, their more selective counterparts appear to prioritize a broader engagement with global and societal issues.

The rest of the paper proceeds as follows. Section 2 summarizes research related to this project. Section 3 describes the unique course catalog dataset used for this project. Section 4 documents inelasticity in the supply of college courses. Section 5 describes how fields adjust course content with changing enrollment. Section 6 uses the diversity of schools in my sample to explore heterogeneity in course supply inelasticity associated with different facets of the university. Section 7 concludes.

2 Related Literature

This paper contributes to a small but growing literature on higher education supply and a robust literature on factors influencing student demand in college. Previous work in higher education supply demonstrates how costs of instruction and instruction technology influence the supply of instructors across fields (Courant and Turner (2017), Hemelt et al. (2021)). Existing research related to margins of course supply response includes work on rationing of courses in high-demand fields (Bleemer and Mehta (2022), Bleemer and Mehta (2021)) and grade inflation (Dickson (1984), Sabot and Wakeman-Linn (1991), Butcher et al. (2014), Ahn et al. (2019), Denning et al. (2022)). Closest to this project is Thomas (2021), who models university preferences using instructor allocation and enrollment in introductory-level courses for a sample university. His work demonstrates the influence of course supply on students' enrollment decisions and considers the welfare trade-offs of expanding sections in high-demand fields with the higher cost of instruction in these fields. My project extends this literature in two main ways. First, I utilize new data that provide insight into both course supply and content. Second, I leverage the diversity of schools in my dataset, which allows me to explore the mechanisms underlying differences in institutional responsiveness.

This paper builds on a much larger literature on factors influencing student decision-making in college and choice of major within college.[7] The work in this area most relevant to my paper studies students' responsiveness to changing conditions in the labor market, where evidence is mixed. Some have found that students respond inelastically to changing wages (Beffy et al. (2012), Wiswall and Zafar (2015), Long et al. (2015)), while other work documents larger responses in terms of completed majors to occupation-specific shocks (Freeman (1976), Acton (2021), Weinstein (2020)) or changing macroeconomic conditions (Blom et al. (2021)). Recent work by Conzelmann et al. (2023) estimate relatively elastic responses of students' enrollment across fields to changing conditions in the labor market measured using job vacancies and using an estimation strategy similar to the one used in this paper. My results align with this more recent work, suggesting that while students may be responsive to changing labor market conditions but that changing wages may be less salient to them.

Finally, this paper contributes to a growing literature in Economics using text data,[8] including research that applies text methods in the economics of education (Eggenberger et al. (2018), Biasi and Ma (2022), Chau et al. (2023)). Using a dataset containing a large cross-sectional sample of course syllabi, Biasi and Ma (2022) and Chau et al. (2023) use novel text analysis techniques to develop measures of course content in relation to the research frontier and skill demand, respectively. Biasi and Ma (2022) document disparities in access to frontier knowledge across institutions of varying selectivity, which aligns with results in this paper of differences in curricular emphasis by institution selectivity. My data have the added benefit of observing the entire set of courses within specific institutions and fields, which allows me to disentangle broader trends in course supply while effectively controlling for institution-specific and field-specific effects.

[7]See Altonji et al. (2016) and Patnaik et al. (2021) for recent reviews of this literature.

[8]Gentzkow et al. (2019) summarize methods and applications to Economics research. Economics research using text data builds on innovations that originally come from the field of Natural Language Processing. Applications of these methods to social science research first grew in fields other than Economics. Although not summarized in this review, this work is also foundational for my project.

3 Data

3.1 Course catalog dataset

To analyze how higher education institutions adjust course offerings in response to changing student demand, I developed a unique "course catalog" dataset containing course-level detail from a sample of US colleges and universities. The dataset includes 24 million individual course section observations offered since 1998 from a sample of 453 US colleges and universities, which collectively enroll 37% of baccalaureate enrollment. I collected the data by scraping universities' online course catalogs and schedules, recording details of each course offered during a specific term.[9]

An example of the typical information recorded for each course can be seen in Figure 1. For a given course, I may observe the name(s) of the instructor(s), the course enrollment, the number of sections offered in a year, the format of instruction (whether it is in-person or online), and a brief text description of the course content.

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 resulting sample aligns with 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.[10] While the sample aligns closely with the average US four-year institution in aspects like selectivity, cost, and resources, it does skew towards larger, public institutions.[11] Extremely small private (often religiously affiliated) institutions are under-sampled in this dataset. Coverage of two-year institutions is much sparser and less representative of the average two-year college. Due to the sparser coverage of these institutions, I omit two-year institutions from the analysis in this paper.

The course catalog dataset offers more granular course supply and enrollment data than previously-used data sources, which typically summarize broader metrics such as completed majors. While the choice of major can be indicative, it represents only a portion of a student's college coursework. Students can acquire new skills or knowledge without switching their majors. Therefore, solely examining major completion might understate students' responses to changing labor market conditions. While some research employs transcript-level data to investigate shifts in students' preferences for specific fields, such datasets often cover a

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

[10]I restrict the analysis and comparisons to non-profit Title-IV eligible degree-granting higher education institutions.

[11]More accurately, as I am weighting by enrollment in this table, the schools reflect the characteristics of the schools most students attend.

restricted and homogenous group of institutions. In contrast, although the course catalog dataset may be slightly less granular, it encompasses a more diverse range of educational institutions.

I impose a series of restrictions to transform the raw course catalog dataset into a sample for analysis.[12] First, I exclude courses offered in non-classroom-based course types (e.g., independent study, internships). Second, to restrict to undergraduate education, I exclude graduate-level and continuing education courses. I divide the remaining courses into lower- and upper-levels based on each institution's course numbering conventions. Third, I restrict to only complete academic years and exclude summer terms. To standardize the data, I manually review each of the more than 20,000 unique department names and categorize them into one of the 54 standardized fields such as History, Education, Economics, and Engineering.[13] In all subsequent analyses, I weight enrollment and course offering counts by the number of credits.

3.2 Supplemental institution and employment data

I supplement the course data with data on institutional characteristics from the National Center for Education Statistics' Integrated Postsecondary Education Data System (IPEDS) and employment figures from the American Community Survey (ACS). The IPEDS data serve two purposes: validating the catalog data and extracting university characteristics, which I use in my mechanisms analysis. In the IV analysis, I use employment data from the 2010 and 2018 ACS, extracted from the Integrated Public Use Microdata Series (IPUMS) 1% samples (Ruggles et al. (2023)).

3.3 Supplemental text data sources

In Section 5, I examine how course content updates in response to student demand. I devise a weighting system that gauges the significance of a word or phrase to a particular theme based on its frequency in a theme-specific corpus relative to its appearance in a neutral corpus. The following sections provide an overview of the supplemental text data sources I utilize. Additional detail on these data sources is available in Appendix D.

3.3.1 New York Times articles

Using the New York Times Developer API, I download the entire set of articles (both in print and digital) published by the New York Times between 2000-2022. For each article, I

[12] For additional detail on the data processing, see Appendix A.

[13] Appendix B delves deeper into the field standardization procedure.

observe the headline and either an abstract for the article or a text snippet that contains the first few sentences of the article. The New York Times data contain 938 thousand articles.

3.3.2 Academic journals abstracts

I construct a corpus of abstracts from academic articles downloaded from Elsevier's SCOPUS. Following Biasi and Ma (2022), I search for abstracts from academic journals that rank in the top 10 by H-index for each field during the period 2000-2022. When available, I download the abstracts of all articles published during this period for each journal. The resulting sample includes 155 thousand abstracts from 180 journals.

3.3.3 Patents

I download patent text from the US Patent and Trademark Office covering the period 2000-2019. The resulting corpus includes the text of nearly 2.5 million patents.

3.3.4 Job descriptions

I source job description data from a dataset by Lightcast (formerly Burning Glass Technologies), containing the near-universe of online job postings. The full set of job descriptions is quite massive, so I build the corpus of job descriptions using job descriptions from a sample of months during my period of analysis. In particular, I include all job descriptions from March and August 2010, 2012, 2014, 2016, and 2018. I restrict to job descriptions with a requirement that applicants have at least a college degree. The resulting corpus contains 2 million documents.

3.3.5 Writings related to social justice

I assemble a corpus of texts related to social justice from a variety of sources. This corpus features the text from the 112 "Issues" web pages from the ACLU's website, which provide summaries of topics related to civil liberties. In addition, it includes the content from 1,800 press releases issued by Planned Parenthood, spanning from 2014 onward. Texts from both the ACLU and Planned Parenthood were scraped from their respective websites. The corpus also includes the full texts of six prominent books that are listed among the top 25 activist-related books on Goodreads: *Between the World and Me* by Ta-Nehisi Coates, *Freedom is a Constant Struggle* by Angela Davis, *Pedagogy of the Oppressed* by Paulo Freire, *This Changes Everything: Capitalism vs. The Climate* by Naomi Klein, *The New Jim Crow* by Michelle Alexander, and *We Should All Be Feminists* by Chimamanda Ngozi Adichie.

Collectively, these sources represent a spectrum of topics, from racial justice, prison abolition, and women's rights to climate change and a more general exploration of civil liberties.

3.3.6 Wikipedia articles

I download the text of all English-language pages published on Wikipedia as of July 1, 2023 using the "Wikimedia dump service." The dataset contains the full text of all Wikipedia pages. The resulting corpus contains 3.8 million documents.

4 Extensive Margin: How universities adjust course supply

In this section, I demonstrate the inelasticity of course supply to changing student demand. I first document this result descriptively, then estimate elasticities using an instrumental variables strategy that accounts for potential endogeneity of enrollment as a measure of demand.

I estimate course supply elasticities over the period 2010-11 to 2018-19. Since universities typically plan over multi-year cycles, it may be implausible to expect short-term adjustments to changing enrollment. Moreover, enrollment can be noisy, and small fluctuations might not necessarily represent genuine changes in demand. Thus, I consider a relatively long period that begins after the Great Recession and extends to the start of the Covid-19 pandemic.

In this analysis, my focus is on the provision of upper-level courses.[14] I provide estimates of course supply elasticity for all courses in Appendix C. These estimates are substantively similar but less precise.

4.1 Descriptive evidence of course supply inelasticity

When the demand for a field of study grows, an institution may choose from four strategies to accommodate the growing demand: it can increase the number of courses offered, increase the number of sections for currently-offered courses,[15] increase the capacity of existing sections,

[14] Conventionally numbered in the 300-400 range, typically elective courses. I impose this restriction for two reasons. First, these are the courses over which students have the most autonomy 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. Second, by the time students are enrolling in upper-level courses, they have acquired information about their aptitude for a given field. Any limitations on their ability to enroll in the student's preferred courses, therefore, may divert a student from the courses for which they are most suited.

[15] A course is essentially an individual class, usually identified by a unique course ID (such as Econ 101 or Econ 102), while a section refers to a specific instance or offering of a 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 of 2 courses in Economics.

or choose not to react at all and restrict enrollment.[16] Each strategy has its own set of associated costs and benefits. Instructors incur fixed costs of creating new courses, but these courses have the potential to benefit the widest student base. Offering additional sections of an existing course involves only marginal costs and benefits primarily students who would otherwise have been rationed out of the course. Expanding the capacity of current sections might be the most efficient in terms of instructional resources, but it places added burdens on the existing faculty and may impact the quality of instruction. Ultimately, the optimal approach hinges on the specifics of the demand shock and the university's preferences for current students' welfare relative to its other objectives.

Given the complexity of the university's objectives, it is not a priori obvious how a university will respond to an increase in student demand for a field. To shed light on this, Figure 3 summarizes university supply behavior in response to enrollment trends. The figure plots the growth trends in course enrollment, course supply, and section supply, aggregated into six field categories: Business/Economics, Education, Humanities, Social Science, STEM (excluding Computer Science), and Computer Science.[17] The figure illustrates a shift in enrollment from Humanities and Education towards fields like Business/Economics, STEM, and Computer Science.[18].

For fields with rapid enrollment growth, like Computer Science, or with declining enrollment, Humanities and Education, a noticeable gap emerges between course enrollment and supply. This gap is illustrative of inelasticity within the university. The extent of inelasticity varies across fields. For fields with modest enrollment growth, including non-Computer Science STEM and Business/Economics, enrollment and course supply grew at comparable rates. For fields experiencing declining enrollment, including Education and the Humanities, course supply is quite flat in comparison to the sharp enrollment declines. For Computer Science, which experienced explosive enrollment growth, course supply grew modestly but did not keep pace with the rapid enrollment growth.[19]

The asymmetry suggests potential rigidities in two directions. First, downward rigidities

[16] Similarly, in the case of a field experiencing declining demand, institutions can respond by reducing the number of courses offered, scaling back sections, reducing the capacity of current courses, or opting to make no changes at all.

[17] Fields like skilled trades, professional degree-granting fields, and interdisciplinary departments are excluded. Additional detail on field classification and selection is available in Appendix B.

[18] This shift in enrollment between fields has been well-documented and is the source of substantial public concern about the "decline of the humanities" (e.g., van Dam (2022))

[19] 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, attenuating some of the immediate need to grow course supply for the 2010s enrollment wave.

that make it harder to respond to shrinking demand than growing demand and rigidities in response to enrollment growth substantially greater than is typical. Commitments to foundational skills and the challenges of reducing tenured faculty might explain why course offerings remain steady even in the face of declining interest. Moreover, the already incurred costs of retaining instructors, especially tenured ones, make the marginal cost of offering a course in a less popular field relatively minimal. Second, the inelastic response to growing Computer Science enrollment is suggestive of rigidities that are triggered when demand for a field grows too quickly.

Though changes in enrollment and course supply align more closely in non-Computer Science STEM and Business/Economics, such alignment does not necessarily indicate a high elasticity in course supply. A limitation of enrollment as a proxy for demand is the inability to observe demand from students who are unable to take courses they would prefer, due to the university's rationing or lack of course offerings. I address this limitation of enrollment as a proxy for supply in the following section.

4.2 Empirical Strategy

In this section, my goal is to estimate how the supply of courses responds to changes in students' demand across different fields of study. Equation 1 shows the OLS specification I use to estimate course supply elasticity:

$$\Delta y_{i,s} = \alpha\overline{\Delta x_i} + \beta\widetilde{\Delta x_{i,s}} + \epsilon_{i,s} \tag{1}$$

$$\widetilde{\Delta x_{i,s}} = \Delta x_{i,s} - \overline{\Delta x_i} \tag{2}$$

Here, the dependent variable, $\Delta y_{i,s}$, denotes the percentage change in the number of courses offered by institution i in field s between 2010-11 and 2018-19. I calculate this change as a long log difference in the credit-weighted number of courses offered across these years.[20] 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 $\overline{\Delta x_i}$,[21] ensuring that the analysis accounts for shifts in course supply tied to broader university-level changes.

After controlling for the influence of overall enrollment growth on course supply, the parameter of interest, β, represents the elasticity of course supply to relative shifts in enrollment across fields. For clarity, the field-specific enrollment growth rate is adjusted by

[20] I credit-weight both changes in course supply and changes in enrollment.

[21] Measured as the percentage change in credit hour enrollment derived from the course catalog dataset.

subtracting the institution's average enrollment growth rate, resulting in $\widetilde{\Delta x_{i,s}}$.[22]

Particularly in cases where universities choose not to accommodate students' changing demand, we might be concerned that enrollment is endogenous to course supply choices made by the university. To illustrate this concern, consider a scenario where a university's Economics Department experiences a sudden surge in demand for its courses. In response, the university does increase its course supply but only enough to accommodate a fraction of the new demand. For example, the university might experience a demand increase equivalent to 200 new students but expand course supply to accommodate only 100 of them. In this case, supply is highly responsive to changing enrollment but the university only addresses half of the new demand for Economics courses.[23] These forms of non-response will bias my OLS estimates of course supply elasticity towards making the university appear more responsive to changing demand than it is in practice.

To estimate a causal relationship between changes in student demand and changes in course supply, I use a shift-share instrumental variables (IV) strategy that identifies a portion of enrollment changes that are solely attributable to shifting student preferences, independent of actions taken by the university. The instrument uses two sources of variation: variation in employment growth prospects across fields (s) and differential exposure to changing employment growth prospects in different parts of the country (based on the Census Division r in which school i is located, which I hereafter refer to as a "region").[24] I construct the instrument using data from the 2010 and 2018 American Community Surveys (ACS), following

[22]This de-meaning becomes important when I allow for different elasticities for fields growing faster versus slower than the institution overall. In Appendix Tables A-8 and A-9, I test an alternative specification that estimates the elasticity of course supply to absolute changes in enrollment, where I do not de-mean but also do not include any controls. These estimates are substantively similar and if anything suggest greater institutional inelasticity than the main results presented in this section.

[23]Further, to the extent that these students are diverted to courses in other fields, the university may appear responsive to inflated demand for other fields when, in reality, students are taking classes they would ideally prefer not to take.

[24]Recent 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. Our analyses differ in the sense that they study the direct effect of changing job demand on completed majors and course supply. In contrast, my analysis focuses primarily on how changing labor market conditions impact course supply 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 their 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)).

Equation 3 below:

$$\Delta E_{s,r} = \sum_{j=1}^{J} \phi_{s,j,r} \left(lnE_{j,r,2018} - lnE_{j,r,2010} \right) \tag{3}$$

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

The instrument fixes ACS respondents' college major (s) to occupation (j) shares $(\phi_{s,j,r})$ in 2010, then projects the change in log employment $(\Delta E_{s,r})$ as the average employment growth rate of college graduates in each occupation (4-digit OCC) between 2010 and 2018. I weight the employment growth by the fixed major-to-occupation shares.

To get the instrument $z_{s,r}$, I subtract from $\Delta E_{s,r}$ the regional average employment growth rate for college graduates, $\overline{\Delta E_r}$. This creates an instrument that captures the differential employment growth of various fields, compared to the regional employment growth for the average college graduate. Each university is quite small relative to the Census division, which encompasses 3-8 states. Thus, each university's contribution to the regional economy is relatively small. To further eliminate the influence of changing course supply on labor market measurements, I construct my instrument using only workers aged 30-65, as they would have completed their college education before the baseline year. The values of the instrument range from -0.208 to 0.188 across field-regions. A larger value indicates that the field has relatively improved job prospects in the region.[25]

To demonstrate how the instrument captures field-by-region differences in changing employment growth prospects, I construct the instrument for Computer Science and Education at a single university located in the South Atlantic Division. In the 2010 American Community Survey, approximately half of workers in the South Atlantic region with Computer Science degrees worked as programmers/engineers, nearly 20% worked in technical administrative roles, 10% worked in sales, and the remaining 20% worked in other occupations.[26] From 2010 to 2018, employment in these occupations grew at a weighted rate of 30.9%, which was 8.1 percentage points faster than the regional average. Similarly, 70% of workers in the South Atlantic region with Education degrees worked in education or education administration and the remaining 30% worked in other occupations. Employment in these

[25] The period of my analysis contains three important trends in labor market conditions that drive much of the variation in projected employment growth across fields. First, innovation in mobile technology and growing use of data fueled growth in technology jobs. Second, stagnant earnings and declining job satisfaction contributed to declining interest in the teaching profession (e.g., Kraft et al. (2020), Knox (2022)). Third, the passage of the Affordable Care Act in 2010 created new demand in healthcare. Fields and regions differ in their exposure to these changes, which creates variation for my estimation.

[26] For clarity of explanation, I describe the occupations in broad categories and round employment shares in this example. When constructing the instrument, I record employment at the level of 4-digit OCC codes.

jobs grew 7.9 percentage points less than the regional average during the same period. The instrument takes values 0.081 and -0.079 for Computer Science and Education in the South Atlantic Division, respectively. The relatively higher growth rate for Computer Science and the lower rate for Education highlight the instrument's ability to discern the differences in relative employment growth prospects between fields.

To illustrate how the instrument differentiates between regions, I construct it for a single field, Computer Science, offered at two different universities: one located at the same institution as in the preceding example and one located in the Pacific Division. In 2010, the occupational distribution of Computer Science majors was quite similar in the Pacific and South Atlantic regions. However, relative employment growth for Computer Science-typical jobs in the Pacific Division grew much faster (13.7 percentage points faster than the regional average, compared to 8.1 percentage points). In essence, the instrument measures how employment growth prospects for a specific field, like Computer Science, vary differently across regions.

I estimate the IV model using two-stage least squares. In the first stage, I estimate the relationship between the de-meaned percent change in enrollment ($\widetilde{\Delta x_{i,s,r}}$) in field s at college i from 2010-11 to 2018-2019 and the relative employment growth ($z_{s,r}$) of occupations typical for graduates of major s in region r:

$$\widetilde{\Delta x_{i,s,r}} = \gamma + \phi \overline{\Delta x_{i,r}} + \kappa z_{s,r} + \eta_{i,s,r} \tag{5}$$

In the second stage, I use the first stage's predicted values, denoted as $\widehat{\Delta x_{i,s,r}}$, 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 2010-2019 ($\Delta y_{i,s,r}$) on this instrumented enrollment change:

$$\Delta y_{i,s,r} = \alpha \overline{\Delta x_{i,r}} + \beta \widehat{\Delta x_{i,s,r}} + \epsilon_{i,s,r} \tag{6}$$

The second stage regression provides an estimate of the causal effect of changes in demand on changes in course supply.

For identification, the instrument must satisfy assumptions of monotonicity, independence, relevance, and the exclusion restriction. Monotonicity requires that growing employment opportunities should make students no less likely to enroll in a field. I demonstrate first-stage monotonicity in Appendix Figure A-6. Insofar as students seek to maximize their return on investment in higher education, improving employment growth prospects should not decrease students' preference of a given field. Independence requires that employment growth be uncorrelated with any unobserved factors that may influence the supply of courses. I select my analysis period, 2010-2019, to represent a distinct phase of the labor market starting at the end of the Great Recession and ending in the last full year before the Covid-19 pandemic.[27] I demonstrate first-stage relevance through a strong first-stage, the results of which are summarized in Appendix Table A-2. The first-stage F-statistic, also included in Table 2, is 108.[28]

The exclusion restriction requires that changes in labor market opportunities affect course supply solely through their impact on student demand. There are potential scenarios where this exclusion restriction might not hold. For example, if universities have a better foresight into employment growth than students, they might adjust their course offerings based on labor market demand rather than solely on student demand. In such cases, we would anticipate a university's course supply changes to precede the realization of students' demand growth, especially in the short term. However, as shown in Appendix Figure A-7, I find no evidence of this occurring, using the growth of Computer Science as an example.

Additionally, the exclusion restriction might not hold if shifting labor market conditions alter the relative costs of hiring instructors in different fields.[29] Robustness tests, which exclude fields that are most exposed to booming labor market opportunities (i.e. those with the highest instrument value), produce similar estimates.[30]

[27] Results estimated using the full course catalog data, spanning the full period 1998-2023, are substantively similar to those presented in the paper. See Appendix Tables A-4 and A-5.

[28] As a validation exercise, I also estimate the first-stage regression using completed majors, reported in IPEDS data, as the measure of changing enrollment. Completed majors are, if anything, more responsive to changing occupation growth than enrollment in upper-level courses. This may suggest that changing conditions in the labor market push marginal students to complete a major with improving employment growth prospects, but these students still take elective classes in fields with poorer employment growth prospects.

[29] For example, growing opportunities for computer scientists outside of academia increases the reservation wage for Computer Science instructors and requires an institution to increase wages for existing and new computer science instructors.

[30] Recent work in the shift-share literature formalize the identification assumptions underlying shift-share instruments (e.g., Goldsmith-Pinkham et al. (2020), Borusyak et al. (2022)). Goldsmith-Pinkham et al. (2020) demonstrates that the Bartik instrument can be viewed as analogous to using shares as instruments, with the exogenous growth rates primarily determining the instrument's relevance. In the context of this project, the "shares" aren't employment shares; rather, they represent major-to-occupation shares.

Identification would be compromised if major-to-occupation shares correlate with external factors that simultaneously influence both student demand and course supply. Three design features reduce concerns of the instrument's endogeneity. First, in line with common practice, I anchor the shares to the base period, ensuring their independence from any contemporaneous labor market shifts that could influence course offerings or student demand. Second, I construct the instrument using the major-to-occupation shares and employment growth rates only of workers age 30-65. Thus, the instrument is not impacted by recent graduates entering the labor market, who might be impacted by course supply inelasticity during the period of my analysis. Third, I define regions at the Census division level to ensure that each university's contribution to the regional labor market is extremely small compared to the size of the market.

The instrument only works to the extent that students pay attention to labor market trends when they are selecting their college courses. If students do not consistently factor in these trends, my IV results would, if anything, understate the true extent to which universities respond inelastically.[31] In short, while I believe my shift-share instrumental variable fulfills the exclusion restriction, it might cause me to understate the true inelasticity of universities.

For my IV, I cluster standard errors at the field-by-region level to address the potential serial correlation within a field-region. 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 the base year. This means I give more weight within the institution to fields with greater enrollment to improve precision. I aggregate departments into 54 fields at a level that is sufficiently granular to leverage variation across fields but general enough to allow for comparisons across institutions (e.g., Economics, English, Biology). These categories are largely similar to the field categories in Blom et al. (2021) and are described in detail in Appendix B.

4.3 Results

Table 2 summarizes OLS and IV estimates for the course supply elasticity regressions. Columns 1 and 2 summarize estimates of the elasticity of number of courses offered with respect to changing enrollment. The estimates suggest that course supply is inelastic to changing enrollment. The IV estimates suggest that fields expand course supply 2.7% for a 10% increase in demand. To illustrate, consider a department the size of Stanford's Economics Department. It would add a new course if the enrollment in upper-level courses rises by 114 seats. This addition corresponds to an underlying demand increase for upper-level

Goldsmith-Pinkham et al. (2020) also raise an identification concern if results are driven by a small number of industries, which, if endogenous, would be particularly problematic for identification. In the context of my project, the concern arises if a small number of fields drive the central results and if these fields are endogenous. I confirm the robustness of my results to the exclusion of fields such as Computer Science and Engineering, for which these concerns might be relevant. The exclusion of these fields does not substantively change the results.

[31]For example, the instrument would pick up growing employment in technology-related fields but not fully reflect the growth in demand for computer science skills. Or, consider the increased demand for health professionals following the passage of the Affordable Care Act. The instrument would pick up such increases in demand to a large extent, but if it is hard for clinics to find enough qualified nurses, the instrument will understate the increases in demand. On the other side, careers in education appear to have suffered from declining prestige, declining job satisfaction, and declining relative earnings over recent years. While my shift-share instrument captures most of the decline in students' interest in educational careers, it is unlikely to capture all of the decline.

Economics classes by 198 seats.[32] Columns 3 and 4 summarize estimates of the elasticity of number of course sections offered on changing enrollment. Although more responsive than courses, section supply is also inelastic. Fields expand course section supply 6.0% with a 10% increase in demand.

The OLS estimates in Table 2 are biased higher than the IV estimates. Because enrollment is an equilibrium outcome, changes in enrollment may reflect either students' changing demand for courses and the extent to which an institution responds to these changes. I cannot observe, for example, demand from students who are rationed out of courses they would prefer to take. Without accounting for this unmet demand, course supply responses will appear to align better with students' changing demand. Similarly, the university may introduce policies like distribution requirements that boost enrollment in courses that students otherwise might prefer not to take. Such policies would attenuate enrollment shifts from declining fields to growing fields. Considering these issues, we might expect the bias in the OLS estimates in the direction of greater course supply elasticity relative to the IV estimates.

The model in Table 2 assumes that a course supply response to increasing enrollment in a field is exactly opposite to a comparable decrease in course enrollment. However, the practical costs of growing versus shrinking a field can differ. Specifically, considering that tenured faculty often have guaranteed contracts, the university might incur little to no marginal cost in allowing faculty in a field experiencing declining enrollment to teach their course. Furthermore, descriptive evidence from Figure 3 suggests potential asymmetry in course supply responses to enrollment changes.

Thus, I consider a more flexible model that allows the course supply elasticity to differ based on whether the course is growing slower or faster than the institution average ($\overline{\Delta x_i}$). I estimate the new model:

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

where the parameters of interest, β_1 and β_2, represent the course supply elasticities when enrollment is growing slower or faster than the institution average, respectively.[33]

[32] In 2018-19, Stanford's Economics department offered 125 credits of upper-level courses and student enrollment totaled 6747 credit hours. A one-course increase in courses supplied would be equivalent to a 4% increase, which, according to the estimates in Table 2, is the result of an 8.4% increase in enrollment (568 student-credit hours) or a 14.7% increase in demand (992 student-credit hours). Dividing by 5 credit hours per course gives the values cited above. Some of the increased enrollment derives mechanically from enrollment in the new course.

[33] I consider an alternative specification in Appendix Tables A-10 and A-11 that estimates elasticities based on whether the field is growing or declining in absolute terms, rather than relative to the institution average. The results are substantively similar.

I also extend the IV model summarized in Equation 6 to allow for asymmetry in course supply responses above and below the institution average. The extended first stage instruments for growing and declining enrollment using separate instruments for when field-specific employment growth is larger and smaller than the regional average, as demonstrated below:

$$\widetilde{\Delta x_{i,s}}\mathbb{I}(\widetilde{\Delta x_{i,s}} > 0) = \gamma_1 + \phi_1 \overline{\Delta x_{i,r}} + \kappa_1 z_{s,r}\mathbb{I}(z_{s,r} < 0) + \kappa_2 z_{s,r}\mathbb{I}(z_{s,r} > 0) + \eta_{i,s,r} \tag{8}$$

$$\widetilde{\Delta x_{i,s}}\mathbb{I}(\widetilde{\Delta x_{i,s}} < 0) = \gamma_2 + \phi_2 \overline{\Delta x_{i,r}} + \kappa_3 z_{s,r}\mathbb{I}(z_{s,r} < 0) + \kappa_4 z_{s,r}\mathbb{I}(z_{s,r} > 0) + \xi_{i,s,r} \tag{9}$$

Table 3 provides a summary of the OLS and IV estimates for the elasticities of course and section supply, taking into account asymmetry. The first row assesses the course supply change due to overall changes in enrollment at the institution. The subsequent rows estimate the elasticity of course supply for fields either growing faster or slower than the institution's overall enrollment growth rate. Both under the OLS and IV specifications, course supply elasticities are higher for fields that grow faster than the institution's rate than those that grow slower. The IV estimates in Column 2 indicate that course supply increases by 3.9% for a field growing 10 percentage points faster than the institution's overall rate, while it decreases by 1.4% when the growth is 10 percentage points slower. Similarly, the IV results in Column 4 suggest that section supply rises by 6.9% when a field's growth surpasses the institution's rate by 10 percentage points, but drops by 5.0% when it lags behind by the same measure. Consistent with the linear model, the OLS estimates appear larger than the IV estimates, implying that rationing and reallocation cause the university to seem more responsive to demand changes than it actually is.

4.4 Discussion

Taken together, the primary takeaway from this section is that course supply reacts inelastically to shifts in student demand, especially when a field's enrollment is below the institution's average growth rate. Such dynamics bear implications for institutional strategy and educational quality. The asymmetry of course supply inelasticity suggests differential rigidities in institutional responses. In Section 6, I examine variation across different types of institutions to suggest potential mechanisms underlying the inelastic and asymmetric course supply responses.

Course supply inelasticity can influence both the quality of education and the choices available to students in multiple ways. First, it may deter students from pursuing their preferred fields of study, especially when this inelasticity results in course non-supply. Second, inelasticity can lead to dramatically larger classes in growing fields and smaller class sizes in shrinking ones. Universities may increase capacity in existing courses to accommodate growing demand, but there is a threshold to enrollment adjustments beyond which student learning may suffer, especially in upper-level courses tailored for smaller student cohorts.[34] These dynamics, especially in fast-evolving fields, may unintentionally create misalignment. Students could graduate with skills less aligned with current job market demands.[35] Additionally, they might not be fully prepared for societal challenges or emerging research areas. Moreover, if the growth in courses offered does not correspond with an overall increase in the university's enrollment, average instructional costs per student will increase. Since most universities rely heavily on tuition or public funding, they might pass the costs of inelasticity onto students through increased tuition.

5 Intensive Margin: How fields adjust course content

A field can adapt to changing student demand by updating course content, such as replacing a course teaching outdated skills with one that imparts high-demand skills. In the preceding section, an institution's only response to students' changing demand was the creation or elimination of courses within a given field of study. Fields that modify their courses in response to changing demand could attenuate enrollment shifts and relieve pressure to reallocate resources from shrinking to growing fields. This section explores how college course content adapts to align with students' interests.

5.1 Measuring course content through course descriptions

To measure the content of courses, I use the course description included with many course catalog entries (for example, see Figure 1). Course descriptions are short (typically fewer than 50 words) text summaries of course content that highlight topics covered in a class, skills students may develop, or the work students will produce. This rich insight into what students learn in their college classes is a unique feature of the course catalog dataset and enables me to identify what distinguishes or connects fields, compare fields across institutions, and track their evolution over time. Importantly, my data's longitudinal structure facilitates comparisons within an institution and field over time.

Although course descriptions provide unique insight into an institution's educational offerings, they possess a few limitations that I must account for in my analysis. For example,

[34] Substantial research shows that larger courses often result in lower student evaluations (e.g., Bedard and Kuhn (2008), Monks and Schmidt (2011)). However, evidence regarding the impact of class size on university-level student performance is more varied (e.g., Kokkelenberg et al. (2008), Bandiera et al. (2010), Bettinger et al. (2017)). I document the changes in average course size by field category in Appendix Figure A-5.

[35] On the other hand, there may be a trade-off between preparing for current job market demands and developing durable skills that will remain relevant far into the future (Deming and Noray (2020)).

instructors may not update these descriptions frequently. In such cases, the description might not reflect recent changes in course content.[36] To the extent that changes in course content are not contemporaneous with changes in course descriptions, the timing of any individual course description change may be unreliable. In my data, most of the changes to a field come through the introduction of new courses, before a course has an opportunity to diverge from the course description, and through the discontinuation of existing courses. I also study changes over a relatively long period of time to avoid reliance on changes in any individual year. Thus, my analysis should not be impacted substantially by lags in course description updates.

In order to measure and analyze course descriptions, I utilize techniques from Natural Language Processing (NLP). These methods represent the course description for each course c offered in field s at institution i in year t as a vector of words. I apply standard pre-processing to each course description.[37] I then represent each document as a $W \times 1$ vector $v_{c,i,s,t}$ with length (W) equal to the size of the dictionary of unique tokens ($w \in W$).[38] Typically, tokens are single words. However, I treat common phrases as distinct single tokens. For example, I treat "climate change" as a single token distinct from "climate" or "change"; likewise, "social media" is distinct from "social" or "media".

The values in $v_{c,i,s,t}$ are assigned according to their Term Frequency-Inverse Document Frequency (TF-IDF) weight, which is a measure of the distinctiveness of a given token to a given document. TF-IDF is the product of the Term Frequency (TF), a given token's share of all tokens in a document, and Inverse Document Frequency (IDF), measuring a token's distinctiveness across all documents. Intuitively, TF captures the intensity of a given skill/topic in a field's curriculum. For example, courses in Economics more typically include the tokens "economics" and "regression analysis" than "Shakespeare" or "cybersecurity." Variation in the occurrence of different words/phrases is captured by the TF weight applied to each token for a given course. IDF assigns more weight to significant tokens, reducing the emphasis on common words. This ensures that changes in word frequency reflect substantive shifts in what student cohorts might learn in different courses. For example, the IDF weight emphasizes the contribution of less common tokens, like "economics" and "regression analysis," over words that appear commonly in course descriptions, like "student" or "exam." See

[36]In my data, 35% of courses are modified or discontinued over a ten-year period (see Appendix Figure A-8).

[37]For example, I remove punctuation, standardize capitalization, remove overly-common "stopwords" (e.g., "the" and "is"), and lemmatize all words (e.g., transform "learns" or "learning" to "learn"). The complete processing procedure is described in Appendix D.

[38]The dictionary is derived from tokens that appear more than 500 times in the full scrape of Wikipedia articles, ensuring the exclusion of uncommon words or phrases that might skew the analysis. I describe the text data processing in greater detail in Appendix D.

Appendix D for a more detailed explanation of the TF-IDF weights and stylized example of how $v_{c,i,s,t}$ is constructed.

5.2 Validating course description data

To validate the effectiveness of course descriptions in assessing course content for this project, I must first demonstrate that they provide meaningful insights into the courses. Specifically, variation in topics or skills across fields or over time should signify genuine distinctions, not just variations in jargon that essentially denote identical concepts. This section aims to descriptively illustrate that the text data and methods reveal differences that are both meaningful and intuitive.

Figure 4 applies the NLP methods described in the previous section to demonstrate that the course descriptions reveal meaningful and intuitive differences in the content emphasized by different fields. The figure displays the 25 most distinctive tokens for a sample of fields. I consolidate all course descriptions from courses offered in 2022-23 into documents by institution and field. I create TF-IDF vectors for each institution-field pair based on the course descriptions, then average the weights across institutions and select the tokens with highest average weight by field. The tokens selected in the figure as having the highest TF-IDF weights within each field include many words and phrases typical of the sampled fields. For example, English classes are characterized by a focus on literature, reading, and writing; Computer Science classes emphasize programming and data analysis. The distinctive tokens include both skills (e.g., reading, programming) and concepts (e.g., markets, theorems).

The efficacy of the text analysis methods also hinge on their ability to detect substantive changes in course content over time, not just shifts in terminology. For example, introducing "climate change" into a course description where no equivalent concept existed previously indicates a substantive change to the course. However, if "climate change" simply replaces the phrase "global warming," the change is likely a terminological update rather than a significant alteration to the course.

In Figure 5, 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.

5.3 Characterizing how curriculum changes

Having demonstrated the information contained in the course descriptions, I now develop a measure of "alignment" between course content and student demand, then analyze how this measure changes over time. Lacking a direct measure of students' preferences for specific topics or skills, I measure the changing relationship between course content and a broad set of themes relevant to students' objectives and the mission of the university. Specifically, I focus on five themes: job relevance (as a response to economic changes), current events relevance and social justice relevance (as a response to societal changes), and technology and scholarship relevance (as a response to technological change and innovation).[39]

I relate course descriptions to these themes by developing a weighting scheme that captures a token's importance to texts highly connected to that theme. For example, "inequality" is a word that might appear frequently in social justice texts and "machine" is a word that might appear frequently in technology texts, but it is unlikely for the word "machine" to frequently appear in social justice texts, and vice versa. To capture the career relevance of a given token, I measure its frequency in job descriptions. To capture a token's importance to current events, I measure its frequency in the text of front-page articles published by the New York Times. To capture a token's relation to research scholarship, I measure its frequency in abstracts for top academic journals.[40] To capture a token's connection to social justice, I measure its frequency in a corpus of books and press releases from organizations oriented towards social justice causes. Finally, to capture a token's relation to technological progress, I measure its frequency in patent text. The text data sources used for quantifying each of these shifts, along with the procedure used to process these data sources, are detailed in Appendix D.

[39] I chose themes based on three main criteria: 1) their general applicability across multiple fields, 2) the availability of text data sources that could help identify relevant words/phrases, and 3) their relevance to intellectual interests students might possess or cultivate during college.

[40] Important work by Biasi and Ma (2022) explores this dimension of course content alignment in much greater detail, albeit slightly differently from the analysis described in this paper. Their analysis uses repeated cross sections of course syllabi to characterize differences in exposure to content on the cutting edge of research across institutions. Their analysis documents differences across universities in the provision of courses on the research frontier, and shows how instructors contribute to the innovative content of courses when they observe a change in instructor. My analysis builds on this important work, yet there are key differences in both the data sources used and our objectives. My dataset contains longitudinal data encompassing the full set of courses offered by a field. This enables me to observe within-institution and field-specific shifts over time and in response to changing enrollment. Biasi and Ma's analysis emphasizes the novelty of course content, whereas my research measure is related to a course's general connection with research-themed topics. My approach considers the relevance of both transitory and enduring research topics, recognizing terms like "research" or "analysis" that perennially indicate research relevance. While not differentiating between cutting-edge and older research content, it provides a comprehensive perspective on a course's alignment with research-themed topics over time.

I construct "relevance weights" for each token w with respect to each theme q.[41] The weights are designed to assess each token's significance to the reference text relative to a neutral text source - in this case, the corpus of Wikipedia articles. Each weight is calculated as the ratio of the token w's share in documents of type q, to the sum of the token's shares both in documents of type q and in Wikipedia articles.[42] To demonstrate, consider the construction of the current events relevance weight of a highly topical token like "climate change." Climate change represents 0.0197% of tokens in the Wikipedia data and 0.002% of tokens in the abstracts of New York Times front page articles. Thus, the current events relevance weight on "climate change" is

$$weight_{\text{climate change}}^{\text{current events}} = \frac{0.000197}{0.000197 + 0.00002} = 0.908$$

In Table 4, I provide relevance weights for a selection of tokens, emphasizing two main features. The top panel presents relevance weights for five tokens, each aligned with one of the five themes. Each token has a high relevance weight in its corresponding theme, underscoring the method's ability to pinpoint significant terms in the thematic documents. The bottom panel demonstrates that word pairs with analogous meanings or usages consistently yield similar relevance weights. Maintaining similar relevance weights for semantically or contextually related word pairs underscores the method's robustness. This consistency ensures that subtle shifts in jargon or lexical choices, which can be commonplace in academic and professional texts, do not skew the alignment scores. In essence, the method demonstrates sensitivity to thematic alignment while being resistant to mere linguistic variations, reinforcing its reliability in assessing course-to-research alignments.

To measure the extent to which a course aligns with a given theme, I calculate a "curriculum alignment score" for each course, year, and theme tuple. The curriculum alignment score is the sum of the relevance weights for tokens in a field's descriptions, weighted by the TF-IDF weights. In essence, the score averages the theme-specific importance of words/phrases in the course descriptions, with greater weight given to words/phrases distinctive to each document. Appendix D provides a detailed example of how a curriculum alignment score is calculated.

[41] Alternative strategies for measuring the curriculum alignment of course descriptions include using a multinomial classifier or a more sophisticated embeddings model. These alternative methods are more flexible than the method described above. The primary advantage of my expression weighting approach is transparency; it is easy to validate the weights assigned to each token and interpret how these weights contribute to the alignment scores.

[42] This weight corresponds to the conditional probability from an experiment where a thematic corpus (q or the corpus of Wikipedia articles) is randomly selected and a token w is subsequently randomly picked from that category. The relevance weight therefore represents the conditional probability that if a particular token w was chosen, it originated from the theme q.

To validate the method, I plot the average scores for courses offered in 2022-23, categorized by field and averaged across institutions, in Figure 6.[43] The figure illustrates the varying alignment of fields with different themes, often in ways that are intuitively understandable. For example,courses in Economics and Business are more closely aligned with themes of current events and job-related skills. In contrast, Humanities courses tend to be less vocational and slightly more in tune with current events. Meanwhile, Computer Science course descriptions include terms related to academic research, vocational skills observed in job descriptions, and technological advancements reflected in patents.

Next, I describe the changes in curriculum alignment over the past 20 years. Figure 7 plots the trend in average curriculum alignment of college courses offered since 2003-04. I estimate course-level regressions of curriculum alignment scores on a vector of time dummies, controlling for institution-by-field fixed effects. The estimates are normalized as the change in curriculum alignment (in standard deviations) relative to the curriculum alignment of the average course in 2013-14.

Figure 7 demonstrates that college course descriptions have gradually incorporated topics that are related to the themes relevant to students' interests.[44] For example, the average college course became 0.064 sd more current events-aligned between 2013-14 and 2022-23. A change of this magnitude is equivalent to each field at a university swapping a course at its 15th percentile of current events alignment with one at its 85th percentile over the course of a decade. Given that I am controlling for institution-by-field fixed effects, this trend is not driven by shifts in the composition of course offerings across fields, but represents within-field changes in the topics covered. The greatest growth during this period is in emphasis on topics related to current events, social justice, and job relevance.

The process through which curriculum adapts to align with these themes has important implications for knowledge dissemination within universities. Should existing courses continually innovate, the persistence of courses offered might not limit students' access to an curriculum adaptive to their demand. Conversely, if curricular adjustments mainly derive from the introduction of new courses and the elimination out of outdated courses, inelasticity in course offerings could limit students' exposure to the most relevant content.

[43] Results are qualitatively similar when I analyze course offerings in other years.

[44] Course content seems to increasingly incorporate the themes described in this section, but it is not obvious that there is a corresponding set of themes declining in importance during this time. This is sensible in the context of the result that the primary margin through which content changes is entry; while the courses that are created may share commonalities, what gets reduced, on average, is everything else. I find examples of themes for which the curriculum alignment trend is flat (for example, History or Agriculture). I plot words that have the greatest decline in importance from 2013-14 to 2022-23, controlling for the composition of courses across fields such that the declines do not simply represent changing emphasis in course offerings from one set of fields to another. Thus, I take these results to suggest that courses are largely aligned in how to evolve course offerings, but exactly what they are replacing does not follow a common theme.

I next assess the sources of growing curricular alignment for each theme. Following Foster et al. (2001), I partition the average change in curriculum alignment into four components. The "within" component measures changes attributable to changing course content for the same course offered in both 2013-14 and 2022-23.[45] The "between" component measures changes attributable to enrollment shifts between the continuously offered courses. The "exit" component measures changes due to the discontinuation of courses offered in 2013-14 but not in 2022-23. And the "entry" component measures changes due to the creation of courses that are offered in 2022-23 but were not offered in 2013-14. I measure changes within each institution and field, aggregate these changes at the institution level based on each field's proportion of total start-of-period enrollment, and then compute an unweighted average across institutions. I describe the decomposition procedure in greater detail in Appendix E.1.

Figure 8 demonstrates that the increasing curriculum alignment of courses in my sample arises primarily due to the entry and exit of courses, rather than changes within courses. For example, the average current events alignment of courses in my sample grew by 0.064 sd standard deviations, of which 61% of the change came from the entry of new courses that are highly current events-aligned. Similarly, the average course alignment with social justice grew by 0.1 standard deviations, of which 65% of the change came from the entry of new courses that are highly social justice-aligned. Meanwhile, for the more modest growth in alignment with academic scholarship, courses became 0.023 sd more aligned, but the majority of this alignment came from the exit of courses that were less scholarship-aligned.

It makes sense for universities to enhance their alignment with current events by introducing new courses. As global events and topics evolve, universities adapt by creating courses that address these shifts. Especially during unexpected global shocks, like the onset of the coronavirus pandemic, it is often more feasible to introduce new courses addressing these subjects than incorporate them into existing courses. The fact that alignment in scholarship and technology grows through course exit implies that courses that emphasize skills and topics in these areas have more durable or enjoy sustained levels of enrollment over many years.

While course content gradually shifts toward increased alignment with the five themes,

[45] The risk with the "within" component is that courses might undergo changes without those changes being reflected in their descriptions. To address this, I evaluate the decomposition over a lengthy period. In cases where I find updates to descriptions for courses that are still being offered, the new and old descriptions typically share similar alignment scores. These scores are calibrated to represent the core themes of a course, which are usually consistent even if the description changes. While minor course adjustments might cause slight variations in these scores, substantial changes often prompt the creation of a completely new course. Many institutions have guidelines that limit the scope of course description modifications; beyond a certain point, a new course is typically introduced.

the paths to this alignment vary. The significance of course entry and exit in driving this alignment provides context for earlier findings in this paper: the supply of courses is inelastic to shifts in student demand. The evidence presented in this section suggests that fields that are more dynamic in their course offerings may more closely align with themes appealing to students. In the next section, I explore heterogeneity among different types of institutions in their responsiveness to evolving student demand and examine differences in the content of their courses.

6 Mechanisms

In this section, I consider three hypotheses that might explain why course supply is inelastic. The hypotheses touch on different facets of the university's incentives and constraints. For each hypothesis, I develop a set of testable predictions that would hold under the hypothesis. I then leverage the diversity of institutions in my course catalog sample to understand which of the hypotheses best explains the variation in the inelasticity that I observe in the data.

6.1 Hypotheses and predictions

The **institutional rigidities** hypothesis proposes that universities may respond inelastically because they have been captured by faculty, staff, or other constituencies who use their power to extract rents.[46] After all, universities are not publicly-traded, for-profit firms. They do not need to report quarterly earnings, they do not have share prices that change daily with news about their productivity, and they are not vulnerable to hostile takeovers. Universities arguably have weak governance or governance in which the employees, especially tenured faculty, play a large role. Under this hypothesis, students try to enroll in new courses or courses with more up-to-date content. Universities do not comply elastically because they are captured by constituencies who would find it onerous to make changes or engage in updates.

This hypothesis posits that universities with a higher percentage of tenured faculty might exhibit greater resistance to change. Such resistance stems from the job security enjoyed by tenured faculty, possibly diminishing their motivation to innovate or increase their teaching load. This could lead to outdated or lower-quality course offerings.

In addition, public universities might be especially inelastic under the institutional rigidities hypothesis. Compared to private institutions, public universities might be more exposed to political agendas and, thus, more prone to interventions from political actors. The gover-

[46] Not by literally taking money but by enjoying an "easy life" or a "quiet life." See e.g., Bertrand and Mullainathan (2003).

nance of public universities presents another layer of complexity. These institutions answer to a broad and diverse group of stakeholders: the voters. Voters elect governing boards, often without a deep understanding of the university's intricate operations. Furthermore, the influence of elected officials in board appointments can sometimes overshadow the university's core educational needs and objectives. Wage-related challenges can also contribute to the inelasticity. Specific regulations, such as pay transparency laws that mandate the public disclosure of faculty salaries, might limit a public university's agility in offering wages that align with the dynamic market demand for certain skills and expertise.[47] Finally, in contrast to private universities, the faculty at public universities often have the option to unionize. When unionized, the faculty might possess certain protections or make demands that can impede swift institutional changes.[48]

The **objective mismatch** hypothesis proposes that universities could be more long-sighted, paternalistic, and/or more socially-minded than students. Under this hypothesis, students are myopic and self-oriented. Students want to learn the "latest" skills that will generate earnings in their first decade after graduating. They are less interested in developing a well-rounded set of skills and knowledge that will allow them to continue to grow their human capital and maintain their relevance well into the final decades of their careers. Owing to the fact that non-profit universities rely heavily on their older alumni to fund the education of their current students,[49] it might be sensible for universities to take the long view (Hoxby (2012)). Under this hypothesis, students might prioritize gaining skills for their immediate benefit, without much concern for how knowledge is created or preserved. For example, if it takes many years for scholars and researchers to develop and deploy their expertise, universities might adopt much longer horizons than students. Also, if universities care about basic research (as opposed to research that is ready to be applied) or about the preservation of knowledge, they might hesitate to eliminate fields of study even if they have no proximate applications or enjoy little current popularity with students.

Predictions from this hypothesis hinge on how universities weight short- and long-term objectives. How the university funds itself informs these weights. For example, universities that primarily derive their funding from the tuition of current students (as opposed to endowments or state funding) have a stronger incentive to align with the demands of these current cohorts. Such tuition-dependent institutions may be more elastic when students'

[47]For example, due to concerns about faculty discontent for pay disparities across fields (Card et al. (2012)).

[48]It is essential to note that some of these features could theoretically make public universities more adaptable. Tenured or unionized faculty, feeling secure in their positions, might willingly invest time in updating courses. Similarly, being largely funded by state appropriations might drive public universities to more swiftly adapt to local labor market shifts than private counterparts.

[49]Through donations in the case of endowed universities and tax revenue in the case of public universities.

demand changes. Conversely, institutions with substantial endowments might feel less influenced by the immediate preferences of current students. Therefore, wealthier institutions would be less elastic under the objective mismatch hypothesis.

The **learning complementarities** hypothesis proposes that both students and faculty value the dynamism and responsiveness of a curriculum. Under this hypothesis, students are not simply seeking to maximize immediate post-graduation income, but rather, they seek courses that align with their evolving interests and ambitions. They seek a curriculum that adapts to societal, technological, and labor market shifts, allowing them to stay current with trends and acquire relevant knowledge and skills. Likewise, faculty members are not solely interested in maintaining a comfortable status quo or focusing only on long-term research objectives. However, updating a curriculum or developing a new course comes with costs—both in terms of resources and time. Creating relevant and rigorous course content, developing teaching materials, aligning the course with accreditation standards, and training faculty to teach new content all require substantial investments. The benefits and costs of these updates vary across student and instructor types. High-achieving students, owing to their greater preparation and higher ability, may be more likely to benefit from a curriculum on the cutting edge of contemporary research or social topics.[50] Similarly, faculty may differ in the cost of developing new courses or incorporating new content into existing courses to the extent that they differ in their interactions with the frontier of research and social issues.

Under this hypothesis, the most substantial changes in course content would occur at institutions that bring together high-achieving students and research-oriented instructors. These institutions have the human capital necessary to bear the costs of regular curriculum updates. Additionally, such changes are also more likely when institutions serve high-aptitude students. These students, owing to their capabilities, are more likely to benefit from, demand, and indeed justify the costs associated with the most updated course content. This mutual relationship between research-intensive institutions and academically driven students fosters an environment favorable for a constantly evolving curriculum. In contrast, less research-oriented and less selective institutions may derive less benefit from a constantly evolving curriculum and therefore be more inelastic.

I leverage the diversity of institutions in my course catalog sample to assess the empirical support for each of these three hypotheses. I use variation in institution control (public vs private) and the share of instructors with tenure to test for the institutional rigidities hypothesis; variation in the share of revenue coming from tuition and endowment per student

[50]To give a concrete example: advanced economics students may not be able to benefit from courses that teach the latest empirical techniques or survey the latest research related to contemporary social issues with only a limited background in math. Institutions where students have lower math preparation, therefore, may not find benefits at scale to offering these classes.

to test for the objective mismatch hypothesis; and variation in the selectivity and research share of expenses to test for the learning complementarities hypothesis.[51]

For each of these characteristics, I study course supply and content heterogeneity in three ways. First, I estimate heterogeneity in course supply elasticities for different kinds of institutions. Second, I examine the average "age" or how outdated the courses are. Third, I highlight the variations in curriculum alignment across different types of institutions.

6.2 Heterogeneity in course supply elasticity

To investigate if the elasticity of course supply differs across university types, I modify the regression framework described in Section 4.2 to explore relationships between course supply elasticity and university characteristics. I consider three extensions to the elasticity regression framework.[52] First, I estimate separate models for each of the six characteristics, introducing an interaction term between the change in course supply and the school characteristic (expressed as a z-score, normalized by the national distribution). I refer to this model as the "Base" specification. Second, acknowledging correlations among these characteristics, I create a "Fully Interacted" specification. This single model includes interaction terms between changing enrollment and each of the six university characteristics.[53] Third, to address the endogeneity of changing enrollment, I run an "IV" specification where I estimate six separate regressions in the style of the IV model described by Equation 6 with a single changing enrollment-characteristic interaction term.

I estimate the interaction coefficients overall and in an extension of the model that allows the course supply elasticity to differ when enrollment is increasing or decreasing, as summarized in Equation 8.[54] My emphasis is mainly on the "Fully Interacted" model because of its capability to address correlations between different characteristics.

The parameters of interest in this analysis are the coefficients on the changing enrollment-characteristic interaction terms. These coefficients reflect the differences in course supply

[51]Specifically, I measure tuition dependence as the share of an institution's total revenue that comes from tuition payments; the research share is the share of current spending devoted to research; the tenure track share is the share of instructor headcount at the Full or Associate Professor level; selectivity as 1 - the percent admit rate; and endowment size is the total endowment per student (undergraduate and graduate). Characteristics data are incomplete for a small number of institutions in my sample; these institutions are omitted from the heterogeneity analysis. For my estimates of heterogeneity in course supply elasticity, I fix institution characteristics as of the base year 2010-11. For estimates of heterogeneity in course age or curriculum alignment, where I am only analyzing courses offered in 2022-23, I fix institution characteristics as of 2021-22 (the most recent IPEDS survey year). The results are robust to estimating all of the heterogeneity analyses using characteristics fixed to either of these years.

[52]For a more detailed methodology, see Appendix Section F.

[53]Appendix Table A-12 details the correlation between these characteristics.

[54]However, interaction term estimates in the IV model are imprecise and are therefore excluded from the analysis.

elasticity corresponding to institutions with different characteristics. A positive coefficient suggests that a school that is “more” of a given characteristic (for example, a more selective institution) is more responsive to changing student enrollment relative to the average institution.

I summarize estimates of the interaction coefficients in Figure 9. Three characteristics stand out in their association with variations in course supply elasticity. First, public schools are notably less elastic than private ones, both when enrollment increases and when it decreases. Second, while an institution’s share of instructors with tenure is not associated with variation in elasticity for enrollment changes overall, these schools appear to respond more elastically to rising enrollment compared to schools with more non-tenured instructors. Third, more selective schools respond more elastically to changing enrollment, driven by larger reductions in courses offered when enrollment in a field declines.

The finding of greater inelasticity in public institutions compared to private institutions provides support for the institutional rigidities hypothesis. The institutional rigidities hypothesis proposes that features of an institution’s governance create opportunities for rent taking or other inefficiencies that will make the institution more inelastic to changing demand. For public universities, the result is inelasticity to both rising and falling demand.

Interestingly, the channel for the institutional rigidities does not appear to be the share of instructors with tenure at the institution. I do not find evidence that a higher tenure share is associated with greater inelasticity to declining enrollment - at least not uniformly. I find suggestive evidence that institutions with a higher share of instructors with tenure are less elastic when enrollment is shrinking. However, these instructors are more elastic in growing course supply for fields with growing enrollment. One explanation for this finding is that instructors expect to offset the high fixed costs of creating new courses by offering a course over many years. Without a guarantee that they will be able to teach the course into the future, it may be harder to induce an instructor to create a new course.

The interpretation of the greater course supply elasticity at selective schools, especially when enrollment decreases, is less straightforward. One potential explanation is that selective institutions experienced demand shocks during this time of a different nature from those experienced by less selective institutions, such that fields experiencing declining enrollment may also have been fields for which it is easier to reduce course offerings. Alternatively, it may be the case that selective institutions offered more advanced curricula in fields that experienced declining enrollment to cater to the higher-achieving students. It could be easier to scale back these advanced offerings without compromising the academic field. In contrast, institutions with a more basic curriculum might find it more challenging to make such reductions.

6.3 Heterogeneity in course age

One consequence of inelastic course supply is that more inelastic institutions will continue to offer courses of little interest to students longer and will be slower to add courses that meet students' changing demand. The result of both of these factors is that more inelastic institutions will offer "older" courses, on average, than more adaptive institutions.

In Figure 10, I test whether institutions vary systematically in the "age" of upper-level courses offered.[55] For each course offered in 2022-23, I calculate the age of the course as the number of years since the course first appears in the course catalog dataset.[56] Figure 10 summarizes heterogeneity in course age by type of institution. I plot the point estimates from a fully-interacted regression of course age on each of the six normalized school characteristics.

The estimates suggest that courses are more contemporary, on average, at more selective and better-resourced institutions. An institution 1 sd more selective (21 pp decrease in admit rate) than the national average offered upper-level courses in 2022-23 that were, on average, 0.31 years more contemporary than at the average institution. To a lesser extent, institutions that are wealthier, more research-intensive, and private also seem to offer courses that are newer on average.

I do not find a strong relationship between course age and the other institution characteristics. In some instances, the characteristic may be associated with offsetting forces. For example, a higher tenure share may insulate instructors who choose not to update their courses to meet students' changing interests, but may also assure instructors creating new courses that they will be affiliated with their institution long enough to benefit from an upfront investment in the course for some time. Similarly, tuition-dependent institutions may be highly attuned to students' current needs in their provision of courses, creating pressure to offer newer courses relevant to students' current interests, but these schools also tend to be smaller and have fewer excess faculty to add new classes.

6.4 Heterogeneity in curriculum alignment

Finally, I measure variation in the curriculum alignment of courses offered at different types of institutions. Among the three heterogeneity exercises conducted in this paper, the variation

[55]Offering more recent courses is not obviously a desirable objective for all courses. Given the high costs of introducing a new course, the ability to offer the course over an extended period of time may incentivize instructors to invest more upfront in creating higher-quality courses. Some courses (e.g., Calculus I, Organic Chemistry) are quite durable and may not need to be reintroduced or updated very frequently. My focus on upper-level elective courses in this exercise does not penalize institutions for offering a stable core curriculum.

[56]For this exercise, I restrict to institutions that I observe continuously from 2013-14 to 2022-23. Because I may not observe the complete history of all courses dating back to the first time they were ever offered, I censor course ages such that courses first offered in 2013-14 or earlier are imposed a start year of 2013-14.

documented in this exercise may be most informative of differences in the focus of student learning at different types of institutions.

To estimate this heterogeneity, I estimate regressions of curriculum alignment score on the six institutional characteristics, controlling for field fixed effects. Observations are at the course level, using courses offered in 2022-23, and I once again restrict to upper-level courses for this analysis. I estimate a single "Fully Interacted"-style regression for each theme to account for correlation between the different institution characteristics. I plot output from this analysis in Figure 11.

Figure 11 demonstrates heterogeneity in the emphasis of courses associated with school selectivity and wealth. In particular, more selective, wealthier, and private institutions offer courses that, on average, align more with current events and social justice, but are less vocationally relevant. Compared to the average school, a school 1 sd more selective offers courses that are, on average, 0.029 sd more related to current events and 0.029 sd less vocational. To put this in context, the difference in current events alignment between the average course at an institution that is 1 sd more selective than the average institution and the average course at a typically selective is about half of the 10-year growth in average current events alignment for all courses from 2013-14 to 2022-23.

In addition, Figure 11 provides suggestive evidence that institutions with greater dependence on tuition offer courses that align with many of the themes related to students' interests. Broad emphasis on each of the themes relevant to students' interests is consistent with the hypothesis that tuition-dependent institutions are particularly attentive to the interests of current students.

6.5 Discussion

The preceding analyses explore the mechanisms underlying how universities respond to students' changing demand. The finding that public universities are less elastic in their response compared to private universities aligns with the institutional rigidities hypothesis. Greater inelasticity in public schools, in the face of both rising and falling demand, underscores the challenges these institutions face due to their governance structures and susceptibility to political influence. Interestingly, tenure is associated with offsetting impacts on an institution's course supply elasticity. While I find suggestive evidence that institutions with a higher share of tenured instructors are less elastic when enrollment shrinking (relative to the school average), I find that these institutions are more responsive in growing course supply when enrollment growth exceeds the school average.

The analysis offers some support for the learning complementarities hypothesis - particularly the between student ability and course content. More selective institutions tend to offer newer courses. As a potential consequence, these courses often emphasize topics related to current events and societal issues rather than immediate job applicability. I do not find strong support for the objective mismatch hypothesis.

The results shed light on the complexity of university objectives and constraints. Universities are not monolithic entities driven by a singular mission but complex institutions that are shaped by a combination of internal dynamics, external pressures, and historical legacies. Their responsiveness, or lack thereof, to changing student demand provides valuable insights into the tension between these competing influences.

Empirical support for the institutional rigidities hypothesis highlights that governance structures, and especially stakeholder influence, play a critical role in how universities operate. It underscores that the extent to which faculty, staff, or other internal constituencies can exert control over decision-making processes can materially impact the dynamism of course offerings. At institutions where these constituencies have substantial power — particularly at public universities — the system appears to favor stability and the maintenance of status quo. This may serve the interests of those who are already entrenched within the institution but may not align with the evolving needs and preferences of students or society more broadly. Such entrenched interests may be driven by the desire for job security, resistance to change, or a preference for existing research agendas over teaching responsibilities.

Support for the learning complementarities hypothesis, especially on the intensive margin, suggests that selective institutions are more adaptive and innovative in their curriculum. More selective institutions offer courses that emphasize current events and social justice over vocational relevance. This is partially due to the advanced preparation of these students, who develop foundational skills earlier in college which allow them to take advantage of courses more closely connected to contemporary social issues. This could also be a reflection of the broader objectives of elite institutions, which aim to nurture critical thinkers and future leaders, not just produce job-ready graduates. The result is a curriculum that is more dynamic and innovative at these institutions, consistent with findings from Biasi and Ma (2022). The curriculum at less selective institutions, meanwhile, is much more stable over time and appears more oriented towards preparing students for immediate entry into the labor force.

7 Conclusion

This paper presents a comprehensive examination of the elasticity of course supply to changing student demand within American universities over a twenty-year period. I utilize a unique dataset that I constructed by scraping online course catalogs to measure how course supply adjusts to changing demand along both extensive and intensive margins.

I document inelasticity in course supply, both in the number and content of college courses. On the extensive margin, I estimate that a 10% change in enrollment for a field results in a 2.7% change in unique courses offered and a 6.0% change in course sections. Notably, course supply is more elastic when enrollment in a field is growing relative to when enrollment is shrinking.

Inelasticity also manifests in the longevity of courses. 65% of courses offered in 2022-23 have been offered for at least a decade, and course descriptions are altered infrequently once a course is introduced. Thus, the primary channel for universities to innovate and align with student demand is through introducing new courses. Course content gradually adopts topics relevant to students' interests, including more topical and vocational content, through the introduction of new courses.

Taken together, the observed inelasticity on the extensive margin, combined with the propensity of fields to introduce new topics primarily through new courses, suggests that this inelasticity could potentially hinder students' human capital development. On the one hand, this inelasticity might be emblematic of a university's objective to instill enduring skills in students. Conversely, institutions hesitant to adjust to evolving student demand might not equip students with the skills they need in an evolving labor force.

To understand the sources of inelasticity in course supply, I evaluated three hypotheses: "institutional rigidities," "objective mismatch," and "learning complementarities." I find support for the institutional rigidities hypothesis in the greater inelasticity at public universities compared to private universities. These universities are more inelastic both when enrollment is increasing and decreasing. Interestingly, the tenured share of instructors at an institution does not appear to be a primary driver of its inelasticity, largely due to the offsetting effects of greater inelasticity when enrollment is declining but more elasticity when enrollment is increasing. I also find support for the learning complementarities hypothesis: selective universities offer courses that emphasize topics related to current events and social justice, whereas less selective institutions offer a more vocational curriculum.

This paper documents course supply inelasticity but leaves for future work the question of its welfare implications. Inelasticity harms students when they cannot secure seats in their preferred courses or when the course content hasn't been updated to reflect relevant topics and skills. Other students benefit from inelasticity, particularly those who get to enroll in smaller courses because of the university's continued support of less popular fields. The extent to which the course supply elasticities I estimate deviate from the socially optimal course supply elasticity depends on the appropriate balance between the welfare gains and costs from course supply modifications. The optimal course supply elasticity is likely greater than 0, such that students can develop human capital necessary to succeed in an evolving economic, social, and technological landscape. However, it is almost certainly less than 1 due to inelasticities in instructor supply. Moreover, the university must balance the welfare of current and future students in a way that may dampen responses to short-run student demand shocks. The socially optimal elasticity depends crucially on social weights placed on the various objectives a university satisfies, and may differ across universities. Estimating the socially optimal level of university elasticity represents a promising area for future research.

A logical extension of this research, and a step toward this estimate, would be to link inelasticity in higher education with students' labor market outcomes, from their initial entry to later career stages. By tying the inelasticity in course supply to such students' outcomes, we can gauge if such inelasticity adversely impacts students. Additionally, as the landscape of higher education shifts with the emergence of disruptors in higher education — like private for-profit universities and bootcamp programs — that compete with traditional four-year institutions by offering a more focused and adaptable curriculum, this paper's insights can guide universities adapt to an evolving higher education landscape.

A related extension would study competition within the university. Amid a period of declining enrollment in the Humanities, and calls from policymakers to make drastic cuts to these departments, understanding how these fields adapt to attract students back into the classroom, and what they sacrifice in the process, bears interesting insights for how individual fields evolve to meet changing needs.

Finally, empirical support for the "learning complementarities" hypothesis underscores potential inequalities in opportunities across universities, particularly between selective and less selective institutions. While my project provides evidence that different institutions cater to diverse student demographics through distinct curricula, it leaves for future research to determine whether such differentiation benefits or hinders students. The text analysis methods and dataset used in this project may permit deeper inquiry into the role the connection between skill development during college and future outcomes.

References

Riley K Acton. Community college program choices in the wake of local job losses. *Journal of Labor Economics*, 39(4):1129–1154, 2021.

Thomas Ahn, Peter Arcidiacono, Amy Hopson, and James R Thomas. Equilibrium grade inflation with implications for female interest in stem majors. Technical report, National Bureau of Economic Research, 2019.

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

David H Autor, Frank Levy, and Richard J Murnane. The skill content of recent technological change: An empirical exploration. *The Quarterly journal of economics*, 118(4):1279–1333, 2003.

Oriana Bandiera, Valentino Larcinese, and Imran Rasul. Heterogeneous class size effects: New evidence from a panel of university students. *The Economic Journal*, 120(549):1365–1398, 2010.

Timothy J Bartik. Who benefits from state and local economic development policies? 1991.

Kelly Bedard and Peter Kuhn. Where class size really matters: Class size and student ratings of instructor effectiveness. *Economics of Education Review*, 27(3):253–265, 2008.

Magali Beffy, Denis Fougere, and Arnaud Maurel. Choosing the field of study in postsecondary education: Do expected earnings matter? *Review of Economics and Statistics*, 94 (1):334–347, 2012.

Marianne Bertrand and Sendhil Mullainathan. Enjoying the quiet life? corporate governance and managerial preferences. *Journal of political Economy*, 111(5):1043–1075, 2003.

Eric Bettinger, Christopher Doss, Susanna Loeb, Aaron Rogers, and Eric Taylor. The effects of class size in online college courses: Experimental evidence. *Economics of Education Review*, 58:68–85, 2017.

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

Zachary Bleemer and Aashish Mehta. College major restrictions and student stratification. research & occasional paper series: Cshe. 14.2021. *Center for Studies in Higher Education*, 2021.

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

Erica Blom, Brian C Cadena, and Benjamin J Keys. Investment over the business cycle: Insights from college major choice. *Journal of Labor Economics*, 39(4):1043–1082, 2021.

Kirill Borusyak, Peter Hull, and Xavier Jaravel. Quasi-experimental shift-share research designs. *The Review of Economic Studies*, 89(1):181–213, 2022.

Kristin F Butcher, Patrick J McEwan, and Akila Weerapana. The effects of an anti-grade inflation policy at wellesley college. *Journal of Economic Perspectives*, 28(3):189–204, 2014.

David Card, Alexandre Mas, Enrico Moretti, and Emmanuel Saez. Inequality at work: The effect of peer salaries on job satisfaction. *American Economic Review*, 102(6):2981–3003, May 2012. doi: 10.1257/aer.102.6.2981. URL https://www.aeaweb.org/articles?id=10.1257/aer.102.6.2981.

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

Johnathan G Conzelmann, Steven W Hemelt, Brad Hershbein, Shawn M Martin, Andrew Simon, and Kevin M Stange. Grads on the go: Measuring college-specific labor markets for graduates. Technical report, National Bureau of Economic Research, 2022.

Johnathan G Conzelmann, Steven W Hemelt, Brad Hershbein, Shawn M Martin, Andrew Simon, and Kevin M Stange. Skills, majors, and jobs: Does higher education respond? Technical report, National Bureau of Economic Research, 2023.

Paul N Courant and Sarah Turner. Faculty deployment in research universities. Technical report, National Bureau of Economic Research, 2017.

David J Deming and Kadeem Noray. Earnings dynamics, changing job skills, and stem careers. *The Quarterly Journal of Economics*, 135(4):1965–2005, 2020.

Jeffrey T Denning, Eric R Eide, Kevin J Mumford, Richard W Patterson, and Merrill Warnick. Why have college completion rates increased? *American Economic Journal: Applied Economics*, 14(3):1–29, 2022.

Vaughan A Dickson. An economic model of faculty grading practices. *The Journal of Economic Education*, 15(3):197–203, 1984.

Christian Eggenberger, Miriam Rinawi, and Uschi Backes-Gellner. Occupational specificity: A new measurement based on training curricula and its effect on labor market outcomes. *Labour Economics*, 51:97–107, 2018.

Lucia Foster, John C Haltiwanger, and Cornell John Krizan. Aggregate productivity growth: lessons from microeconomic evidence. In *New developments in productivity analysis*, pages 303–372. University of Chicago Press, 2001.

Richard B Freeman. A cobweb model of the supply and starting salary of new engineers. *ILR Review*, 29(2):236–248, 1976.

Matthew Gentzkow, Bryan Kelly, and Matt Taddy. Text as data. *Journal of Economic Literature*, 57(3):535–574, 2019.

Paul Goldsmith-Pinkham, Isaac Sorkin, and Henry Swift. Bartik instruments: What, when, why, and how. *American Economic Review*, 110(8):2586–2624, 2020.

Steven W Hemelt, Kevin M Stange, Fernando Furquim, Andrew Simon, and John E Sawyer. Why is math cheaper than english? understanding cost differences in higher education. *Journal of Labor Economics*, 39(2):397–435, 2021.

Caroline M Hoxby. Endowment management based on a positive model of the university. Technical report, National Bureau of Economic Research, 2012.

Liam Knox. Teacher shortage tied to education programs' enrollment drop, 2022. URL https://www.insidehighered.com/news/2022/08/29/teacher-shortage-tied-education-programs-enrollment-drop#:~:text=Between%202008%20and%202019%2C%20the,of%20Colleges%20for%20Teacher%20Education.

Edward C Kokkelenberg, Michael Dillon, and Sean M Christy. The effects of class size on student grades at a public university. *Economics of Education review*, 27(2):221–233, 2008.

Matthew A Kraft, Eric J Brunner, Shaun M Dougherty, and David J Schwegman. Teacher accountability reforms and the supply and quality of new teachers. *Journal of Public Economics*, 188:104212, 2020.

Mark C Long, Dan Goldhaber, and Nick Huntington-Klein. Do completed college majors respond to changes in wages? *Economics of Education Review*, 49:1–14, 2015.

W Bentley MacLeod and Miguel Urquiola. Why does the united states have the best research universities? incentives, resources, and virtuous circles. *Journal of Economic Perspectives*, 35(1):185–206, 2021.

James Monks and Robert M Schmidt. The impact of class size on outcomes in higher education. *The BE Journal of Economic Analysis & Policy*, 11(1), 2011.

Arpita Patnaik, Matthew Wiswall, and Basit Zafar. College majors 1. *The Routledge handbook of the economics of education*, pages 415–457, 2021.

Steven Ruggles, Sarah Flood, Matthew Sobek, Danika Brockman, Grace Cooper, Stephanie Richards, and Megan Schouweiler. Ipums usa: Version 13.0 [dataset]. 2023. URL https://doi.org/10.18128/D010.V13.0.

Richard Sabot and John Wakeman-Linn. Grade inflation and course choice. *Journal of Economic Perspectives*, 5(1):159–170, 1991.

James Thomas. What do course offerings imply about university preferences? *FTC Bureau of Economics Working Paper*, (340), 2021.

Andrew van Dam. The most-regretted (and lowest-paying) college majors, September 2022. URL https://www.washingtonpost.com/business/2022/09/02/college-major-regrets/. Accessed on 2023-02-12.

Russell Weinstein. Local labor markets and human capital investments. *Journal of Human Resources*, pages 1119–10566R2, 2020.

Matthew Wiswall and Basit Zafar. Determinants of college major choice: Identification using an information experiment. *The Review of Economic Studies*, 82(2):791–824, 2015.

Figure 1. Sample entry in the course catalog dataset

ECON 43: Introduction to Financial Decision-Making

The purpose of the class is for you to obtain greater comfort making the major financial decisions your life journey will require. Illustrative examples, case studies, historical and statistical evidence, and some simple analytical tools will be presented. We hope to help students avoid damaging mistakes in the decisions that will determine their financial flexibility and safeguard them against life's uncertainties. Students will learn how to keep more options open and to live with fewer constraints by making sound financial decisions. Topics include making a financial plan and budget, managing money, saving, investing in stocks and other assets, purchasing insurance, taxes and inflation, inheritance, financial markets and financial advisors.

Terms: Spr | Units: 5 | UG Reqs: WAY-SI

Instructors: Boskin, M. (PI) ; Shoven, J. (PI) ; Jimenez, M. (TA) ; Kee, Y. (TA) ; Light, J. (TA) ; Walton, D. (TA) ; Zhang, A. (TA) fewer instructors for ECON 43 «

Schedule for ECON 43

2020-2021 Spring

ECON 43 | 5 units | UG Reqs: WAY-SI | Class # 31825 | Section 01 | Grading: Letter or Credit/No Credit Exception | LEC | Session: 2020-2021 Spring 1 | Remote: Synchronous | Students enrolled: 226

03/29/2021 - 06/04/2021 Mon, Wed 10:00 AM - 11:20 AM at Remote with Boskin, M. (PI); Shoven, J. (PI); Jimenez, M. (TA); Kee, Y. (TA); Light, J. (TA); Walton, D. (TA); Zhang, A. (TA)

Instructors: Boskin, M. (PI); Shoven, J. (PI); Jimenez, M. (TA); Kee, Y. (TA); Light, J. (TA); Walton, D. (TA); Zhang, A. (TA)

Additional Resources: (Login to view additional resources)

ECON 43 | UG Reqs: WAY-SI | Class # 32388 | Section 02 | Grading: Letter or Credit/No Credit Exception | DIS | Session: 2020-2021 Spring 1 | Remote: Synchronous | Students enrolled: 138 / 200

03/29/2021 - 06/04/2021 Wed 4:00 PM - 5:00 PM at Remote with Boskin, M. (PI)

Instructors: Boskin, M. (PI)

ECON 43 | UG Reqs: WAY-SI | Class # 33914 | Section 03 | Grading: Letter or Credit/No Credit Exception | DIS | Session: 2020-2021 Spring 1 | Remote: Synchronous | Students enrolled: 88

03/29/2021 - 06/04/2021 Thu 4:30 PM - 5:30 PM at Remote with Shoven, J. (PI)

Instructors: Shoven, J. (PI)

Source: Stanford University.

Figure 2. Geographic coverage of the course catalog dataset

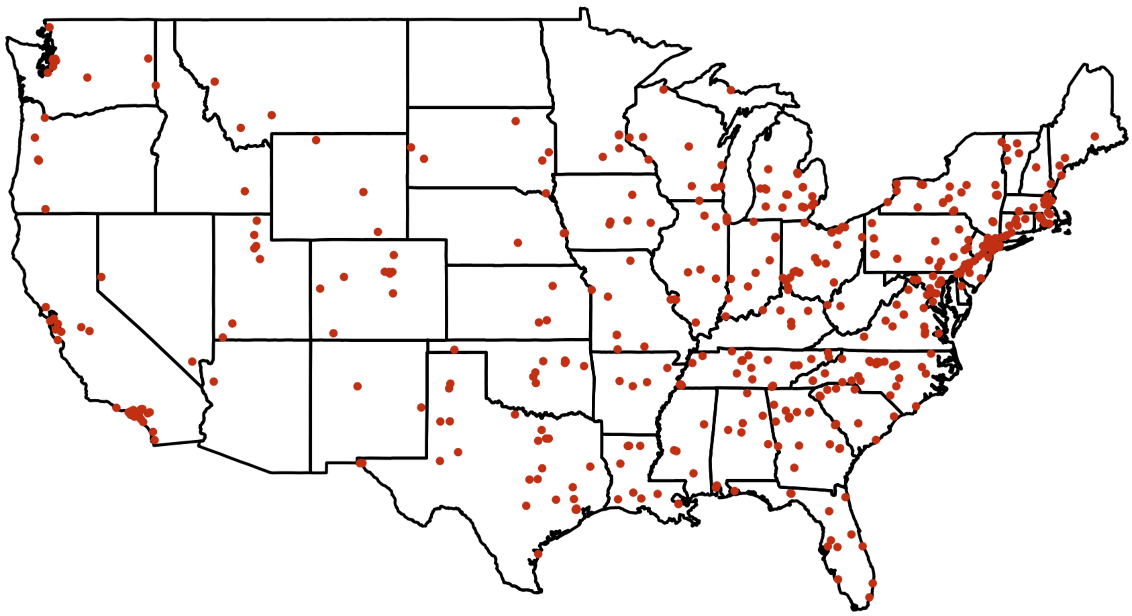


Table 1. Characteristics of course catalog sample

4 year institutions

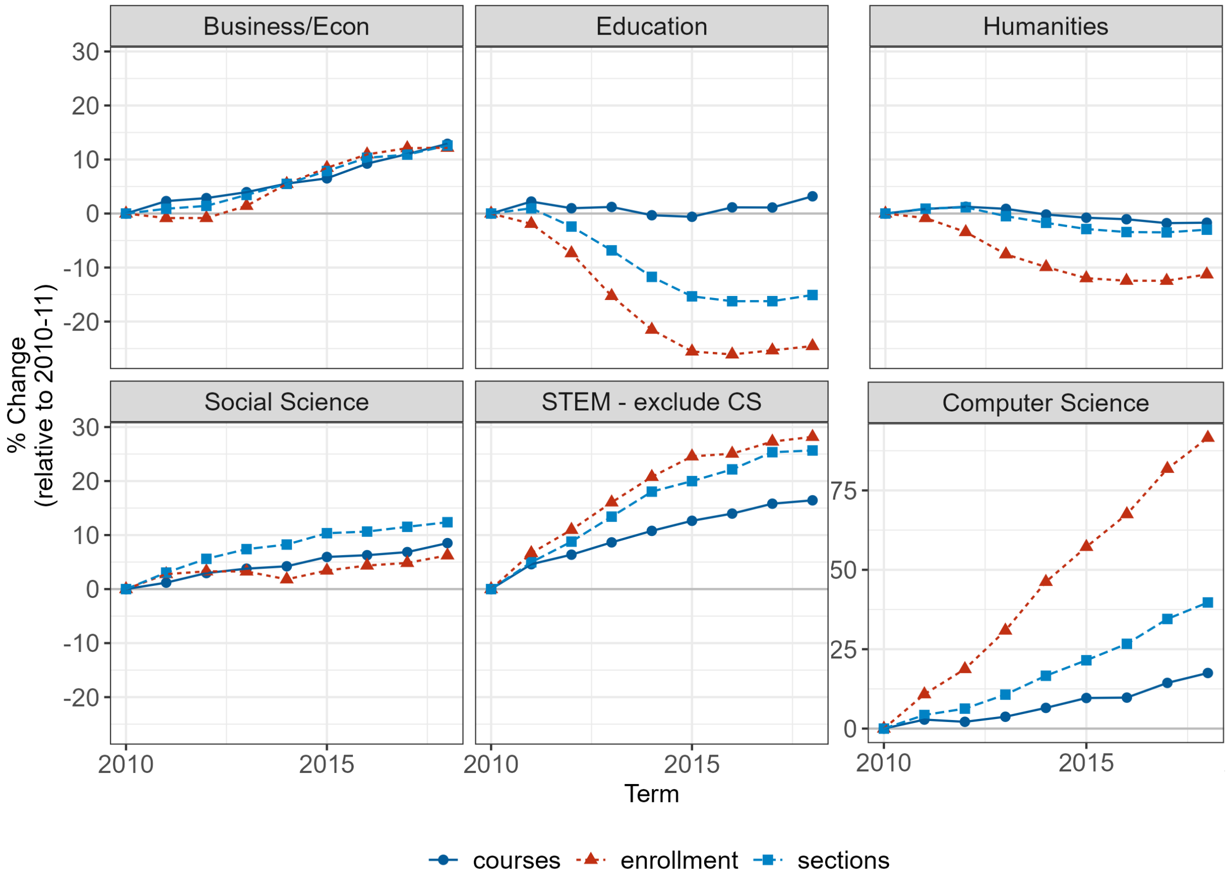
	Population		Catalog Sample		Enrollment Sample	
	mean	sd	mean	sd	mean	sd
Enrollment	19,200	20,303	17,736	11,875	17,383	10,405
Public share	72.54	44.63	81.67	38.69	82.66	37.86
Average tuition	16,779	15,370	16,721	15,647	16,668	15,456
Average price	16,797	8,458	17,202	7,818	17,622	7,508
Admit rate	71.88	22.63	69.59	23.97	71.06	23.54
Tenure share	51.47	19.27	55.33	9.99	55.61	9.84
Student-faculty ratio	17.42	5.39	17.35	4.66	17.03	4.19
6-year graduation rate	59.61	19.65	64.99	16.97	65.63	16.84
Endowment per student	59,477	215,928	76,609	271,207	78,509	301,476
Tuition % of revenue	34.05	19.84	30.65	13.93	30.89	12.89
Research % of spending	8.79	11.97	11.65	13.82	13.08	15.42
N	1,972		380		220	

2 year institutions

	Population		Catalog Sample		Enrollment Sample	
	mean	sd	mean	sd	mean	sd
Enrollment	14,200	16,543	18,719	18,600	11,827	8,917
Public share	99.34	8.11	100	0.00	100	0.00
Average tuition	3,495	1,978	3,629	1,444	3,921	839
Average price	7,973	3,079	7,960	2,459	6,210	1,965
Student-faculty ratio	19.29	5.38	18.89	3.59	18.10	4.72
N	933		73		12	

Notes: Institution characteristics from IPEDS for the 2021-22 academic year. Only non-profit, Title IV-eligible, degree-granting institutions are included. Values 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 3. Trends in course enrollment and supply: comparison to 2010-11



Notes: This figure plots the mean changes in course enrollment and supply relative to 2010-2011. Restrict to institutions observed in the dataset from 2010-11 to 2018-19. Field-level data within each institution are aggregated to the field category level, then indexed to 2010-11 values. The mean of the indexed values across institutions are plotted.

Table 2. Estimates of course supply elasticity

	# Courses		# Sections	
	OLS	IV	OLS	IV
	(1)	(2)	(3)	(4)
% enrollment change - overall	0.367	0.367	0.683	0.683
	(0.041)	(0.036)	(0.043)	(0.028)
% enrollment change - field	0.475	0.272	0.726	0.604
	(0.027)	(0.050)	(0.019)	(0.034)
First Stage F-stat		108		108
Observations	3,540	3,540	3,540	3,540
R^2	0.452	0.383	0.732	0.716

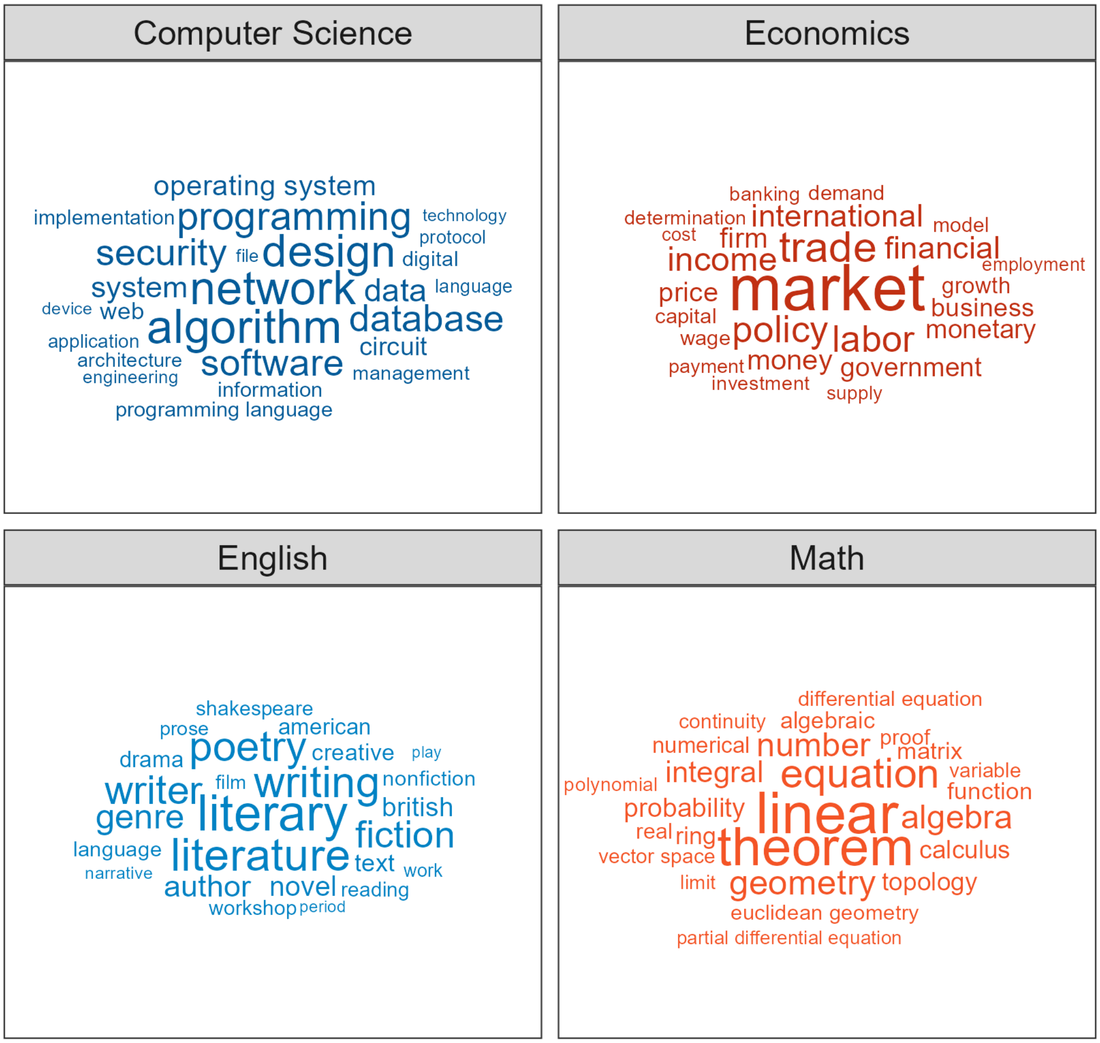
Notes: Observations are at the institution-by-field level. The analysis regresses change in upper-level course supply on change in enrollment, each represented as log differences from 2010-11 to 2018-19. Supply and enrollment are credit hour-weighted. Each institution receives equal weight; within each institution, fields are weighted by start-of-period enrollment. In Columns 1 and 3, standard errors are clustered at the institution level; in Columns 2 and 4, standard errors are clustered at the Census division by field level — the level of variation for the instrument.

Table 3. Asymmetry of course supply elasticity

	# Courses		# Sections	
	OLS	IV	OLS	IV
	(1)	(2)	(3)	(4)
% enrollment change - overall	0.380	0.405	0.697	0.712
	(0.039)	(0.035)	(0.041)	(0.029)
% enrollment change - growing	0.520	0.390	0.779	0.693
	(0.027)	(0.053)	(0.022)	(0.050)
% enrollment change - shrinking	0.438	0.135	0.682	0.497
	(0.044)	(0.050)	(0.032)	(0.040)
Observations	3,540	3,540	3,540	3,540
R^2	0.455	0.358	0.735	0.711

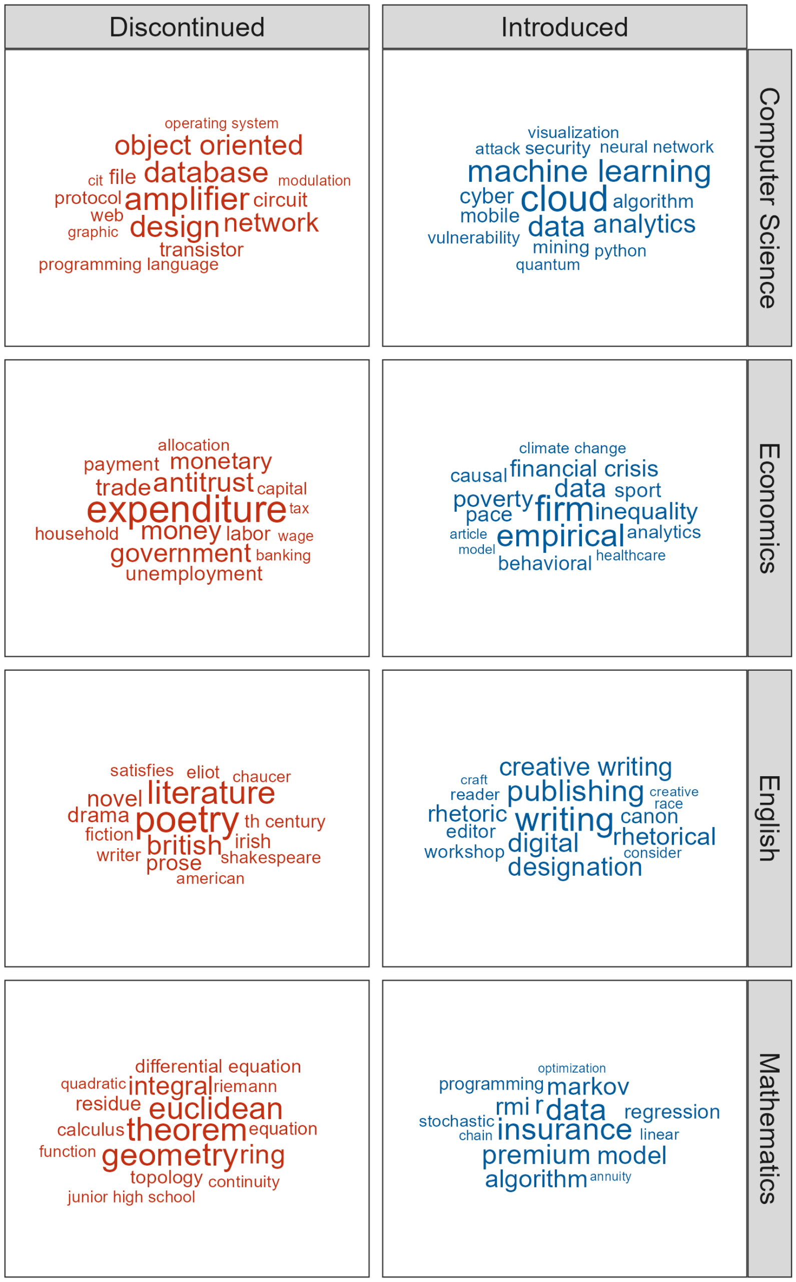
Notes: Observations are at the institution-by-field level. The analysis regresses change in upper-level course supply on change in enrollment, each represented as log differences from 2010-11 to 2018-19. Supply and enrollment are credit hour-weighted. Each institution receives equal weight; within each institution, fields are weighted by start-of-period enrollment. In Columns 1 and 3, standard errors are clustered at the institution level; in Columns 2 and 4, standard errors are clustered at the Census division by field level — the level of variation for the instrument.

Figure 4. 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 5. Evolution of token significance in discontinued vs introduced courses



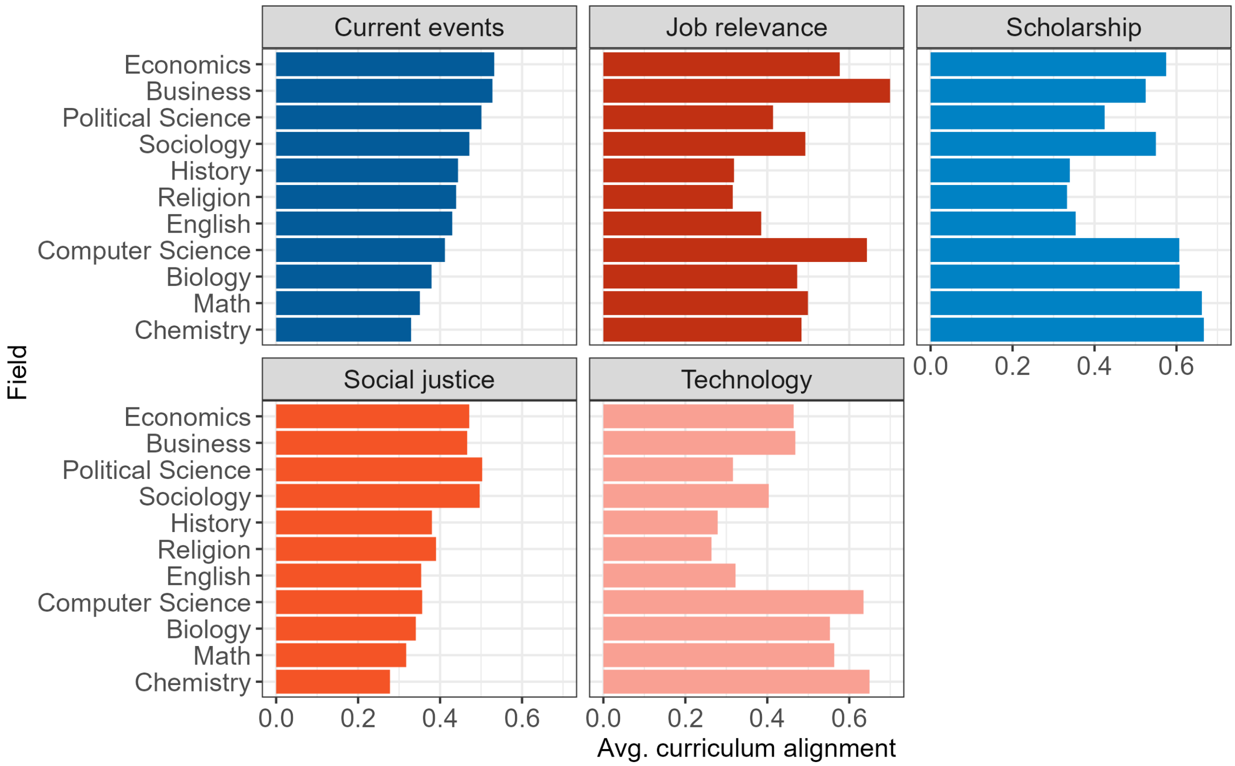
Notes: This figure contrasts the distinctive words of courses from 2013-14 to those of 2022-23. "Discontinued" courses are those offered in 2013-14 but no longer offered by 2022-23. "Introduced" courses are those not offered before 2013-14 but offered in 2022-23. Descriptions are grouped by field and course cateogry (discsontinued vs introduced). The visualization presents 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.

Table 4. Relevance weights for sample tokens

	Token	Current events	Job relevance	Scholarship	Social justice	Technology
Distinctive tokens	financial crisis	0.88	0.03	0.45	0.41	0.01
	customer service	0.69	0.99	0.26	0.51	0.68
	regression	0.10	0.92	0.99	0.70	0.84
	injustice	0.67	0.06	0.29	0.93	0.00
	invention	0.38	0.17	0.03	0.48	0.99
Pairs of similar words	king	0.30	0.03	0.00	0.09	0.01
	queen	0.63	0.05	0.00	0.06	0.01
	dog	0.61	0.08	0.03	0.13	0.19
	cat	0.49	0.14	0.07	0.07	0.24
	blackberry	0.83	0.68	0.00	0.40	0.53
	iphone	0.90	0.69	0.00	0.77	0.50
	global warming	0.93	0.07	0.86	0.38	0.71
	climate change	0.84	0.17	0.83	0.36	0.14

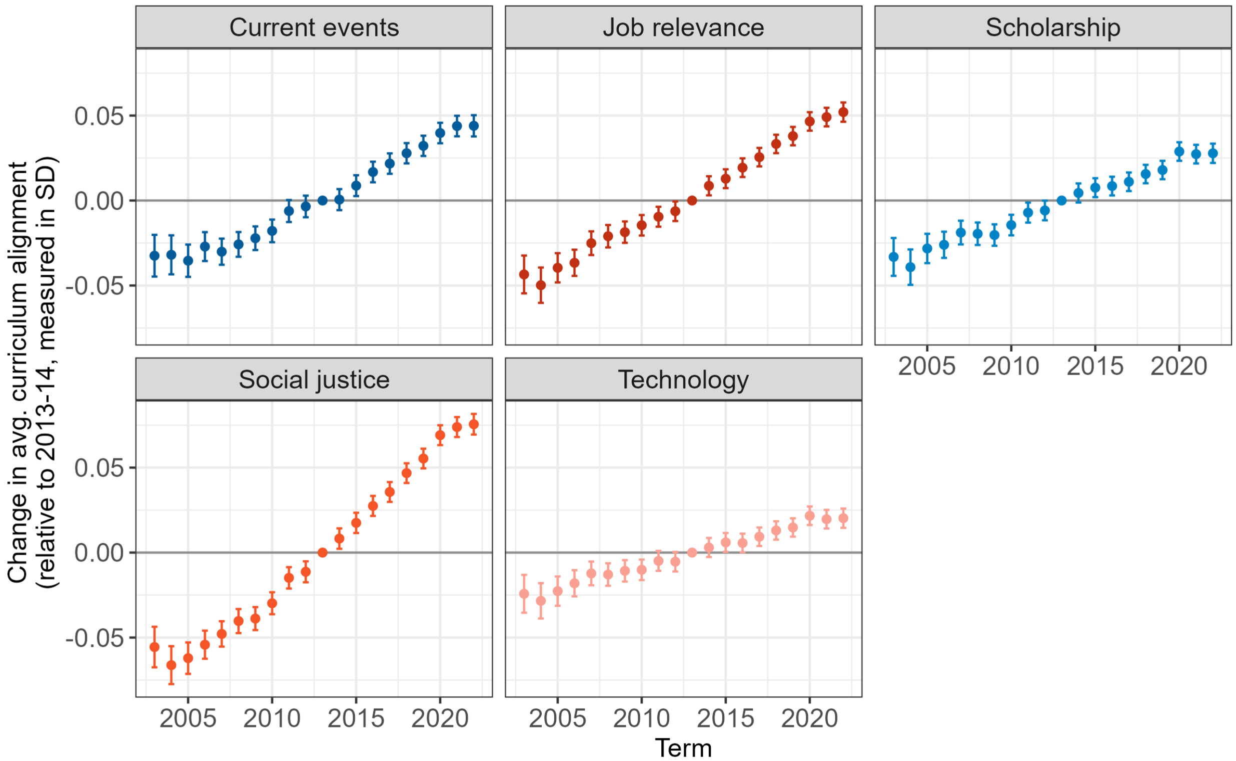
Notes: This table presents relevance weights of selected tokens. These weights measure a token's significance in a document related to a specific theme (e.g., a job description for job relevance) relative to its significance in a neutral text reference, such as the entirety of Wikipedia. Weights range from 0 to 1, with higher values indicating greater frequency in the thematic document compared to Wikipedia.

Figure 6. Average curriculum alignment across sampled fields (2022-23)



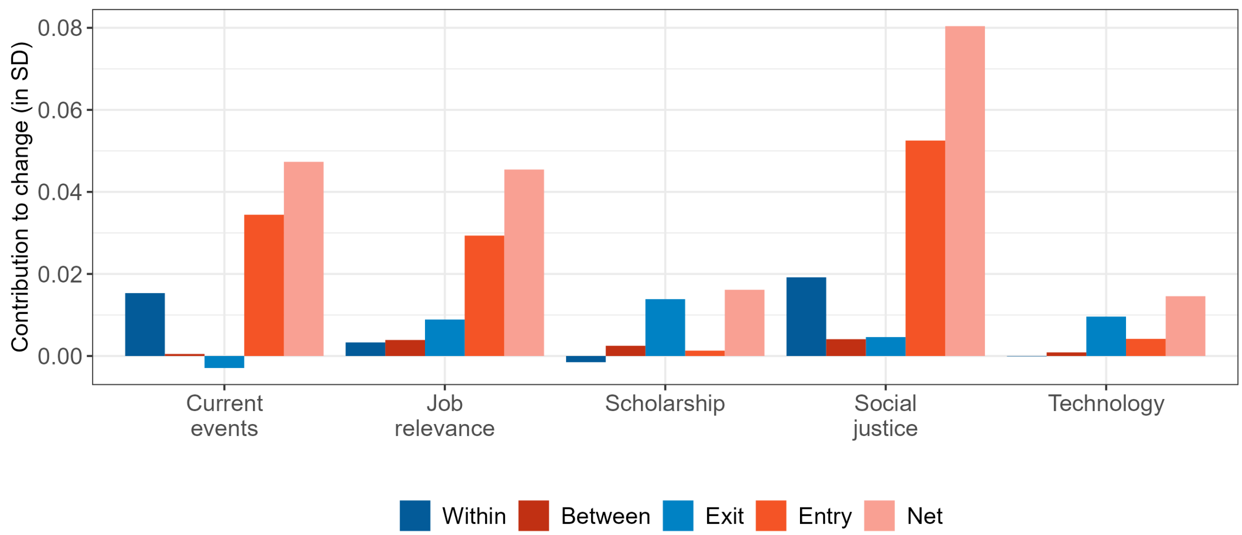
Notes: This figure displays the average curriculum alignment for selected fields. Each upper-level course from 2022-23 is scored for its curriculum alignment to each of the five themes. Within each theme, curriculum alignment scores are averaged within each field. Fields are sorted from highest to lowest alignment with current events.

Figure 7. Change in curriculum alignment: 2003-2022



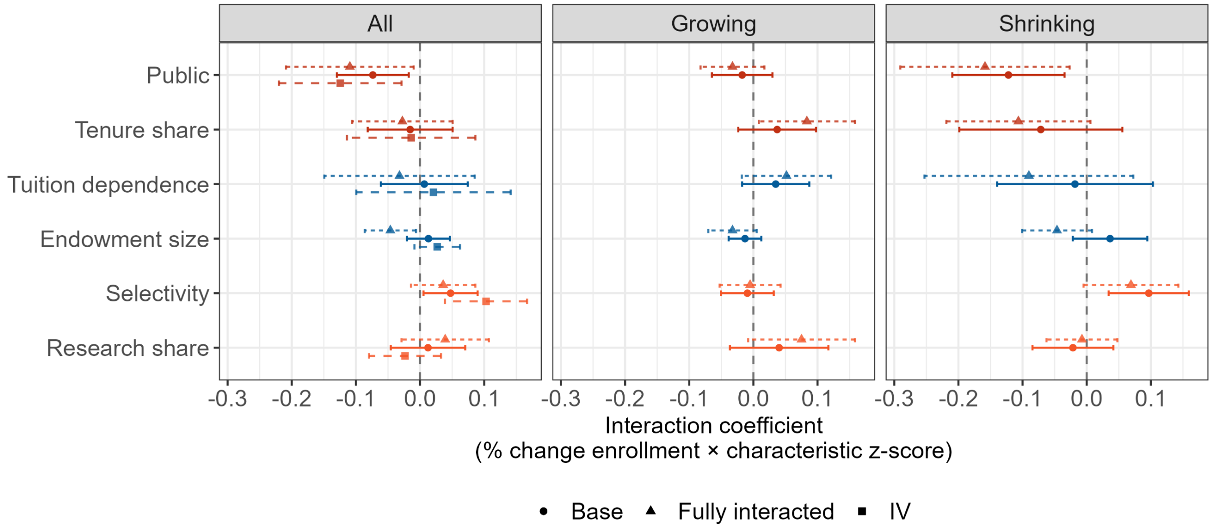
Notes: This figure plots the evolution of curriculum alignment scores for courses over two decades. Alignment estimates are estimated in separate course-level regressions of a course's curriculum alignment score for a given theme on a vector of year dummies, controlling for institution-by-field fixed effects. Standard errors are clustered at the institution-field level. Changes are relative to the average curriculum alignment score in 2013-14 and measured in standard deviations.

Figure 8. Decomposition of curriculum alignment changes: 2013-14 to 2022-23



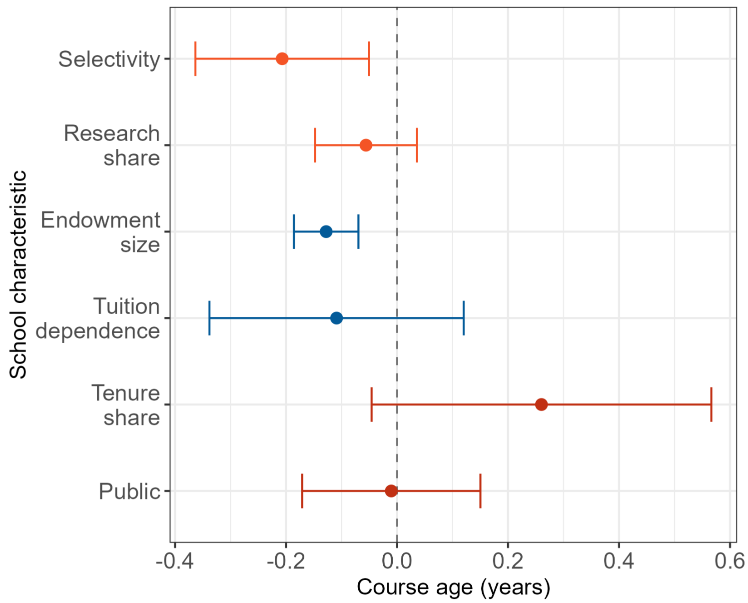
Notes: This figure decomposes down the shift in curriculum alignment between 2013-14 and 2022-23. Utilizing an approach based on Foster et al. (2001), the evolution in curriculum alignment at the institution-by-field level is decomposed into four components: updates within continuously-offered courses, changes due to shifts in enrollment across courses continuously offered by a field, discontinuations of courses, and introductions of new courses. Each institution receives equal weight; within each institution, fields are weighted by enrollment in 2013-14.

Figure 9. Differential course supply elasticity by school characteristics



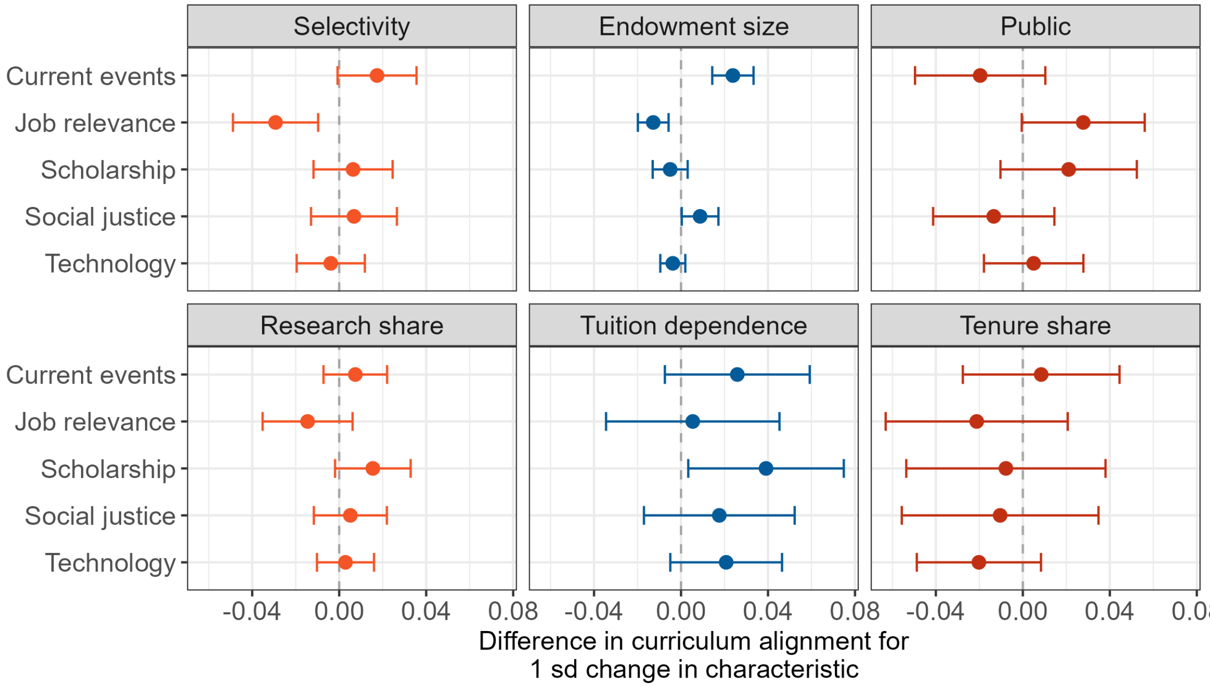
Notes: Using school characteristic data from IPEDS, this figure plots interaction term estimates of school characteristics with enrollment changes across three models: "Base," "Fully Interacted," and "IV." The "Base" specification estimates separate characteristic-changing enrollment interaction regressions for each characteristic. The "Fully Interacted" specification consolidates interactions of all school characteristics with changing enrollment in one regression. The "IV" specification estimates separate characteristic-changing enrollment interaction regressions in an IV framework for each characteristic. The "All" panel estimates a linear model of course supply on enrollment; the "Growing" and "Shrinking" segments estimate a model with separate changing enrollment terms when the change in enrollment is positive and negative. IV estimates are omitted in the asymmetric specification because they are estimated imprecisely. School characteristics are standardized according to national distributions for degree-granting, Title IV-eligible non-profit institutions. Standard errors are clustered at the institution level in the "Base" and "Fully Interacted" specifications and the field by Census division level.

Figure 10. Variation in average course age by school characteristics



Notes: Using school characteristic data from IPEDS, this figure plots the association between average course age and various school characteristics. School characteristics are standardized according to national distributions for degree-granting, Title IV-eligible non-profit institutions. Course age, restricted to upper-level courses offered in 2022-23, is calculated as the number of years since the course's introduction, with 2013-14 as the earliest potential starting year. Analysis is limited to institutions consistently available in the dataset from 2013-14 to 2022-23. Point estimates are obtained from separate course-level regressions of course age against each characteristic, controlling for field fixed effects. Estimates represent the difference in average course age associated with a one standard deviation change in the specific school characteristic. Standard errors are clustered at the institution-by-field level.

Figure 11. Variation in curriculum alignment by school characteristics



Notes: Using school characteristic data from IPEDS, this figure plots the relationship between curriculum alignment scores and various standardized school characteristics. These characteristics are standardized based on national distributions for degree-granting, Title IV-eligible non-profit institutions. The plotted point estimates are derived from individual course-level regressions of curriculum alignment scores, for upper-level courses from 2022-23, on the institution characteristics, controlling for field fixed effects. Standard errors are clustered at the institution level.

A 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. A manual search was conducted on 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 453 institutions, including 380 4-year schools and 73 2-year schools. The 4-year schools make up 19% of schools and enroll 37% of the students at all 4-year non-profit, bachelor's degree-granting Title IV-eligible institutions. The 2-year schools make up 8% of and enroll 14% of the students at 2-year non-profit, degree-granting Title IV-eligible institutions. The relatively limited coverage of 2-year schools can be attributed to both an emphasis on 4-year schools during dataset construction and the scarce online archives of course catalogs at 2-year schools. Owing to this limited coverage and reduced representativeness, this paper primarily focuses on the analysis of 4-year schools.

The data dates back to 1998, with the most dense coverage appearing in the last decade. Figure A-1 plots the number of institutions for which course descriptions or course enrollment data are observed annually. Data availability shows a consistent growth over time. 56% of institutions in my sample have data first available in 2010 or earlier, and 84% have data first available in 2015 or earlier.

To validate the course catalog data, it can be compared with publicly available course enrollment details from IPEDS. Institutions report to IPEDS the total number of undergraduate credit hours completed. My course-level enrollment data can be aggregated to calculate a corresponding measure for schools in my sample. Figure A-2 shows a comparison between the total credit hours in the course catalog dataset and those in IPEDS. I plot the share of undergraduate credits from IPEDS observed in the course catalog dataset, with each observation being an institution-term and observations spanning the period 2006-2018. The histogram suggests a strong alignment between the course catalog dataset and the data reported in IPEDS: I record between 90-105% of credits for 70% of terms in the course catalog data.

There are several reasons for potential discrepancies between the total credit hours reported in the course catalog data and IPEDS data. First, some courses offer a range of credit hours. In such cases, I assign the minimum number of credits (e.g. for a course offering 3-5 credits, I assign 3 credit hours). This approach may underestimate credit hours if students select higher values within the range. Second, in the benchmark figure, no exclusions are made based on the field name; only graduate courses are excluded based on credit hours. As a result, the total undergraduate credits might be overstated if some graduate courses are given course numbers typical of undergraduate courses, especially in professional degrees like medicine or law. Detailed restrictions on the field of study, which are discussed later, are implemented in my analysis. Third, the reporting of credit hours to IPEDS may differ from how a course's credits/units are represented in the course schedule. Finally, errors either in the construction of the course catalog sample or in the data provided to IPEDS may lead to discrepancies. When such discrepancies occur, I perform detailed quality checks at the institution-by-term level, which result in the complete exclusion from the course catalog dataset of a small number of schools with clearly anomalous enrollment data.

To alleviate concerns about the potential impact of the aforementioned sources of error on the reliability of the data, I illustrate in Figure A-3 that enrollment growth trends in the course catalog data consistently align with those reported in IPEDS. For each institution-term, I index total credits in the course catalog data as a percentage of total credits in 2018-19 and plot these indexed values against the corresponding values from IPEDS. When the points lie along the 45° line, the credits reported in the IPEDS data and the course catalog data are growing at nearly the same rate. This suggests that errors from the miscounting of credits for variable-credit courses or other errors do not affect within-institution comparisons of enrollment over time. The series are highly correlated (correlation coefficient 0.94), implying that variations in the data stem from genuine enrollment trends rather than any error in data collection or processing.

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

In the analysis estimating course supply 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. Courses like independent study, internship, supervised research, thesis, study abroad, student teaching, private lessons, teaching assistantships are excluded due to their asynchronous nature. 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.[57]

[57]The overwhelming majority of the sections dropped are for courses in the Humanities and Arts; to the

Course levels (pre-undergraduate, lower, upper, graduate) are assigned according to the institution's numbering convention. Occasionally, the course schedule distinguishes between lower/upper/graduate courses, and in these cases, I defer to the course-specific designation.

Instances occur where a single class is cross-listed across multiple fields or levels, and these are not always explicitly indicated in the course schedule. In such cases, I infer cross-listing based on details in the course catalog data. I identify cross-listed courses as those sharing the same instructors, meeting days, meeting times, meeting location, course title, and section number. Each field and level (e.g., upper-level Economics) associated with the course is credited for a portion of the cross-listed course. For example, a course may be listed as Econ 101 and Business 101 sharing all cross-listed identifiers. In some instances, I will separate enrollment totals for Econ 101 and Business 101. In such a case, I attribute credit to the Economics department for supplying this course in proportion to the share of students enrolled in Econ 101 vs Business 101. When I observe only a single enrollment total for the joint-Econ/Business 101, I apportion both enrollment and credit for supplying the course in proportion to enrollment in other courses in that field-level cell.[58]

B Fields of study

The names of more than 20,000 departments are manually classified into 54 fields for 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 summarized 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. "College of Humanities" 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 also exclude courses associated with professional degrees, including any Medicine, Law,

extent that I am erroneously dropping some small courses that actually ran, I am if anything understating course supply stickiness by removing these small sections.

[58]For example, suppose that Econ 101 and Business 101 are both lower-level classes. Suppose further that 100 students are enrolled in lower-level Economics courses not counting Econ 101 and 50 students are enrolled in lower-level Business courses not counting Business 101. I would apportion 2/3 of the enrollment and course supply credit for Econ/Business 101 to the Economics department and 1/3 to the Business department.

Nursing, Pharmacy, and Architecture courses. Medicine and Law courses are rarely offered at the undergraduate level, but the course numbering for these courses does not often explicitly indicate them as graduate courses. Thus, I exclude any course in a department classified as Medicine or Law. The exclusion of Nursing, Pharmacy, and Architecture courses relates more to students' margin of response to changing labor market conditions. These departments are often siloed within the university, making it structurally difficult for current students to enter these courses when demand is growing or leave these courses when demand is declining. Moreover, due to the regulated nature of careers stemming from these fields, picking up a course or two in any of these fields does not unlock job opportunities in the same way as, for example, Computer Science or Business might. Thus, the motivation for my instrumental variables strategy may not work for these professional degree-oriented programs and I exclude them from my analysis.

Finally, I exclude skilled trade programs from my analysis (e.g. Beautician or Mechanic programs); course enrollments for these fields is very low at the baccalaureate level, and in most instances there are too few observations in the ACS to construct a reliable instrument for employment growth in occupations related to these majors.

C Extensive margin

C.0.1 Reduced form estimates

Enrollment serves as a natural proxy of demand, albeit with the inherent limitations detailed in Section 4. At its core, enrollment is an equilibrium outcome, influenced both by students' course preferences and the university's ability to provide these courses. It might not fully represent the demand for courses that are not available or those with capped capacities. Additionally, enrollment may give the illusion of demand for mandatory courses or courses that students join due to the lack of their preferred options. To address these limitations, my shift-share instrument capitalizes on variations in local employment growth by field. This instrument aims to isolate a component of changing enrollment solely driven by evolving student demand.

My analysis is that fluctuations in the labor market influence the university's course offerings primarily through changes in enrollment. This perspective is intuitive for two primary reasons. First, to the extent that universities are reacting to changes in the labor market, it is sensible to think that these changes are channeled through enrollment. Otherwise, universities would devote substantial resources towards creating courses that students do not want to take. Second, measuring changing course offerings in response to enrollment changes provides a more easily interpreted metric (course supply elasticity) than direct responses to labor market shifts.

The reduced form provides additional insights. The reduced form estimates, summarized in Table A-3, suggest that a 1% increase in local employment for jobs typical of graduates in a specific field correlates with a 1.4% growth in unique courses offered and a 3.1% increase in sections for that field.

D Text data processing

D.1 Supplemental text data description

In addition to text data from course descriptions scraped from college and university course catalogs, I use text data from five different types of sources to study how course content aligns with various applications of students' learning. I measure alignment with current events using data from front page articles published in the New York Times, academic advancement using data from abstracts for academic journals, technological progress using text from patent applications, skill demand using text from job descriptions, and social justice from a combination of books related to activism and online materials published by organizations oriented towards social justice and civil liberties. I also use text data from the complete set of Wikipedia articles as a neutral corpus as a benchmark for the distribution of words against which I can identify words that are highly distinctive of each application of student learning. I describe each of these data sources in greater detail in the sections below.

D.1.1 New York Times articles

I download the complete set of articles published by the New York Times (either in print or digitally) between 2010-2019 using the New York Times Developer API. For each article, I observe the headline and either an abstract for the article or a text snippet that contains the first few paragraphs of the article. I define a document by concatenating an article's headline and the snippet or abstract (depending on which is provided). The New York Times data contain 938 thousand articles, and articles on average contain 29 words. I make no restrictions on the section of the New York Times in which an article is posted, nor do I make restrictions on whether the article was published in print vs online.

D.1.2 Academic journals abstracts

I construct a corpus of abstracts from academic articles downloaded from Elsevier's SCOPUS. Following Biasi and Ma (2022), I search for abstracts from academic journals that rank in the top 10 by H-index for each field during the period 2010-2019. When available, I download the abstracts of all articles published during this period for each journal. The resulting sample includes 155 thousand abstracts from 180 journals. The average document in this corpus contains 163 words.

The distribution of tokens in academic journals will in part reflect differences across fields in the use of academic journals for publishing research. Specifically, journals in the sciences publish more editions and more articles per edition than journals in the humanities and arts. Thus, when I construct word weights using these documents, the weights will be biased towards science-oriented words and phrases simply due to the composition of this corpus. For my analysis, I typically make comparisons within an institution-field pair over time or control for field fixed effects, which will absorb some bias inherent in the construction of the corpus.

D.1.3 Patents

I download patent text from the US Patent and Trademark Office covering the period 2010-2018. The resulting corpus includes the text of 2.5 million patents, which contain on average 250 tokens per document.

D.1.4 Job descriptions

Job description data come from a dataset collected by Lightcast (previously Burning Glass Technologies) that contains the near-universe of online job posts. The full set of job descriptions is quite massive, so I build the corpus of job descriptions using job descriptions from a sample of months during my period of analysis. In particular, I include all job descriptions from March and August 2010, 2012, 2014, 2016, and 2018. I restrict to job descriptions with a requirement that applicants have at least a college degree. The resulting corpus contains 2 million documents, which contain on average 162 words per document.

D.1.5 Writings related to social justice

I assemble a corpus of texts related to social justice from a variety of sources. This corpus features the text from the 112 “Issues” web pages from the ACLU’s website, which provide summaries of topics related to civil liberties. In addition, it includes the content from 1,800 press releases issued by Planned Parenthood, spanning from 2014 onward. Both the ACLU and Planned Parenthood text were scraped from their respective websites. The corpus also includes the full texts of six prominent books that are listed among the top 25 activist-related books on Goodreads. These include *Between the World and Me* by Ta-Nehisi Coates, *Freedom is a Constant Struggle* by Angela Davis, *Pedagogy of the Oppressed* by Paulo Freire, *This Changes Everything: Capitalism vs. The Climate* by Naomi Klein, *The New Jim Crow* by Michelle Alexander, and *We Should All Be Feminists* by Chimamanda Ngozi Adichie.

Collectively, these sources provide insights into a spectrum of topics, from racial justice, prison abolition, and women's rights to climate change and a more general exploration of civil liberties.

D.1.6 Wikipedia articles

I download the text of all English-language pages published on Wikipedia as of July 1, 2023 using the "Wikimedia dump service." The dataset contains the full text of all Wikipedia pages. I restrict to articles (e.g. filter out redirect pages and media). I process the raw article entries to exclude lists of references, links, metadata not included in the article, and section headers. The resulting corpus contains 3.8 million documents, which contain on average 183 words per document.

D.2 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, removing stopwords, and lemmatizing the text (e.g., transforming "regressions" to "regression").

However, my approach incorporates two non-standard pre-processing steps. First, I exclude "boilerplate" language from the text data. I am concerned about capturing phrases that are overly common in a specific text but lack relevance to the essence of the content. For instance, 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 skill demand, whereas their usage in job descriptions, specifically for non-discrimination clauses, is unrelated to the skill demand of the job. 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 of documents, 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 the Wikipedia corpus. 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 due to being composed of common words, rather than representing a distinct concept. Specifically, 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.[59]

Finally, to reduce the size of the dictionary and minimize the impact of words that are distinctive due to misspellings or unique to specific types of documents, I project all corpora onto a dictionary of tokens that appear at least 500 times in the complete Wikipedia text. As a result, the focus is on commonly recognized words rather than theme-specific jargon, which aids in drawing meaningful comparisons between different text data sources.[60]

Enrollment and course description data typically 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 where a course description is available. For continuously-offered courses, course descriptions change somewhat infrequently and rarely change substantively (see, for example, Figure A-8).

D.3 Details on TF-IDF weights

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

[59]Incidentally, the longest phrases counted as a single token are "church [of] jesus christ latter day" and "united nation[s] security council resolution."

[60]To illustrate, consider the frequent appearances of specific terms like a website URL or the name of a job board in job descriptions. Including these "jargony" terms in the analysis might yield the misleading impression that they are distinctive features of job-related language, when, in reality, they are simply artifacts of the source or format of the content.

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:

$$IDF(w) = log\left(\frac{\sum_{d \in D} 1_{w \in d}}{||D||}\right)$$

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

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

I use the TF-IDF representations of field curricula to construct a series of measures of a field's changing curriculum. My preferred measure calculates the syntactic distance between a field's curriculum in 2018 relative to 2010. Let $v_{i,s,t}$ be the vector representation of the TF-IDF weights from course descriptions at institution i in field s in year t. I normalize each $v_{i,s,t}$ to have a magnitude of 1. Then, I calculate the cosine distance between the vector representation of the field's content.:

$$dist_{i,s} = \frac{v_{i,s,2018} \cdot v_{i,s,2010}}{||v_{i,s,2018}||\ ||v_{i,s,2010}||}$$

D.4 Details on curriculum alignment scores

I construct curriculum alignment scores as a means to quantify the level of overlap between course content and specific applications of student learning. These scores are derived from a combination of TF-IDF weights and a "relevance weight" assigned to each token in a course description based on its importance to a particular application of student learning. The relevance weight aims to highlight tokens that are distinctive to a given application of student learning. While Term Frequency helps in identifying commonly appearing tokens in a corpus, it does not address the need to downweight tokens that are commonly used in general language. To overcome this, I create weights that compare a token's importance within a particular corpus (linked to a specific application of student learning) to its importance in a "neutral corpus," which, in this case, consists of the complete text of Wikipedia articles. Tokens that are part of common language (e.g. "the," "a") should appear with similar frequency in any corpus. When a token appears significantly more often in a corpus related to an application of student learning than in the Wikipedia text, it is likely to be of greater importance to that specific application.

To calculate the relevance weights b_w^q for each token w with respect to each application of student learning q, I divide token w's share of all tokens in the q corpus (W^q) by token w's share of all tokens in the Wikipedia corpus (W^{Wiki}):

$$b_w^q = \frac{\frac{\sum_{w' \in W^q} \mathbb{I}(w' = w)}{||W^q||}}{\frac{\sum_{w' \in W^q} \mathbb{I}(w' = w)}{||W^q||} + \frac{\sum_{w' \in W^{Wiki}} \mathbb{I}(w' = w)}{||W^{Wiki}||}}$$

Tokens with relevance weights closer to 0.5 have similar frequencies in both the Wikipedia corpus and the application corpus. Tokens with higher relevance weights hold more significance in the application corpus compared to the Wikipedia corpus. Table 4 provides the relevance weights of some example tokens for reference.

I calculate the curriculum alignment score for each field's curriculum with each application of student learning by taking the TF-IDF-weighted sum of relevance weights specific to that application. To ensure consistent and interpretable scores, I normalize the weights in the TF-IDF vector representation of each field's curriculum, making sure they add up to 1. This normalization guarantees that each curriculum alignment score falls within the range of 0 to 1, providing a meaningful measure of alignment. Higher scores indicate a stronger connection between the curriculum and the intended student learning application, while lower scores imply less relevance between the two. Table **??** provides examples of course descriptions with particularly high and low alignment scores.

An alternative approach to applying relevance weights would involve calculating the average syntactic distance between a given course description and each individual document from external text data sources, normalized by the average syntactic distance between the course description and all the Wikipedia articles. This alternative strategy requires more computational effort to make essentially a similar comparison. Both approaches aim to measure the similarity between the frequency distributions of text in course descriptions and text in another document type. Greater similarity suggests higher alignment between a curriculum and a particular application of student learning. However, the approach used in this paper pools all documents into a single one and calculates the distribution of words across the entire corpus. This approach sacrifices some variation that might arise from very distinctive documents in the corpus. Given that my interest is describing the frequency distribution of words that might appear in some corpus, giving relatively less weight to unusual documents seems consistent with the objectives of this exercise. The focus here is to capture the overall alignment between course content and student learning applications across the entire dataset.

E Intensive margin analysis

E.1 Decomposition

Following Foster et al. (2001), I decompose the total change in average curriculum alignment over the ten-year period 2013-14 and 2022-23 into changes resulting from entry, exit, within, and between. Within course changes measures the contribution from changing course descriptions for courses offered continuously over this period. Between course changes measure the contribution from changing student enrollment across continuously offered courses but within the same field of study. Exit measures the contribution from courses that were offered in 2013-14 but were not offered in 2022-23. Entry measures the contribution of courses that were offered in 2022-23 but were not offered in 2013-14.

The decomposition proceeds as follows: For each institution i and field s, let $S_{i,s}$ be the set of courses offered continuously between 2013-14 and 2022-23, $E_{i,s}$ be the set of courses offered in 2022-23 but not offered in 2013-14 or earlier, and $X_{i,s}$ be the set of courses offered in 2013-14 but discontinued before 2022-23. I denote a course belonging to any of these groups as x (for simplicity, I will omit the i and s subscripts when referring to a course).

let $S_{i,s,t}$ be the set of courses offered at institution i in field s during year $t \in \{1,2\}$, and denote courses by $x \in S_{i,s,t}$ (for simplicity, I will omit the i and s subscripts when I refer to a course). Let $s_{x,t}$ be course x's share of enrollment at institution i in field s, and $\varphi^q_{x,t}$ be course x's curriculum alignment to theme q. Finally, let $\Phi^q_{i,s,t}$ be the average curriculum alignment to theme q across all courses at institution i in field s during term t. The decomposition proceeds as follows:

$$
\begin{aligned}
\Delta\Phi^q_{i,s} = & \underbrace{\sum_{x\in S} s_{x1}\left(\varphi^q_{x2}-\varphi^q_{x1}\right)}_{\text{within}} + \underbrace{\sum_{x\in S}\left(s_{x2}-s_{x1}\right)\left(\varphi^q_{x1}-\Phi^q_1\right)+\sum_{x\in S}\left(s_{x2}-s_{x1}\right)\left(\varphi^q_{x2}-\varphi^q_{x1}\right)}_{\text{between}} \\
& + \underbrace{\sum_{x\in E} s_{x2}\left(\varphi^q_{x2}-\Phi^q_1\right)}_{\text{entry}} - \underbrace{\sum_{x\in X} s_{x1}\left(\varphi^q_{x1}-\Phi^q_1\right)}_{\text{exit}}
\end{aligned}
$$

Having computed the components $\Phi^q_{i,s}$ for each institution-field pair, I aggregate first up to the institution level, then average across institutions for the final decomposition. I aggregate up to the institution level as the average of each component of $\Phi^q_{i,s}$ weighted by each field s's share of enrollment in the base period. This gives me the components of Φ_i^q for each school. I average each of the components across schools to produce the values plotted in Figure 8.

F Mechanisms

This section summarizes the procedure for estimating changing enrollment-school characteristic interaction terms analyzed in Section 6.2.

Base Specification

In the "Base" specification, the elasticity of course supply is individually modeled in relation to each of the six university characteristics. I introduce an interaction term between the change in course supply and a given characteristic. Each characteristic is standardized as a z-score relative to the national distribution. Formally, for a given characteristic k of institution i, I estimate the equation:

$$\Delta y_{i,s} = \alpha_i^k + \beta^k \Delta x_{i,s} + \theta^k (\Delta x_{i,s} \times q_i^k) + \epsilon_{i,s}^k$$

In this equation, $\Delta y_{i,s}$ represents the log change in courses offered at institution i in field s between 2010-11 and 2018-19, $\Delta x_{i,s}$ represents the corresponding change in enrollment. The z-score q_i^k is the standardized value of characteristic k, and θ^k is the coefficient capturing the differential response of course supply to changing enrollment for a one sd change in the characteristic.

Kitchen Sink Specification

To account for the correlations among the six university characteristics, the "Kitchen Sink" specification includes all these characteristics simultaneously in one comprehensive model. The specification is thus:

$$\Delta y_{i,s} = \alpha_i + \beta \Delta x_{i,s} + \sum_{k=1}^{6} \theta^k (\Delta x_{i,s} \times q_i^k) + \epsilon_{i,s}$$

F.0.1 IV Specifications

Extending the methodology to the instrumental variable (IV) approach, the interaction term between changing enrollment and one university characteristic is introduced. The first stage equation becomes:

$$\Delta x_{i,s,r} = {\gamma^{k\prime}}_i + \kappa^{k\prime} z_{s,r} + \lambda^k(\Delta x_{i,s,r} \times q_i^k) + {\eta^{k\prime}}_{i,s,r}$$
$$\Delta x_{i,s,r} \times q_i^k = {\gamma^{k\prime}}_i + \kappa^{k\prime} zs, r + \lambda^{k\prime}(\Delta x_{i,s,r} \times q_i^k) + {\eta^{k\prime}}_{i,s,r}$$

The second-stage becomes:

$$\Delta y_{i,s,r} = \alpha_i^k + \beta^k \widehat{\Delta x_{i,s,r}} + \theta^k (\Delta x\widehat{_{i,s,r} \times} \, q_{i,s}) + \epsilon_{i,s,r}^k$$

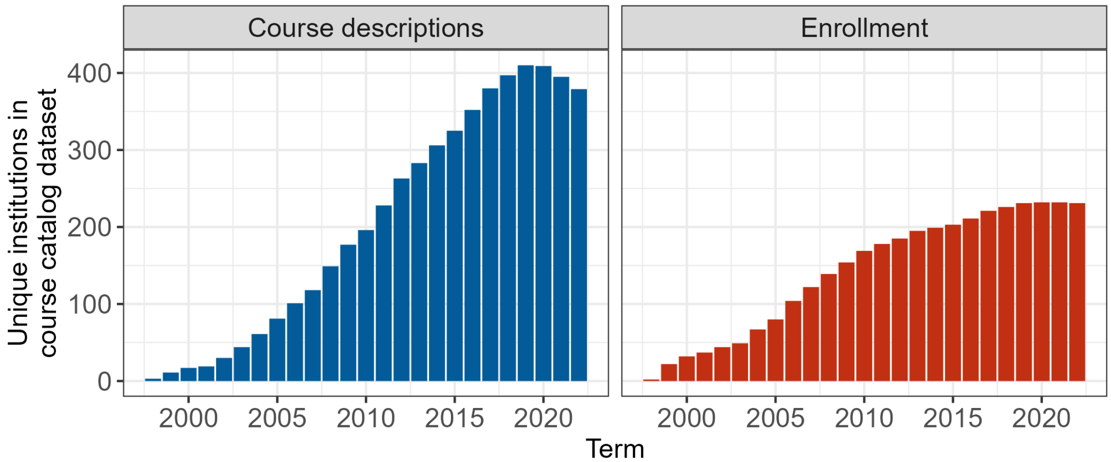
Where the coefficients θ^k represent the differential response of course supply to instrumented enrollment changes due to the specific university characteristic.

F.0.2 Asymmetric model

For specifications that permit differential course supply responses based on whether enrollment is increasing or decreasing, I modify the terms involving $\Delta x_{i,s}$. Specifically, I introduce interaction terms between $\Delta x_{i,s}$ and two indicator variables: one for positive $\Delta x_{i,s}$ (indicating an increase in enrollment) and another for negative $\Delta x_{i,s}$ (indicating a decrease in enrollment).

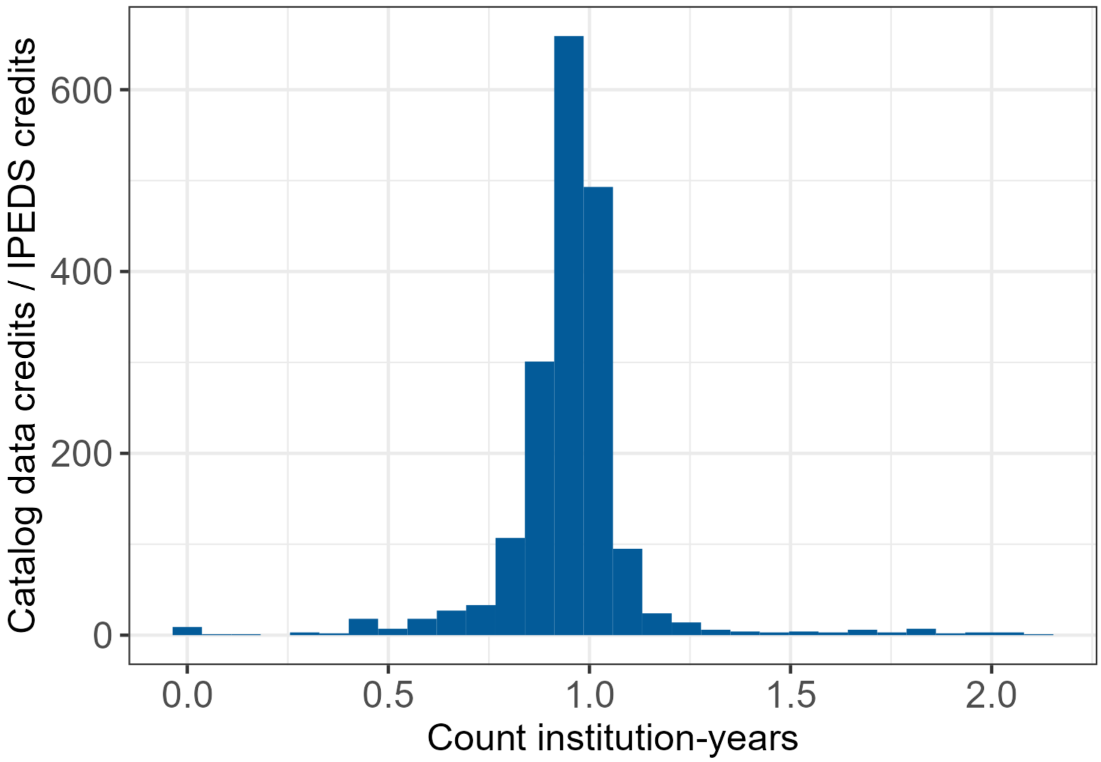
Data

Figure A-1. Annual coverage of course catalog data



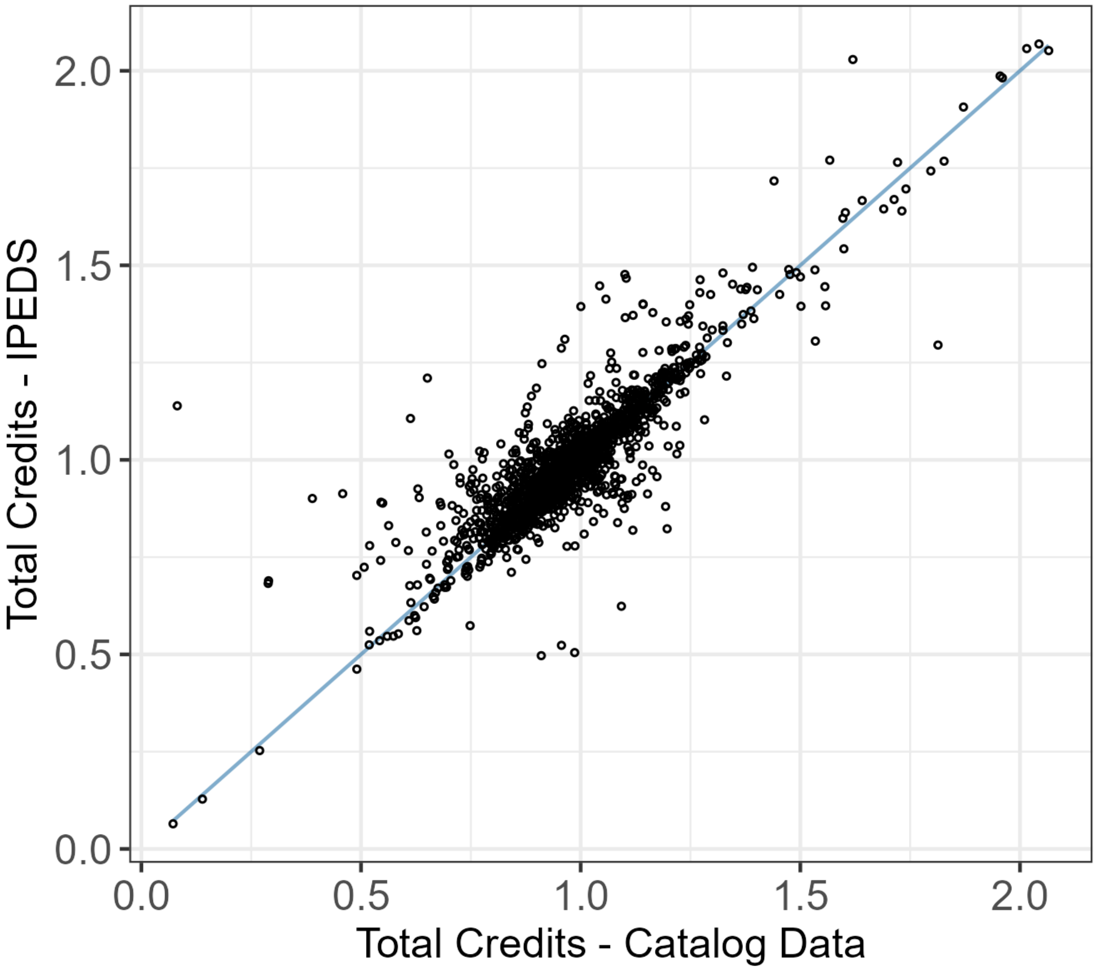
Notes: The figure counts the number of institutions in the course catalog dataset by year. The left panel counts the number of institutions with course description data; the right panel counts the number of institutions with enrollment data. For many institutions, the data record both enrollment and course descriptions.

Figure A-2. Compare total credits in catalog data to IPEDS



Notes: The figure compares total credits for enrollment in undergraduate courses in the course catalog data to total undergraduate credits reported in IPEDS. Observations divide total credits in the course catalog data by credits reported in IPEDS at the institution-year level.

Figure A-3. 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 0.94.

Table A-1. Field names

Field category	Field	Sub-field
Business	Business	Accounting
		Business Administration
		Business Math
		Finance
		Leadership
		Management
		Marketing
		Operations
		Organization Studies
		Real Estate
		Statistics - Business
	Consumer Science	Decision Science
	Economics	Economics
	Human Resources	Human Resources
	Math	Risk Management
	Other	Admin
Education	Education	Early Childhood Education
		Education
		Elementary Education
		Higher Education
		Secondary Education
		Special Education
		Teaching
Humanities	Anthropology	Anthropology
		Archeology
	Arts	Art
		Art History
		Dance
		Film
		Music
		Theater
	Consumer Science	Fashion
		Human Development
	English	English
		Literature
		Writing
	History	History
	Humanities	Classics
		Humanities
	Language	Asian Languages
		Asian Studies
		Germanic Languages
		Language - Other
		Mideast Languages
		Romance Languages
		Slavic Languages
	Library	Library

Figure A-4. Trends in course enrollment and supply (2005-2023)

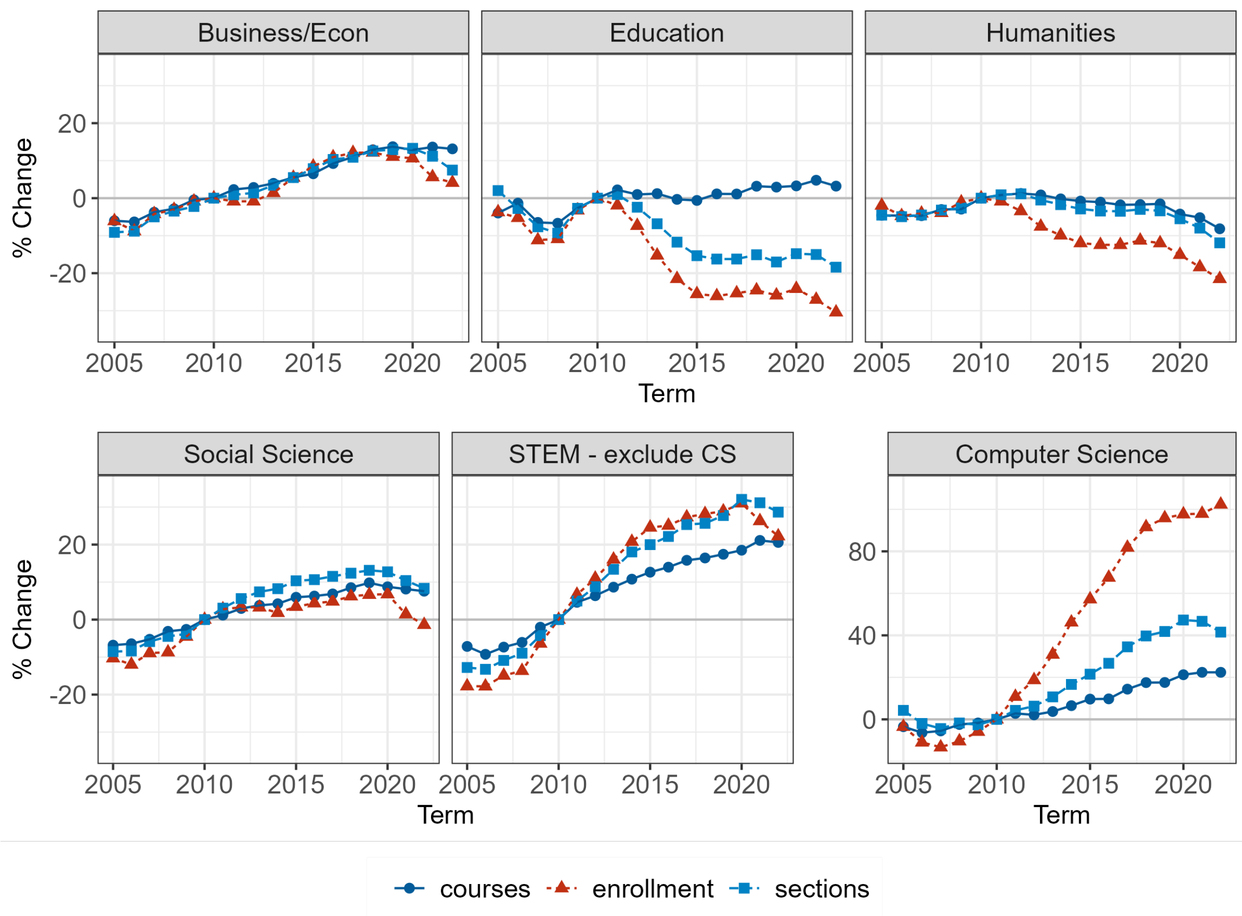


Figure A-5. Change in average course size, 2010-2018

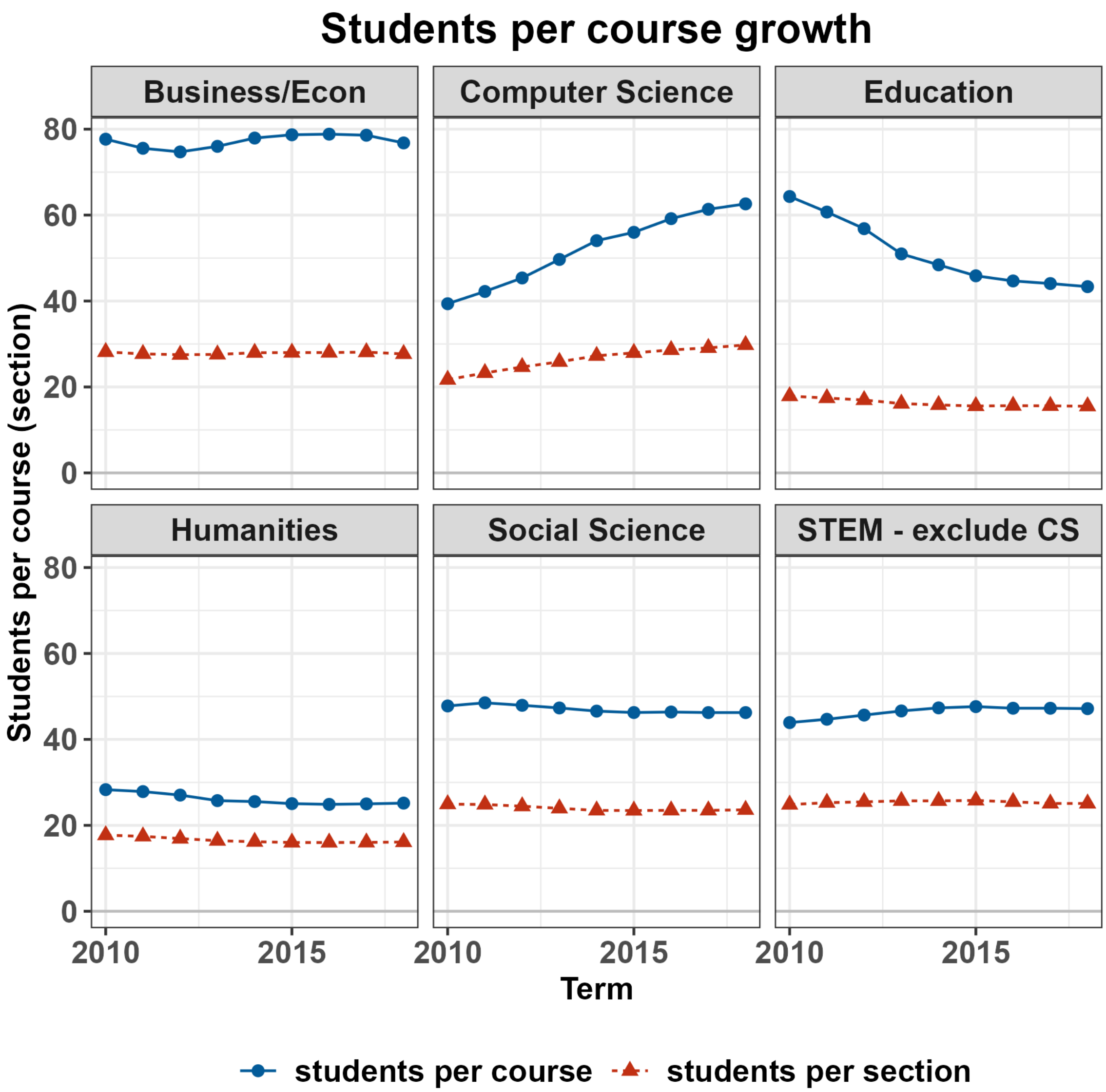


Figure A-6. First-stage monotonicity

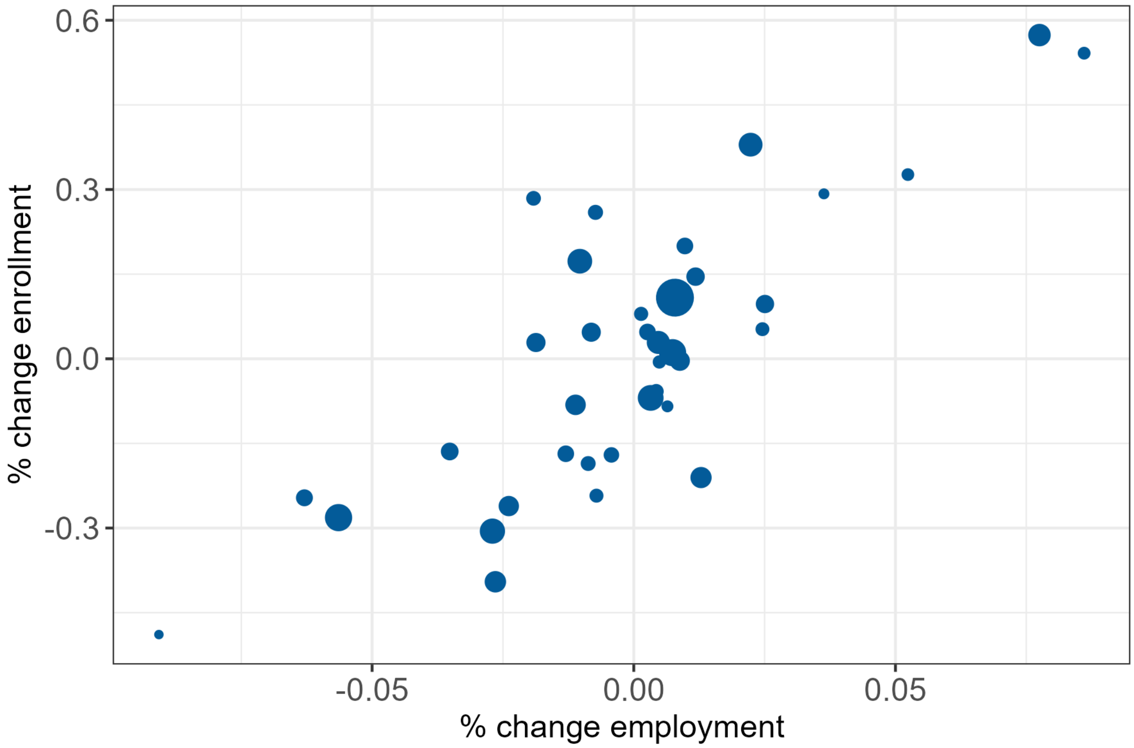


Table A-2. First-stage estimates

	Catalog data		IPEDS
	All undergraduate	Upper-level	Completed degrees
	(1)	(2)	(3)
(Intercept)	0.009	0.006	0.003
	(0.009)	(0.014)	(0.016)
% enrollment change - overall	-0.019	-0.034	-0.034
	(0.031)	(0.039)	(0.053)
Occupation growth	2.499***	4.417***	4.615***
	(0.303)	(0.424)	(0.474)
F-stat	68	108	95
Observations	3,823	3,540	3,510
R^2	0.070	0.122	0.089

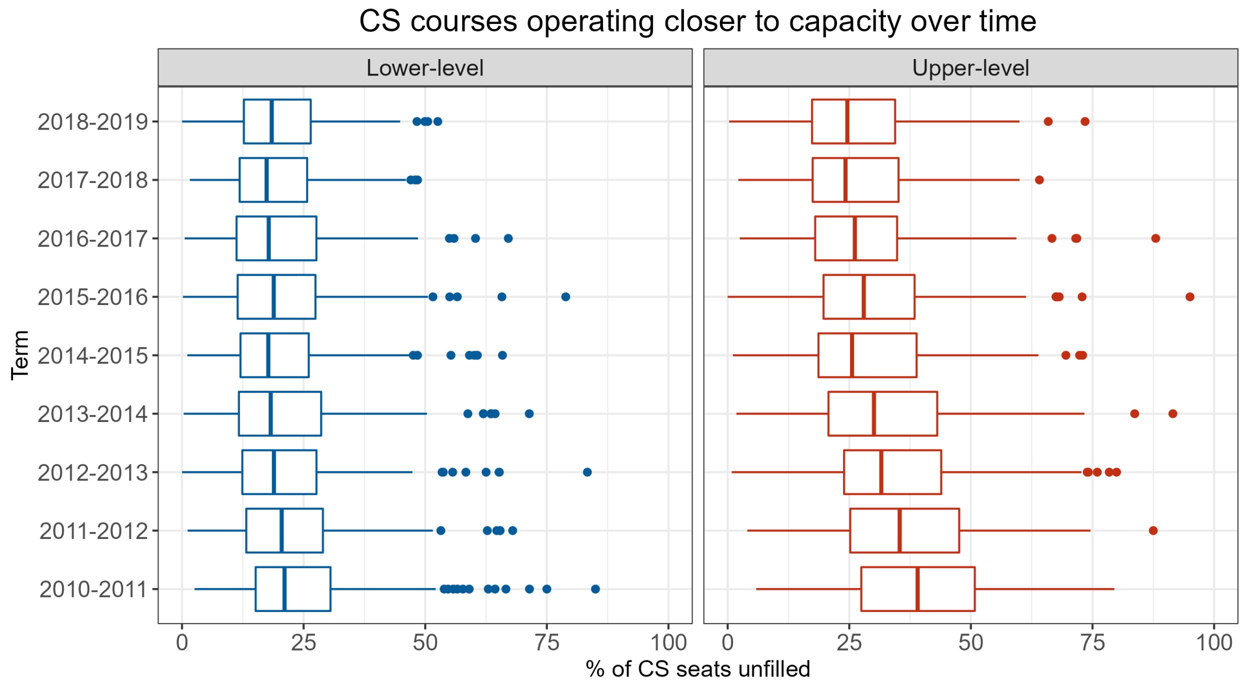
Notes: Observations are at the institution-by-field level. I regress the log change in enrollment on the shift-share instrument reflecting major-typical employment growth in the Census division where the institution is located. Columns 1-2 measure changing enrollment using the course catalog data; Column 3 measures changing enrollment using completed degrees data from IPEDS. 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 Census division by field level.

Table A-3. Reduced form

	# of Courses (1)	# of Sections (2)
shift_share_all	1.367	3.008
	(0.2048)	(0.3436)
Observations	3,540	3,540
R^2	0.15	0.25
School fixed effects	✓	✓

Notes: Observations are at the institution-by-field level. I regress the average annual change in the number of upper-level courses on an instrument that captures variation in employment growth in occupations typical of graduates for the given field in the Census division where the institution is located. The "number of sections" counts total course occurrences in a year (e.g., if Econ 101 is given in two lectures in Fall and once in Spring, it amounts to three sections for Econ 101). Both course supply and enrollment are weighted by credit hours. Excluded from the regression are fields not consistently offered between 2010-2018. 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 Census division by field level—the level of variation used for the instrument in the IV specification.

Figure A-7. Testing for leads in Computer Science course supply change



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

Table A-4. Course supply elasticity regression - expanded period

	4-year diffs (1998-2022)		8-year diffs (1998-2022)		Single diff (2010-2018)	
	Rolling	Staggered	Rolling	Staggered	OLS	IV
	(1)	(2)	(3)	(4)	(5)	(6)
% enrollment change - overall	0.383	0.459	0.371	0.387	0.367	0.367
	(0.043)	(0.074)	(0.022)	(0.044)	(0.036)	(0.036)
% enrollment change - field	0.475	0.481	0.478	0.465	0.475	0.272
	(0.020)	(0.028)	(0.016)	(0.021)	(0.029)	(0.050)
First Stage F-stat						108
Observations	107,779	31,025	108,169	31,135	3,540	3,540
R^2	0.340	0.405	0.379	0.402	0.452	0.383

Notes: Observations are at the institution-by-field level. I regress the average annual change in the number of upper-level courses on the average annual change in course enrollment. The "number of courses" quantifies distinct courses taught in a year (e.g., Econ 101 and Econ 102 are separate courses). The "number of sections" counts total course occurrences in a year (e.g., if Econ 101 is given in two lectures in Fall and once in Spring, it amounts to three sections for Econ 101). Both course supply and enrollment are weighted by credit hours. Excluded from the regression are fields not consistently offered during each period. 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.

Table A-5. Section supply elasticity regression - expanded period

	4-year diffs (1998-2022)		8-year diffs (1998-2022)		Single diff (2010-2018)	
	Rolling	Staggered	Rolling	Staggered	OLS	IV
	(1)	(2)	(3)	(4)	(5)	(6)
% enrollment change - overall	0.777	0.820	0.768	0.788	0.683	0.683
	(0.026)	(0.041)	(0.014)	(0.022)	(0.026)	(0.028)
% enrollment change - field	0.763	0.768	0.776	0.773	0.726	0.604
	(0.016)	(0.016)	(0.012)	(0.014)	(0.019)	(0.034)
First Stage F-stat						108
Observations	107,779	31,025	108,169	31,135	3,540	3,540
R^2	0.682	0.734	0.738	0.769	0.732	0.716

Notes: Observations are at the institution-field-period level, where is the pair of comparison years differenced to measure percent changes. The analysis regresses change in upper-level course supply on change in enrollment, each represented as long log differences. Supply and enrollment are credit-hour weighted. Each institution receives equal weight; within each institution, fields are weighted by start-of-period enrollment. Columns 1-2 estimate elasticities using four-year differences; Columns 3-6 estimate elasticities using six-year differences. Columns 1 and 3 use overlapping periods (e.g. 2010-2014, 2011-2015); all other columns use adjacent periods or only a single period. In Columns 1-5, standard errors are clustered at the institution-by-period level; in Column 6, standard errors are clustered at the field-by-Census division level, which is the level of variation for the instrument.

Table A-6. Course supply elasticity regression - expanded period, lower + upper level courses

	4-year diffs (1998-2022)		8-year diffs (1998-2022)		Single diff (2010-2018)	
	Rolling	Staggered	Rolling	Staggered	OLS	IV
	(1)	(2)	(3)	(4)	(5)	(6)
% enrollment change - overall	0.383	0.459	0.371	0.387	0.348	0.348
	(0.043)	(0.074)	(0.022)	(0.044)	(0.030)	(0.031)
% enrollment change - field	0.475	0.481	0.478	0.465	0.447	0.369
	(0.020)	(0.028)	(0.016)	(0.021)	(0.022)	(0.075)
First Stage F-stat						68
Observations	107,779	31,025	108,169	31,135	3,823	3,823
R^2	0.340	0.405	0.379	0.402	0.317	0.309

Notes: Observations are at the institution-field-period level, where is the pair of comparison years differenced to measure percent changes. The analysis regresses change in course supply on change in enrollment, each represented as long log differences. Supply and enrollment are credit-hour weighted. Each institution receives equal weight; within each institution, fields are weighted by start-of-period enrollment. Columns 1-2 estimate elasticities using four-year differences; Columns 3-6 estimate elasticities using six-year differences. Columns 1 and 3 use overlapping periods (e.g. 2010-2014, 2011-2015); all other columns use adjacent periods or only a single period. In Columns 1-5, standard errors are clustered at the institution-by-period level; in Column 6, standard errors are clustered at the field-by-Census division level, which is the level of variation for the instrument.

Table A-7. Section supply elasticity regression - expanded period, lower + upper level courses

	4-year diffs (1998-2022)		8-year diffs (1998-2022)		Single diff (2010-2018)	
	Rolling	Staggered	Rolling	Staggered	OLS	IV
	(1)	(2)	(3)	(4)	(5)	(6)
% enrollment change - overall	0.777	0.820	0.768	0.788	0.785	0.785
	(0.026)	(0.041)	(0.014)	(0.022)	(0.022)	(0.024)
% enrollment change - field	0.763	0.768	0.776	0.773	0.775	0.589
	(0.016)	(0.016)	(0.012)	(0.014)	(0.016)	(0.047)
First Stage F-stat						68
Observations	107,779	31,025	108,169	31,135	3,823	3,823
R^2	0.682	0.734	0.738	0.769	0.723	0.695

Notes: Observations are at the institution-field-period level, where is the pair of comparison years differenced to measure percent changes. The analysis regresses change in course supply on change in enrollment, each represented as long log differences. Supply and enrollment are credit-hour weighted. Each institution receives equal weight; within each institution, fields are weighted by start-of-period enrollment. Columns 1-2 estimate elasticities using four-year differences; Columns 3-6 estimate elasticities using six-year differences. Columns 1 and 3 use overlapping periods (e.g. 2010-2014, 2011-2015); all other columns use adjacent periods or only a single period. In Columns 1-5, standard errors are clustered at the institution-by-period level; in Column 6, standard errors are clustered at the field-by-Census division level, which is the level of variation for the instrument.

Table A-8. Alternative course elasticity regression specification - no controls

	4-year diffs (1998-2022)		8-year diffs (1998-2022)		Single diff (2010-2018)	
	Rolling	Staggered	Rolling	Staggered	OLS	IV
	(1)	(2)	(3)	(4)	(5)	(6)
% enrollment change	0.445	0.472	0.435	0.428	0.448	0.227
	(0.022)	(0.044)	(0.015)	(0.029)	(0.028)	(0.039)
First Stage F-stat						108
Observations	107,779	31,025	108,169	31,135	3,540	3,540
R^2	0.337	0.405	0.374	0.399	0.447	0.339

Notes: Observations are at the institution-field-period level, where is the pair of comparison years differenced to measure percent changes. The analysis regresses change in upper-level course supply on change in enrollment, each represented as long log differences. Supply and enrollment are credit-hour weighted. Each institution receives equal weight; within each institution, fields are weighted by start-of-period enrollment. Columns 1-2 estimate elasticities using four-year differences; Columns 3-6 estimate elasticities using six-year differences. Columns 1 and 3 use overlapping periods (e.g. 2010-2014, 2011-2015); all other columns use adjacent periods or only a single period. In Columns 1-5, standard errors are clustered at the institution-by-period level; in Column 6, standard errors are clustered at the field-by-Census division level, which is the level of variation for the instrument.

Table A-9. Alternative section elasticity regression specification - no controls

	4-year diffs (1998-2022)		8-year diffs (1998-2022)		Single diff (2010-2018)	
	Rolling	Staggered	Rolling	Staggered	OLS	IV
	(1)	(2)	(3)	(4)	(5)	(6)
% enrollment change	0.767	0.790	0.773	0.780	0.715	0.568
	(0.017)	(0.028)	(0.010)	(0.016)	(0.016)	(0.030)
First Stage F-stat						108
Observations	107,779	31,025	108,169	31,135	3,540	3,540
R^2	0.682	0.733	0.738	0.769	0.732	0.701

Notes: Observations are at the institution-field-period level, where is the pair of comparison years differenced to measure percent changes. The analysis regresses change in upper-level course supply on change in enrollment, each represented as long log differences. Supply and enrollment are credit-hour weighted. Each institution receives equal weight; within each institution, fields are weighted by start-of-period enrollment. Columns 1-2 estimate elasticities using four-year differences; Columns 3-6 estimate elasticities using six-year differences. Columns 1 and 3 use overlapping periods (e.g. 2010-2014, 2011-2015); all other columns use adjacent periods or only a single period. In Columns 1-5, standard errors are clustered at the institution-by-period level; in Column 6, standard errors are clustered at the field-by-Census division level, which is the level of variation for the instrument.

Table A-10. Alternative course elasticity regression specification - asymmetric, no controls

	4-year diffs (1998-2022)		8-year diffs (1998-2022)		Single diff (2010-2018)	
	Rolling	Staggered	Rolling	Staggered	OLS	IV
	(1)	(2)	(3)	(4)	(5)	(6)
% enrollment change - growing	0.468	0.463	0.465	0.427	0.514	0.374
	(0.017)	(0.020)	(0.020)	(0.028)	(0.029)	(0.048)
% enrollment change - shrinking	0.435	0.475	0.413	0.428	0.408	0.182
	(0.031)	(0.057)	(0.021)	(0.044)	(0.041)	(0.040)
Observations	107,779	31,025	108,169	31,135	3,540	3,540
R^2	0.337	0.405	0.375	0.399	0.453	0.366

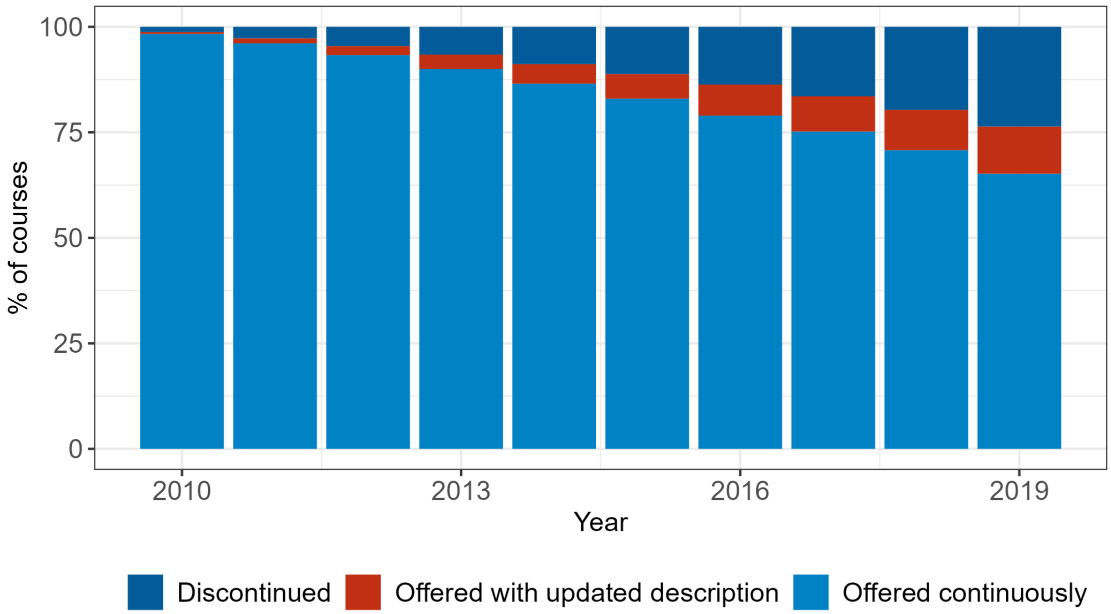
Notes: Observations are at the institution-field-period level, where is the pair of comparison years differenced to measure percent changes. The analysis regresses change in upper-level course supply on change in enrollment, each represented as long log differences. Supply and enrollment are credit-hour weighted. Each institution receives equal weight; within each institution, fields are weighted by start-of-period enrollment. Columns 1-2 estimate elasticities using four-year differences; Columns 3-6 estimate elasticities using six-year differences. Columns 1 and 3 use overlapping periods (e.g. 2010-2014, 2011-2015); all other columns use adjacent periods or only a single period. In Columns 1-5, standard errors are clustered at the institution-by-period level; in Column 6, standard errors are clustered at the field-by-Census division level, which is the level of variation for the instrument.

Table A-11. Alternative section elasticity regression specification - asymmetric, no controls

	4-year diffs (1998-2022)		8-year diffs (1998-2022)		Single diff (2010-2018)	
	Rolling	Staggered	Rolling	Staggered	OLS	IV
	(1)	(2)	(3)	(4)	(5)	(6)
% enrollment change - growing	0.772	0.764	0.802	0.794	0.782	0.679
	(0.013)	(0.016)	(0.014)	(0.011)	(0.024)	(0.051)
% enrollment change - shrinking	0.766	0.798	0.751	0.771	0.675	0.532
	(0.023)	(0.034)	(0.017)	(0.027)	(0.023)	(0.037)
Observations	107,779	31,025	108,169	31,135	3,540	3,540
R^2	0.682	0.734	0.738	0.769	0.736	0.712

Notes: Observations are at the institution-field-period level, where is the pair of comparison years differenced to measure percent changes. The analysis regresses change in upper-level course supply on change in enrollment, each represented as long log differences. Supply and enrollment are credit-hour weighted. Each institution receives equal weight; within each institution, fields are weighted by start-of-period enrollment. Columns 1-2 estimate elasticities using four-year differences; Columns 3-6 estimate elasticities using six-year differences. Columns 1 and 3 use overlapping periods (e.g. 2010-2014, 2011-2015); all other columns use adjacent periods or only a single period. In Columns 1-5, standard errors are clustered at the institution-by-period level; in Column 6, standard errors are clustered at the field-by-Census division level, which is the level of variation for the instrument.

Figure A-8. Course survival plot



Notes: Figure plots the survival path of courses offered in 2010-2011. In each year, the course can occupy 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. The figure cuts off in 2019-2020 to ensure that courses are not erroneously counted as discontinued when they are in fact offered infrequently. Each course receives equal weight in this analysis.

Table A-12. Correlation of school characteristics

char1	Selectivity	Endowment size	Tenure share	Public	Tuition dependence	Research sha
Selectivity	1	0.56	0.16	-0.39	-0.34	0.19
Endowment size		1.00	0.11	-0.33	-0.35	0.16
Tenure share			1.00	-0.21	0.09	0.03
Public				1.00	-0.30	0.19
Tuition dependence					1.00	-0.28
Research share						1.00

Notes: School characteristics from IPEDS, each normalized by the national distribution for degree-granting Title IV-elig non-profit institutions.