Student Demand and the Supply of College Courses *

Jacob Light†

September 29, 2023

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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? I extracted the information contained in the course catalogs of over 450 US universities spanning two decades (2000-2022). When there are changes in student demand (demand changes that I identify using a shift-share instrument), 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 and those with a higher prevalence of tenured faculty. 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.

*Thanks to Nick Bloom, Eric Hanushek, Caroline Hoxby, Petra Persson for substantial guidance and support. I also thank seminar participants at Stanford and the All California Labor Economics Conference for helpful feedback. This research was supported by grants from George P. Shultz Dissertation Support Fund at SIEPR, the Institute for Research in the Social Sciences at Stanford University, and the Leonard W. Ely and Shirley R. Ely Graduate Student Fellowship through a grant to the Stanford Institute for Economic Policy Research. All errors are my own.

†Department of Economics, Stanford University. jdlight@stanford.edu

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. For example, the accelerating pace of technological change increases how quickly the human capital requirements change if a person is going to succeed in the labor market (e.g. Autor et al. (2003)). Whether universities adapt is important not only for individual student outcomes but also for the development of a skilled workforce and for the universities' continued relevance.

Whether universities are, in fact, adaptable and nimble in response to changing demands on them is a question broadly debated in higher education, yet lacking systematic empirical evidence. I endeavor to bridge this gap by producing evidence of two main types. First, I show how elastic universities are to changes in student demand for skills and knowledge more broadly. I consider multiple margins along which universities could respond to changing demand, including the quantity and content of college courses, and find that universities respond inelastically along each of these margins. Second, demonstrated this inelasticity, I then investigate which factors explain why some fields and universities are more elastic than others.

To measure course supply and demand, I constructed a novel dataset containing granular course-level information for a large and nationally representative sample of US universities. The dataset contains 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 compiled 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.

[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.

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. Along the extensive margin, universities meet changing demand for courses in a field by expanding the number of courses or sections.[2] Along the intensive margin, fields within the university 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 offered by a field to changing demand for courses that field. Such estimation is complicated because course enrollment, my best proxy for demand, is an equilibrium outcome and is likely endogenous to the courses supplied. 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 I 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, as opposed to 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 enrollment changes the number of courses by 2.9% and number of course sections by 6.3%. 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 demands 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 course content rather than through the sheer number of courses, represents the university's intensive margin of response. To the extent that fields respond to students' changing demand on the intensive margin, the extensive margin elasticities described above may not fully capture the

[2]For example, a large lecture course in the Principles of Economics might be offered at multiple times, in multiple terms, 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 100 quintupled but the university only expanded course offerings to add a few more seats. We might naively think that demand for Economics 100 was tepid when, in fact, it was surging. In public universities especially, courses may impose a ceiling on enrollment (see, for example, Bleemer and Mehta (2021)).

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

university's responsiveness to changing demand.

To measure changes in course content, I apply Natural Language Processing (NLP) techniques to the course descriptions. Lacking a direct measure of students' preferences for specific topics or skills, I develop a method that gauges course content in relation to broader themes that students might prioritize when selecting courses.[5] Essentially, this method pinpoints salient topics and skills from each course description and gauges their relevance to specific themes based on their prevalence in emblematic documents, such as how often they appear in New York Times articles for a course's relation to current events or job descriptions for a course's job relevance.

In general, the courses a university offers are highly stable: 65% of upper-level courses offered in 2022-23 have been offered for a decade or longer, and the 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, course content has gradually trended in the direction of incorporating content related to these themes, primarily current events and social justice. 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 sd more aligned to job relevance. In practical terms, the size of the change over the period of a decade is equivalent to adding the phrase "climate change" to one in every seven classes offered by an institution.

Collectively, my results demonstrate inelasticity in the provision of college courses, both in number and content. I next examine why universities do not adjust course supply more quickly and why the course supply adjustments I document are asymmetric when enrollment is growing versus shrinking. I consider three hypotheses prevalent in varying degrees in policy discussions around the responsiveness of the university yet lacking empirical evidence for or against them. The "incentive mismatch" hypothesis predicts that universities prioritize courses connected to basic science over applied/vocational courses, and that a stronger emphasis on research and reduced reliance on tuition to fund the university reduce responsiveness to short-term changes in student demand. The "institutional capture" hypothesis predicts that universities, particularly public ones, might be constrained by entrenched stakeholders, such as tenured faculty, who may resist change, stymieing swift adaptation to changing demand. The "learning synergies" hypothesis proposes that the most flexible institutions are those with the greatest resources and the most accomplished students. I test the validity of each hypothetical explanation for this stickiness in course supply by generating

[5] I relate each course to five themes: current events, job relevance, scholarship, social justice, and technology. I selected these themes to broadly reflect topics relevant to students' immediate job opportunities and topics of broader social and intellectual pursuits potentially influencing their course or major choices.

predictions and testing them empirically.

My findings most strongly support the "institutional capture" hypothesis. Universities where individual stakeholders have the ability to extract rents tend to be less responsive to students' changing demand for courses. Specifically, inelasticity in the face of declining enrollment is more pronounced at institutions with a higher share of instructors with tenure (relative to institutions with lower tenure shares) and public universities (relative to private universities).[6] I also provide some support for the "learning synergies" hypothesis, particularly on the intensive margin. 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.

The paper makes three central contributions to existing research. First, I introduce a novel dataset that provides detailed insight into higher education instruction through course-level enrollment and course description data. The detail in this dataset can detect trends in students' sorting across fields more quickly and at a finer level than 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 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 are highly policy relevant but often are not grounded in rigorous evidence. My findings indicate that public universities and those with more tenured faculty are less responsive to student demand, 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 that institutions may prioritize their missions differently: 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.

[6]The scope for "institutional capture" is greater at public universities because these entities are governed by an expansive group of stakeholders: the electorate. Such governance can result in decisions made without comprehensive knowledge of the institution's inner workings, while political influence in board nominations might neglect the primary educational goals.

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 stickiness associated with different facets of the university. Section 7 concludes.

2 Related Literature

I expand on previous research on the factors affecting college students' major choices by analyzing course supply, a channel that affects students' choices but has been overlooked in existing work. Additionally, the project links to studies on the changing skill demands in the job market by demonstrating how universities are incorporating these important skills into their course offerings.

Directly related to my project is a growing body of work on the factors that influence allocation of resources, such as instructor wages and instruction technology, across college fields (Courant and Turner (2017), Hemelt et al. (2021b), Thomas (2021)). Thomas (2021) specifically examines resource allocation at a single institution, highlighting the role of implicit college preferences in shaping student course selection. My project extends this research by studying the process of modifying course offerings at a diverse set of institutions, which allows for an evaluation of potential mechanisms that explain institutional responses. My project also builds on recent work by Conzelmann et al. (2023), which measures the effect of changing job demand on students' major selection and course supply. While their project studies the direct effect of labor market changes on course supply, my analysis highlights the importance of channeling these changing labor market conditions through changing student demand. This project also connects to work by Biasi and Ma (2022) that compares course content to the research frontier, and by Eggenberger et al. (2018) and Chau et al. (2023) which connect college coursework to work activities and earnings in the labor market. My project is distinct from theirs in its use of longitudinal data on the complete set of courses offered within a field to study how curriculum changes over time, thus characterizing course supply more completely than existing work that uses repeated cross-sectional samples of course syllabi.

The project also adds context to a literature on determinants of students' college major choices by considering course supply adjustments to changing enrollment.[7] Previous research has shown that students may consider labor market conditions when selecting their majors,

[7] See Altonji et al. (2016) for a recent review of this literature.

but responses to changing returns are relatively muted (Beffy et al. (2012), Wiswall and Zafar (2015), Long et al. (2015)). Other work documents larger responses in terms of completed majors to occupation-specific shocks (Freeman (1976), Acton (2020), Weinstein (2020)) or changing macroeconomic conditions (Blom et al. (2021)). This project demonstrates that course selection and major completion are highly responsive to relative growth or declines in employment, which may be more easily observable to students than changes in wages. Additionally, the project documents how the courses schools offer change in response to changing student enrollment.

The project also extends research on changing labor market skill demand by showing how college-educated workers develop skills of growing labor market importance. Evidence suggests that cognitive and social skills are increasingly associated with high earnings(Deming and Kahn (2018)). The growth of cognitive skill demand in the labor market can be attributed to both technological Autor et al. (2003)) and cyclical (Hershbein and Kahn (2018)) factors. Employment in occupations that require social skills has also grown in recent decades. The complementarities between social and cognitive skills are associated with growing earnings and employment (Weinberger (2014), Deming (2017)). Using the same Burning Glass Technologies job description data used in this project, Hemelt et al. (2021a) show that employers associate different majors with different skill sets. Despite mounting evidence of the importance of and returns to social and cognitive skills, little research documents where workers develop these skills. The course catalog data in this project connect the skills students develop in college to skill demand in the labor market and provide new evidence of how skill offerings update as the labor market changes.

Finally, this project contributes to a growing literature in Economics using text data for analysis.[8] My text analysis combines two elements. First, I use a method called Term Frequency-Inverse Document Frequency (TF-IDF) that is used commonly to represent text documents as vectors, where entries correspond to words and the values are weighted in proportion to the importance of a given word to a given document. Second, I develop an approach to measuring the similarity of a document to specific themes. To my best knowledge, the approach that I describe is novel. The method is essentially an extension of TF-IDF and similarity measures used in Natural Language Processing, but offers advantages of transparency and interpretability. I considered alternative approaches that incorporate recent innovations in NLP methods, such as using a multinomial classifier or a more sophisticated embeddings model. These methods offer greater flexibility at the expense of transparency

[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 social science fields other than Economics. Although not summarized in this review, this work is also foundational for my project.

and interprability. In describing the method in this paper, I present evidence suggesting that the approach produces output comparable to the more flexible approaches.

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 observations of 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 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. Although the sample is not random insofar as it only includes universities with online course catalogs, the resulting sample aligns with the broader population in several important respects. Table 1 compares the characteristics of schools in the catalog sample to 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. Extremely small private (often religiously affiliated) institutions are under-sampled in this dataset.[11] 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 data on course supply and enrollment than previously-used data sources, which typically focus on broader metrics such as completed majors. While majors give insight, they represent only a portion a student's college courses. Moreover, a student does not need to wholesale switch majors to develop new skills

[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 in this paper to four-year Title-IV eligible degree-granting higher education institutions, largely due to stronger coverage of four-year schools in my sample and because these schools enroll the majority of full-time students.

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

as the labor market demands them. Thus, major completion might not capture the full breadth of students' responses to changing labor market conditions. Other research uses transcript-level data to analyze students' changing preferences for fields. While rich in content, these datasets often include a limited and homogenous set of institutions. In contrast, the course catalog dataset, even if slightly less detailed, spans a broader and more varied set of schools.

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-traditional instruction modes (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 catalog 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. My IV analysis uses the 2010 and 2018 waves of the ACS to create an instrument for projecting major-specific employment growth.

3.3 Supplemental text data sources

In Section 5, I examine how enrollment changes influence course content updates. I've designed a weighting system, giving prominence to words or phrases based on their significance in specific thematic documents versus a neutral corpus. The supplemental text data sources are detailed below; additional detail on these data sources is available in Appendix D.

[12] For additional detail on the data processing, see Appendix A.
[13] Appendix B delves deeper into the field standardization procedure.

3.3.1 New York Times articles

I download the complete set of articles published by the New York Times (either in print or digitally) between 2010-2018 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 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 2010-2018. 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 2010-2018. The resulting corpus includes the text of nearly 2.5 million patents.

3.3.4 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.

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. 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: *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

This section demonstrates that course supply is highly inelastic to changing student demand. I first document this result descriptively, then estimate elasticities in an instrumental variables framework that accounts for potential endogeneity of enrollment as a measure of demand. Throughout this analyses, I focus on the provision of upper-level courses. These are the courses that students have most autonomy over in their selection, and, as a result, fluctuations in enrollment more accurately reflect students' changing demand. I provide estimates of course supply elasticity for all courses in the Appendix. Estimates are substantively similar but less-precisely estimated.

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 is noisy and small fluctuations do not necessarily represent student preferences. Thus, I consider a relatively long period that begins after the Great Recession and extends to the start of the Covid-19 pandemic.

4.1 Conceptual framework

To motivate this section, it is instructive to consider the structure of the market for college courses and the features that distinguish this market from those more familiar to economists.

Student demand: Adapting Arcidiacono (2004), students select a portfolio of courses to maximize the return on their investment in education. Students select courses that equip them with human capital that they can bring to the labor market for higher wages. However, students incur costs in developing this human capital: the financial costs of tuition,

opportunity costs of delayed entry into the labor market, and psychic costs associated with the effort needed to develop their human capital. Students vary in their innate interests and aptitude for various skills, which determines the extent of the psychic costs a student incurs and is the source of variation in students' responses to changing conditions in the labor market.

University supply: Universities function as multi-product firms, producing both instructional and non-instructional services, including research, training graduate students, and sports. Yet, their operational dynamics stand in contrast to traditional firms. Notably, the objective function of a university is more complex and not as well-defined. Universities may pursue multiple, sometimes competing, objectives: from profit-maximization and producing and disseminating knowledge, to meeting local skilled labor demand, especially in the case of public universities.

An inherent ambition of universities is their desire for self-perpetuation and reputation enhancement. This long-term vision, intertwined with their myriad objectives, often subjects them to various pressures. Internally, the drive for academic diversity might push them to support or even "rescue" disciplines with dwindling student interest. Externally, they might grapple with influences such as political pressures shaping their academic offerings. This same ambition also influences their investment decisions, with a forward-looking approach to infrastructure and faculty, especially those on the tenure track.

Tenure is a distinctive and complicating feature of the university's labor market. Hiring tenured professors represents a significant, long-term investment that encourages academic freedom. However, this commitment also limits a university's flexibility in adapting its labor force to shifting academic demands. Professors often wear multiple hats, engaging in research, teaching, and institutional service. Their proficiency in one role does not necessarily correlate with excellence in another (e.g, Figlio and Schapiro (2021)). Given these multifaceted roles and potential misalignments in expertise, recruitment and retention strategies may not always align directly with the objective of maximizing student learning.

Equilibrium: An important feature distinguishing the market for courses from markets more familiar to economists is the lack of prices as a mechanism for reaching equilibrium. Universities typically do not use prices to moderate demand across courses.[14] Instead, course availability and sometimes even admission into specific programs or fields are rationed in different ways, often based on academic performance or on a first-come-first-served basis.

Additional features complicate the extension of theoretical insights from standard markets to this setting. One such feature is information asymmetry. Incoming students, particu-

[14]Institutions may impose course-specific fees, but they are often associated with higher course- or field-specific costs of instruction (Stange (2015)).

larly first-year undergraduates, often face challenges in accessing comprehensive information about course content, future labor market returns, and their own academic aptitudes. This lack of perfect information can lead to suboptimal course choices, potentially affecting both individual outcomes (like future earnings) and institutional outcomes (such as course over-subscription or under-enrollment). While universities may attempt to mitigate this through guidance counseling and orientation programs, the asymmetry is never fully resolved.

Responding to demand shocks: When 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, or choose not to react at all and restrict enrollment.[16]

4.2 Descriptive evidence of course supply stickiness

Figure 3 summarizes university supply behavior in response to enrollment trends. The figure plots the growth trends in course enrollment alongside the number of unique courses and sections offered, categorized by six fields: Business (inclusive of Economics), Education, Humanities, Social Science, STEM (excluding Computer Science), and Computer Science.[17] The figure shows enrollment shifting away from Humanities and Education towards Business, STEM, and Computer Science.[18].

For fields like Computer Science with rapid enrollment growth, or Humanities and Education with enrollment decline, a noticeable gap emerges between course enrollment and supply. This gap is illustrative of "stickiness" within the university: the university's tendency towards stability in course supply despite large and persistent changes in demand.

The extent of stickiness varies across fields. For fields with modest enrollment growth, including non-Computer Science STEM and Business, 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

[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 and 2 courses.

[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 for clarity. More detailed field classification 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))

modestly but did not keep pace with the rapid enrollment growth.[19] The asymmetry is suggestive of downward rigidities that make responses to growing demand easier than responses to shrinking demand. 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.

While enrollment and course supply align more closely for non-Computer Science STEM and Business/Economics, this alignment does not necessarily imply 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 to take owing to the university's rationing or non-supply. I address this limitation of enrollment as a proxy for supply in the following section.

Stickiness in course supply carries several implications that affect the educational quality students receive. First, stickiness results in dramatically larger classes in growing fields and reduced class sizes in shrinking fields.[20] Second, to the extent that growth in the number of courses supplied is not a response to overall growing enrollment at the university, it suggests a rise in the average instructional costs per student.[21] Given that most universities predominantly depend on tuition or public financing, it is plausible that the costs of stickiness are passed on to students in the form of higher tuition. Finally, stickiness, especially when it results in non-supply, might deter students from pursuing their preferred study fields, potentially leading to sub-optimal human capital development. This paper documents the extent of stickiness but leaves the welfare implications of stickiness for future research.

4.3 Empirical Strategy

In this section, I estimate the elasticity of course supply to students' changing demand for courses. Universities may increase capacity in existing courses to accommodate growing demand, but there is a limit to how much enrollment can change before student learning starts to deteriorate, particularly in upper-level courses that are designed for relatively small

[19] Computer Science is a unique field for its boom-and-bust cycles. The growth in CS enrollment during the period of my analysis follows a nadir in Computer Science enrollment that declined after 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.

[20] 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)).

[21] During my study period, enrollment in four-year universities remained relatively stable, and the average undergraduate headcount growth rate for institutions in my sample is almost zero [NTD - exact number].

groups of students. The elasticity of course supply to changing demand measures how responsive universities are to students' changing preferences and speaks to the capacity of universities to meet the evolving needs of students.

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

$$\Delta y_{i,s} = \alpha_i + \beta \Delta x_{i,s} + \epsilon_{i,s} \tag{1}$$

The dependent variable, $\Delta y_{i,s}$, represents the average annual percentage change in the number of courses supplied at institution i in field s from 2010-11 to 2018-19.[22] The independent variable, $\Delta x_{i,s}$, represents the average annual percentage change in course enrollment at institution i in field s over the same period.[23] The institution-fixed effect term, α_i, controls for institution-specific trends (e.g., growth or decline in undergraduate enrollment), allowing the estimates to reflect the response of the institution to field-specific changes in enrollment that deviate from the overall trend at the institution. The parameter of interest, β, represents the average percentage change in the number of courses offered in response to a given percentage change in course enrollment.

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 shock that causes demand for Economics courses at a hypothetical university to double. If the university does not offer any additional courses or sections to accommodate this demand, and restricts capacity such that the number of enrollments remains unchanged, course supply would appear to move (rather, not move) in tandem with demand when in reality the university is highly inelastic to changing demand.[24] To estimate a causal relationship between changes in student demand and changes in course supply, I use an instrumental variables (IV) strategy that isolates a portion of enrollment changes that are solely attributable to shifting student preferences, independent of the actions taken by the university.

I construct a shift-share instrument that isolates a portion of enrollment changes that can be attributed solely to exogenous changes in labor market conditions. The instrument uses two sources of variation: variation in employment growth prospects across fields (s) and

[22] I credit-weight both changing course supply and changing enrollment.

[23] I use the percent change on percent change specification, rather than the more standard log-log specification, because I am interested in estimating elasticities over a relatively long time period. The percent change specification uses more of the data and is less sensitive to anomalous course supply or enrollment in any single year than a long log differences specification. My estimates are substantively identical when I regress log differences between the first and last year.

[24] Further, to the extent that these students are diverted to courses in other fields, the university may appear responsive to spurious demand shocks in other fields when, in practice, students are taking classes they would ideally prefer not to take.

differential exposure to changing opportunities 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").[25] I construct the instrument using data from the 2010 and 2018 American Community Surveys (ACS), following Equation 2 below:

$$\Delta E_{s,r} = \sum_{j=1}^{J} \phi_{s,j,r} \left(lnE_{j,r,2018} - lnE_{j,r,2010} \right) \tag{2}$$

$$z_{s,r} = \Delta E_{s,r} - \overline{\Delta E_r} \tag{3}$$

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 results in an instrument that only captures the relative changes in the attractiveness of different fields. To eliminate the influence of changing course supply on labor market measurements, I concentrate on the employment growth of 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.[26]

To demonstrate how the instrument captures field-by-region differences in changing employment growth prospects, consider the cases of 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

[25] 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 analysis differs in the sense that they study the direct effect of changing job demand on completed majors and course supply, whereas my analysis is primarily concerned with the effects of changing labor market conditions on course supply only insofar as they impact students' demand. They 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). I confirm using their data (Conzelmann et al. (2022)) that, on average, more than 80% of graduates from the schools in my sample work in the same Census division where the institution is located.

[26] 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). 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.

roles, 10% worked in sales, and the remaining 20% worked in other occupations.[27] 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 jobs grew 7.9 percentage points less than the regional average during the same period. The instrument captures differences in relative employment growth rates across fields.

To demonstrate how the instrument captures differences across regions, consider how the instrument captures variation in job growth 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, evolve differently across regions.

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

$$\Delta x_{i,s,r} = \gamma_i + \kappa z_{s,r} + \eta_{i,s,r} \tag{4}$$

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 average annual change in the number of courses in field s at college i between 2010-2018 ($\Delta y_{i,s,r}$) on this instrumented enrollment change:

$$\Delta y_{i,s,r} = \alpha_i + \beta \widehat{\Delta x_{i,s,r}} + \epsilon_{i,s,r} \tag{5}$$

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

For identification, the instrument must satisfy assumptions of monotonicity, indepen-

[27] 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.

dence, relevance, and the exclusion restrictions. 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-4. 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, 2010-2018, 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. 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 130.7.[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-5, I find no evidence of this occurring, using the growth of Computer Science as an example.

The exclusion restriction may also be violated if changing labor market conditions change the relative costs of hiring instructors across fields.[29] Robustness tests that exclude fields where we might expect changing reservation wages to be most pronounced (e.g., Computer Science at Stanford) produce similar estimates.[30]

[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 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

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, I believe that my shift-share instrumental variable fulfils the exclusion restriction but it may lead me to understate just how inelastic universities truly are.

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 2010-11. 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. These categories are largely similar to the field categories in Blom et al. (2021) and are described in detail in Appendix B.

4.4 Results

Table 2 summarizes OLS and IV estimates for the course supply elasticity regressions.[32] Columns 1 and 2 summarize estimates of the elasticity of number of courses offered with respect to changing enrollment. The estimates strongly suggest that course enrollment does

graduates entering the labor market, who might be impacted by course supply stickiness 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.

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.

[32] For this section, I focus on course supply responses to changing enrollment for upper-level courses (typically numbered 300 or above, although the numbering convention differs at different schools). These are the courses for which enrollment shifts corresponding to changing employment conditions are strongest, and over which students have the most discretion in their course selection. As a result, the first-stage IV for these courses is strongest. Appendix A-4 summarizes estimates for all courses. The results are qualitatively similar, although less precisely estimated.

not respond 1-for-1 to changing enrollment. In my preferred IV specification, the estimates suggest that fields expand course supply 2.9% for a 10% increase in demand. Put differently, a department the size of Stanford's Economics Department adds a new course when enrollment in upper-level courses increases by 120 seats and the underlying demand for upper-level Economics classes increases by 190 seats.[33] 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 6.3% 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 will reflect both 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 estimated in Table 2 imposes that the course supply response to a field with increasing enrollment is precisely the inverse of 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 such an instructor of 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 ($\bar{\Delta x_i}$). I estimate the new model:

$$\Delta y_{i,s} = \alpha \bar{\Delta x_i} + \beta_1(\Delta x_{i,s} - \bar{\Delta x_i})\mathbb{I}(\Delta x_{i,s} < \bar{\Delta x_i}) + \beta_2(\Delta x_{i,s} - \bar{\Delta x_i})\mathbb{I}(\Delta x_{i,s} > \bar{\Delta x_i}) + \epsilon_{i,s} \quad (6)$$

[33] In 2018-19, Stanford's Economics department offered 125 credits of upper-level courses and student enrollments 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 8.8% increase in enrollment (600 student-credit hours) or a 14.5% increase in demand (950 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.

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

Table 3 summarizes the OLS estimates for the elasticities of course and section supply allowing for asymmetry. For both the number of courses and number of sections, the course supply elasticity is larger when enrollment is increasing than when enrollment is decreasing. In the case of the number of courses, a field in which enrollment grows 10 percentage points faster than the school average typically expands course supply by 5.3 percentage points more than average, while a field growing 10 percentage points less than the school average expands course supply 3.6 percentage points less than average.

Taken together, the central result of this section is that course supply responds inelastically to changing student demand, and the extent of the inelasticity is greater when enrollment growth is less than the institution's overall growth rate. In Section 6, I examine variation across different types of institutions to suggest potential mechanisms underlying the inelastic and asymmetric course supply responses.

While the number of unique courses offered by a field gives a clear indication of the breadth of curriculum, it may not necessarily capture the depth or nuance of how fields adjust their teachings in response to shifting demand. To the extent that fields modify the courses they offer in response to changing demand, substantial reallocation from fields with declining enrollment to fields with growing enrollment may not be necessary. In the next section, I consider how course content evolves to meet changing student demand.

5 Intensive Margin: How fields adjust course content

A field can also meet changing student demand by changing the content of courses offered (for example, by replacing a course that teaches outmoded skills with a course that teaches high-demand skills). This section considers how the content of college courses evolves to meet 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 they will produce. This rich insight into what students learn in their college classes is a unique feature of the course catalog dataset and allows me to summarize what makes fields different or similar, how fields compare across

different institutions, and how they evolve over time. Crucially, the longitudinal structure of my data allows me to make comparisons within an institution and field, across 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, instructors may not update these descriptions frequently. When this is the case, the description will lag the unobserved course content changes. In my data, 35% of courses are modified or discontinued over a ten-year period (see Appendix Figure A-6). To the extent that changes in course content lead 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 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). I represent the text description of each course c offered in field s at institution i in year t as a single document $d_{c,i,s,t}$. I apply standard pre-processing to each document.[34] 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 $(w \in W)$.[35] Tokens typically are a single word, although I represent common n-grams as single tokens (for example, I treat "climate change" as a single token distinct from "climate" or 'change"; similarly, I treat "social media" as a distinct token 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), which measures the distinctiveness of a given token 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 words "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,

[34]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.

[35]The dictionary is derived from tokens that appear more than 500 times in 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.

reducing the emphasis on common words. This ensures that changes in word frequency genuinely reflect substantive shifts in what different student cohorts might learn within a course. 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 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 Descriptive evidence of curriculum change

I apply the TF-IDF weighting technique to analyze changes in a course's content over time. I first demonstrate that course descriptions contain meaningful information about what students learn in college classes, and then show that changes in a field's curriculum description signify meaningful changes in the available learning content.

Figure 4 illustrates how the NLP methods described in the previous section pick out distinctive words in course descriptions. The figure displays the 25 most distinctive tokens for a sample of fields. I consolidate all course descriptions from courses offered in 2022-23, grouping them 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 conventionally associated with 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, operating systems).

The effectiveness of the TF-IDF method hinges on detecting substantive changes in course content, 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 substantive changes in the topics and skills emphasized by courses over the last decade. 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 and analyze how this measure changes over time. Lacking a direct measure of students' preferences for specific topics or skills, I instead measure the changing relationship between course content and a broad set of themes relevant to student's 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).

I relate course descriptions to these themes by developing a weighting scheme that captures a tokens' 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 the reverse is unlikely to be true. To capture the career relevance of a given token, I measure the frequency with which it appears in job descriptions. To capture a token's importance to current events, I measure the frequency with which it appears in the text of front-page articles published by the New York Times. To capture a token's relation to research scholarship, I measure the frequency with which it appears in abstracts for top academic journals.[36] To capture a token's connection to social justice, I use a corpus of books and press releases from organizations oriented towards social justice causes.[37] Finally, to capture a token's relation to technological progress,

[36]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 data sources and objectives. The "course catalog" dataset contains longitudinal data encompassing the full set of courses offered by a field. This enables me to observe within-institutional and field-specific shifts over time and in response to changing enrollments. While Biasi and Ma specifically delve into the juxtaposition of newer versus older research-related content, I measure a course's general connection with research-themed topics. My method does not distinguish between current and obsolete research content, but it captures terms consistently associated with research, such as "research" or "analysis," thereby offering insights into a course's research relevance.

[37]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: *Between the World and Me* by Ta-

I measure the frequency with which it appears in patent text. The text data sources used for quantifying each of these shifts, along with the procedure used to handle these data sources, are detailed in Appendix D.

I construct "relevance weights" for each token w and each theme q.[38] The weights are designed to assess, for each token, how much more important the token is to the reference text than some 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.[39] For example, 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

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

In Table 4, I demonstrate 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. A relevance weight close to 1 for these tokens signifies their strong association with the respective theme, underscoring the method's ability to pinpoint important terms in the source documents. Conversely, 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 unduly skew or misrepresent the alignment scores. In essence, the method demonstrates sensitivity to thematic alignment while being resistant to mere linguistic variations, reinforcing its utility and reliability in assessing course-to-research alignments.

In order to measure how much a course connects with a given theme, I calculate a

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.

[38] 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.

[39] This weight corresponds to the conditional probability from an experiment where a document category (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.

"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, where greater weight is assigned to words/phrases that are more distinctive of each document. Appendix D provides a detailed example of how a curriculum alignment score is calculated.

To demonstrate differences in courses and fields based on curriculum alignment scores, Figure 6 plots the average scores for courses offered in 2022-23, categorized by field and averaged across institutions.[40] The findings are telling: fields differ in their alignment with different themes, often in an intuitive manner. For example, Economics and Business courses are closely linked to 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 courses feature terms related to academic research, vocational skills observed in job descriptions, and technological advancements reflected in patents.

Next, I characterize how the average curriculum alignment of courses offered has changed over the last 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, with institution-by-field fixed effects. The estimates are normalized as growing 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.[41] 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. For example, the average college course became 0.064 sd more current events-aligned between 2013-14 and 2022-23. This would be equivalent to incorporating a highly current events-relevant phrase like "climate change" into one out of every seven courses offered in 2013-14 over the course of the decade. Given that I am controlling for institution-by-field fixed effects, this trend is not driven by shifts in the

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

[41] Despite the growing emphasis on a clear set of themes, I have not been able to identify a corresponding set of themes with declining emphasis. 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).

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 up-to-date curriculum. Conversely, if curricular adjustments mainly derive from the introduction of new courses and the elimination out of outdated courses, stickiness in course offerings could limit students' exposure to the most relevant content.

To measure the channel through which course content becomes increasingly aligned with themes relevant to students' interests, I decompose the growing curriculum alignment recorded in Figure 7. In particular, I perform a decomposition of the average change in curriculum alignment into four components in the style of Foster et al. (2001). The "within" component measures changes attributable to changing course content for the same course offered in both 2013-14 and 2022-23.[42] 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. Thus, I am measuring changes within institution-by-field, and the results do not include compositional shifts related to student's movement across fields or relative growth/decline of courses supplied across fields.

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.

[42]The "within" component is vulnerable to mismeasurement if courses are changing but the course description is not updated. I measure this decomposition over a long time period to alleviate this concern.

It is sensible that universities increase their alignment with current events by introducing new courses. As global events and topics evolve, universities adapt by creating courses that address these shifts. Particularly when the world changes in unforeseen ways, such as the onset of a 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 drifts toward increased alignment with the five themes, 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 highly inelastic to shifts in student demand. The evidence presented in this section suggests that fields that are more dynamic in their course offerings may enhance their relevance to themes relevant to student interests. 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 distinct hypotheses that explain why course supply is sticky. 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 variation in stickiness I observe in the data.

6.1 Hypotheses and predictions

The **incentive 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, say, 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, it might be sensible for universities to take the long view (Hoxby (2012)). Also, under this hypothesis, students might care only about gaining skills for themselves but do not care about 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.

Under this hypothesis, one central prediction is that universities should be more protective of their core or basic research fields even if this results in slower growth for vocational programs that cater to immediate job market demands. This would ensure the perpetuation of knowledge that might not be immediately applicable or popular, but is crucial for societal advancement and students' long-term growth. Another prediction is that research-oriented, older institutions would make decisions with a longer time horizon in mind, making them less responsive to short-term changes in student preferences. Such institutions, valuing the creation and preservation of knowledge, might be more resistant to rapid course updates based on potentially fleeting trends. A third prediction is that schools funded primarily through tuition from current students (rather than endowments or state funding) have a greater incentive to be attuned to the demands of these current cohorts of students. Such tuition-dependent institutions may be less sticky when students' demand changes.

The **institutional capture** hypothesis proposes that universities may respond inelastically because they have been captured by faculty, staff, or other constituencies who use their power to take rents.[43] After all, universities are not publicly-traded, for-profit firms that need to report quarterly earnings, whose share price changes daily with news about their productivity, and that are potentially 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. This could lead to outdated or lower-quality course offerings.

In addition, public universities might be especially susceptible to stickiness under the institutional capture hypothesis. One contributing factor is their potential vulnerability to political influence. Unlike private institutions, public universities can find themselves more exposed to political agendas and, thus, more prone to interventions from political actors. The governance of public universities presents another layer of complexity. These institu-

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

tions 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 inertia. 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.[44] Finally, in contrast with private universities, the faculty at public universities often have the option to unionize. When unionized, the faculty might possess certain protections or demands that can impede swift institutional changes.[45]

The **learning synergies** hypothesis proposes that the dynamism and responsiveness of a curriculum is valued by both students and faculty. 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. They find fulfillment in teaching courses that align with their expertise, field trends, and the changing interests of their students. 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.

Therefore, under this hypothesis, one would expect the most substantial changes in course content to occur at well-resourced institutions. These institutions have the financial and 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 latest course content. This symbiotic relationship between well-resourced institutions and high-quality students would create an environment conducive to a dynamic, responsive curriculum.

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

[45] It is essential to note, however, 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.

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 institutions' research outlays and tuition dependence to test the incentive mismatch hypothesis; I use an institution's control (public vs private) and tenure track share of instructors to test the institutional capture hypothesis; and I use institutions' selectivity and endowment size to test the learning synergies hypothesis.[46]

For each of these characteristics, I study heterogeneity in three ways. First, I estimate heterogeneity in course supply elasticities for different kinds of institutions. Second, I compare the average "age" of courses. Third, I document differences in curriculum alignment for courses offered at different kinds of institutions.

6.2 Heterogeneity in course supply elasticity

To investigate if the elasticity of course supply differs across university types, I refine the regression framework described in 4.3 to explore relationships between course supply elasticity and university characteristics. I introduce three extensions to the elasticity regression framework.[47] First, I design separate models for each of the six characteristics, introducing an interaction term between the change in course supply and the school feature (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 "Kitchen Sink" specification. This single model includes characteristic-changing enrollment interaction terms for all six university attributes.[48] Third, to address the endogeneity of changing enrollment, I incorporate "IV" specifications. This specification estimates six separate regressions in the style of the IV model described by Equation 5 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 enroll-

[46] Specifically, I measure tuition dependence as the share of an institution's total revenue that comes from tuition payments; research outlays are the share of current spending devoted to research; the non-instructional budget is the non-instructional share of total payroll; the tenure track share is the share of instructor headcount at the Full or Associate Professor level; selectivity as 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 2022-23, I fix institution characteristics as of 2021-22 (the most recent IPEDS survey year). The results are roubst to estimating all of the heterogeneity analyses using characteristics fixed to either of these years.

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

[48] Appendix Table A-8 details the correlation between these characteristics.

ment is increasing or decreasing, as summarized in Equation 6.[49] My emphasis is mainly on the "Kitchen Sink" model because of its capability to address correlations between different characteristics.

The focal point in this analysis is the coefficient attached to the changing enrollment-characteristic interaction term(s). This coefficient reflects the differences in course supply 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 rises and falls. Second, more selective schools respond more elastically to changing enrollment, driven by larger reductions in courses offered when enrollment in a field declines. Third, 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 and less elastically to falling enrollment compared to schools with more non-tenured instructors.

These estimates offer strongest support for the institutional capture hypothesis and some backing for the learning synergies hypothesis. As per the institutional capture theory, the course supply's elasticity to changing student demand is more pronounced at schools where stakeholders have more opportunities to exploit the system, potentially generating stickiness. For public universities, the result is inelasticity to both rising and falling demand. For universities with a higher share of instructors with tenure, these rents may protect instructors in department experiencing a drop in enrollment but do not seem to impede growth in departments where enrollment is rising.

The more significant adaptability of course supply to student demand at selective schools, especially when numbers decrease, is a more complex issue. The following section suggests that less selective schools maintain a more consistent curriculum over time, possibly making them less responsive to a drop in demand. On the other hand, elite schools might have experienced unique enrollment pressures during my study, complicating the comparison between expanding and contracting fields. For example, the advanced mathematical skills of students at top-tier schools could have increased the demand for STEM or Computer Science courses, while rising demand at less elite schools might have been in business-focused fields. Considering this variability in demand, especially when contrasting different schools, these

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

findings should be approached with caution.

6.3 Heterogeneity in course age

One consequence of course supply stickiness is that stickier 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 consequence of both of these factors is that stickier 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.[50] 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.[51] Figure 10 summarizes heterogeneity in course age by type of institution. I plot the point estimates from separate course-level regressions of course age on each of the six normalized school characteristics.

The estimates suggest that courses are "fresher," 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 year "fresher" 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.

[50] 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.

[51] 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.

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 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 "kitchen sink"-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 Appendix Figure A-8, I show that this divergence in course content between institutions of varying selectivity manifests across most fields of study.

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

Taken together, the preceding analyses explore the mechanisms underlying how universities respond to students' changing demand. The results provide strongest support for the institutional capture hypothesis. The observation that public universities responded less elastically compared to private universities and the nuanced response of institutions based on the tenure of their faculty both align with the institutional capture theory. The fact that more tenured faculty equated to both more elasticity in response to increasing demand and

less elasticity to decreasing demand indicates that tenured positions may provide instructors with security against negative trends while still allowing them to capitalize on positive ones. Greater stickiness in public schools, in the face of both rising and falling demand, underscores the potential challenges these institutions face due to their governance structures and susceptibility to political influence.

The analysis offers some support for the learning synergies hypothesis. More selective and better-resourced institutions indeed had newer courses, and perhaps as a consequence the courses offered at these institutions emphasize topics related to current events and societal issues over immediate job applicability. I do not find strong support for the incentive mismatch hypothesis; I do not detect meaningful differences in the course supply elasticity, average course age, or thematic alignment of courses at institutions corresponding to their tuition dependence or research intensity.

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 balance and tension between these competing influences.

Empirical support for the institutional capture 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 and those with a higher percentage of tenured faculty — 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 the broader society. 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 synergies hypothesis, particularly on the intensive margin, suggests that adaptation and innovation in curriculum occurs to a greater extent at well-resourced and selective institutions. More selective and wealthy institutions offer courses that emphasize current events and social justice over vocational relevance. This might reflect the broader objectives of elite institutions to nurture critical thinkers and global citizens, rather than merely job-ready graduates. It could also be a reflection of their student body's preferences, who, given their background, might prioritize broader educational outcomes over immediate job prospects. 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. The fact that this trend is consistent across multiple fields of study indicates a strategic choice by these institutions rather than an incidental outcome.

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. Utilizing a unique dataset compiled by scraping online course catalogs, I measure how course supply adjusts to changing demand along 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% increase enrollment for a field results in only a 2.9% increase in unique courses offered and a 6.3% increase in course sections. Notably, course supply is more responsive when enrollment in a field is growing relative to when enrollment is shrinking.

Stickiness also manifests in the longevity of courses. Remarkably, 65% of courses in the 2022-23 dataset had been around for at least a decade, with infrequent alterations in their descriptions. 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, stickiness on the extensive margin and the tendency of fields to introduce new topics mainly through new courses indicate that such stickiness could potentially hinder the progression of students' learning. 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 demands might not equip students adequately for success in the workforce.

To understand the observed inelasticity of course supply, I evaluated three hypotheses: "incentive mismatch," "institutional capture," and "learning synergies." My findings offer the most support for the learning synergies hypothesis: I show that selective schools are more responsive on the extensive margin, and that the thematic content of courses offered at selective schools differs markedly from less selective schools. In particular, selective institutions emphasize topics related to current events and social justice, whereas less selective institutions offer a more vocational curriculum. This variation has implications for students'

preparation for the labor force, both for entry and across their careers.

This paper documents course supply inelasticity but leaves unanswered the question of its welfare implications. Students are harmed by inelasticity when they are unable to secure seats in courses that they would prefer to take or when course content has not updated to reflect relevant topics and skills. Other students benefit from stickiness, particularly those who persist in fields with declining enrollment. A logical extension of this research would link stickiness in higher education to students' labor market outcomes, from their initial entry to later stages in their careers. By tying the inelasticity in course supply to such students' outcomes, we can gauge if such stickiness 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 bears interesting insights for how individual fields evolve to meet changing needs.

Finally, empirical support for the"learning synergies" hypothesis underscores potential inequalities in opportunities across universities, particularly between selective and less selective institutions. While my study 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.

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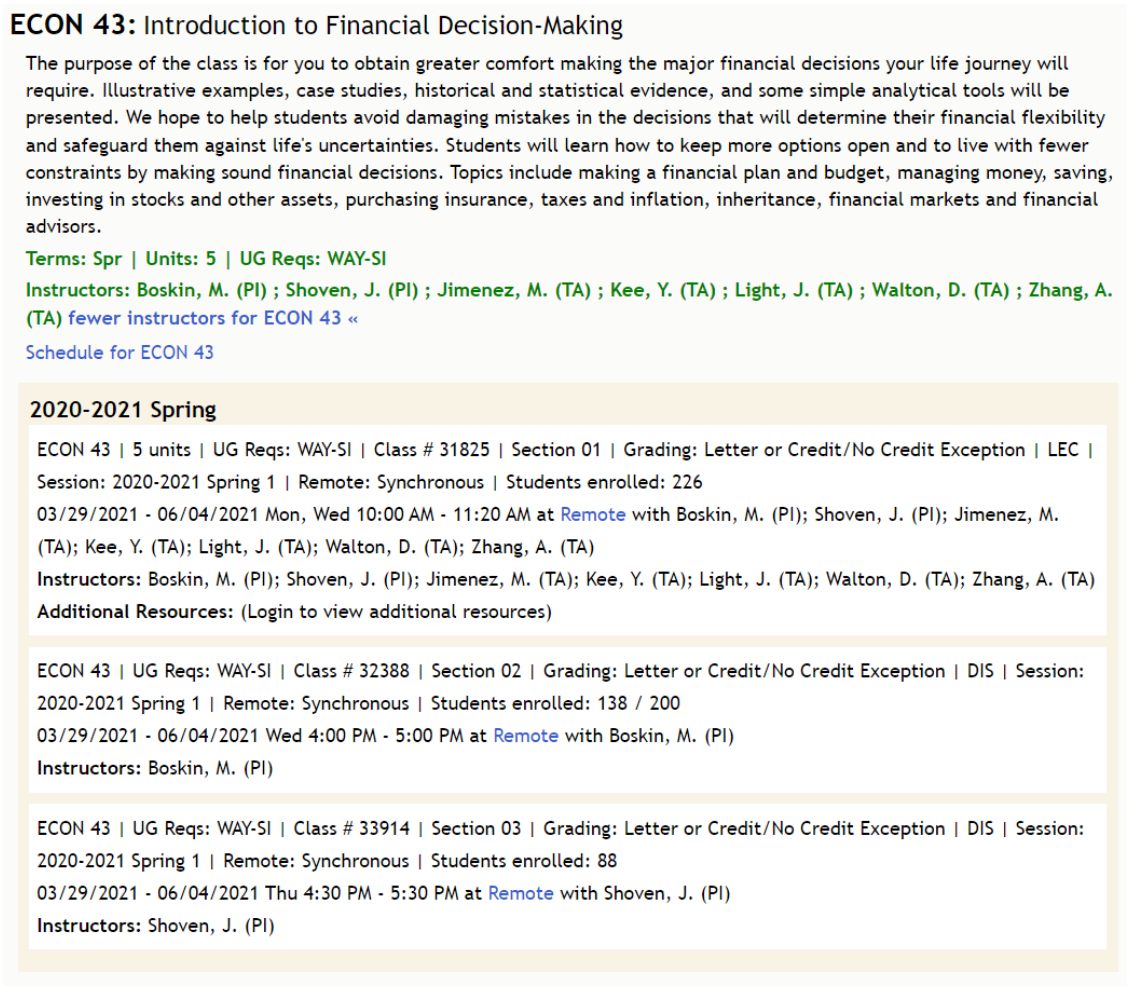
Figure 1. Sample entry in the course catalog dataset



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

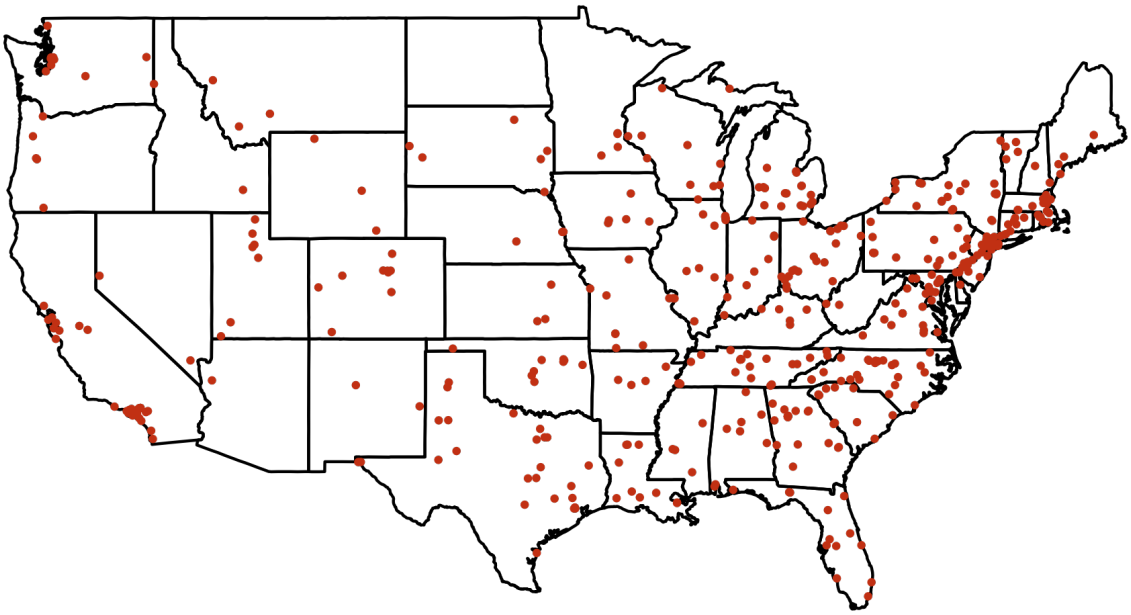


Table 1. Characteristics of course catalog sample

4 year institutions

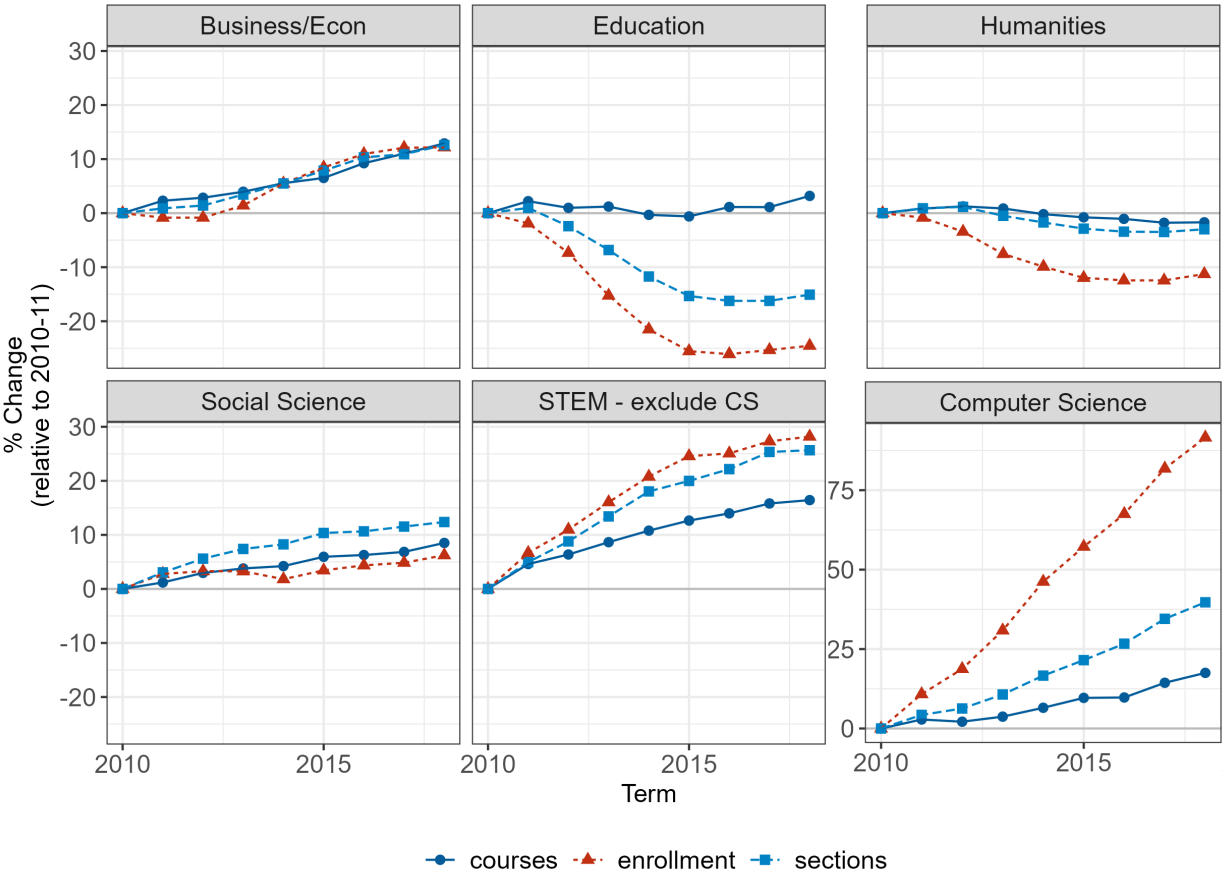
	Population		Catalog Sample		Enrollment Sample	
	mean	sd	mean	sd	mean	sd
Enrollment	19,200	20,303	17,736	11,875	17,383	10,405
Public share	72.54	44.63	81.67	38.69	82.66	37.86
Average tuition	16,779	15,370	16,721	15,647	16,668	15,456
Average price	16,797	8,458	17,202	7,818	17,622	7,508
Admit rate	71.88	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	2158.19	76,609	2717.28	78,509	3016.75
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		73.00		12.00	

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 'With Enrollment' sample includes those with course-level enrollment data.

Figure 3. Trends in course enrollment and supply: comparison to 2010-11 baseline



Notes: This figure plots the mean changes in course enrollment and supply relative to 2010-2011. Analysis covers institutions consistently 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 are plotted.

Table 2. Estimates of course supply elasticity

	# of Courses		# of Sections	
	OLS	IV	OLS	IV
	(1)	(2)	(3)	(4)
Course Enrollment	0.4526	0.2938	0.7091	0.6260
	(0.0219)	(0.0434)	(0.0169)	(0.0305)
Observations	3,540	3,540	3,540	3,540
R^2	0.50282	0.45943	0.77326	0.76569
F-stat First Stage		130.67		130.67
School fixed effects	✓	✓	✓	✓

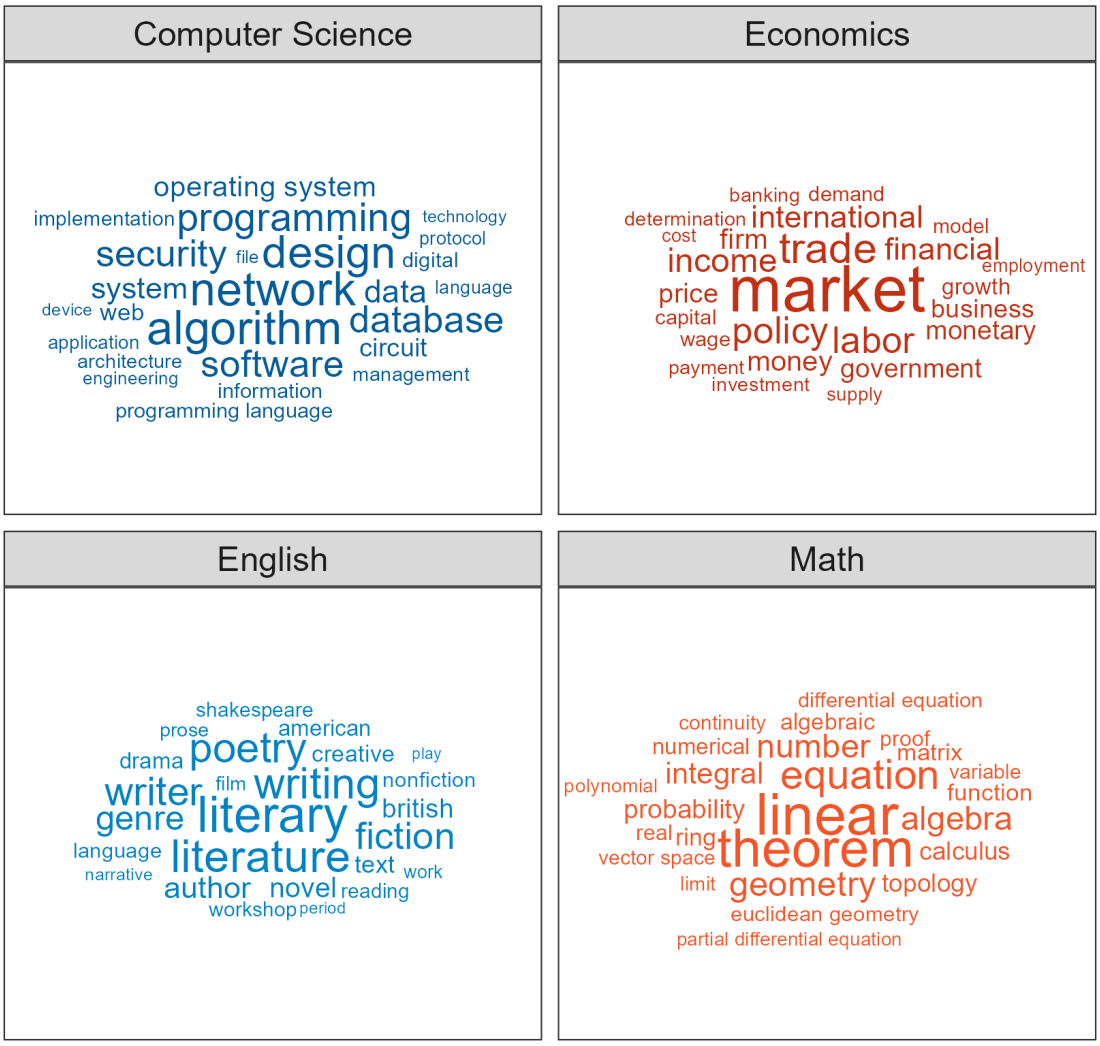
Notes: Observations are at the institution-by-field level. The analysis regresses change in upper-level course supply on change in enrollment, each represented as log differences. Supply and enrollment are credit-hour weighted. Each institution receives equal weight; within each institution, fields are 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

	# of Courses (1)	# of Sections (2)
% change enrollment - growing	0.5372	0.8325
	(0.0294)	(0.0392)
% change enrollment - shrinking	0.3562	0.5847
	(0.0347)	(0.0368)
Observations	3,540	3,540
R^2	0.30687	0.51427

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. Supply and enrollment are credit-hour weighted. Each institution receives equal weight; within each institution, fields are weighted by start-of-period enrollment. Standard errors are clustered at the institution level

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 older vs. newer courses (2022-23)

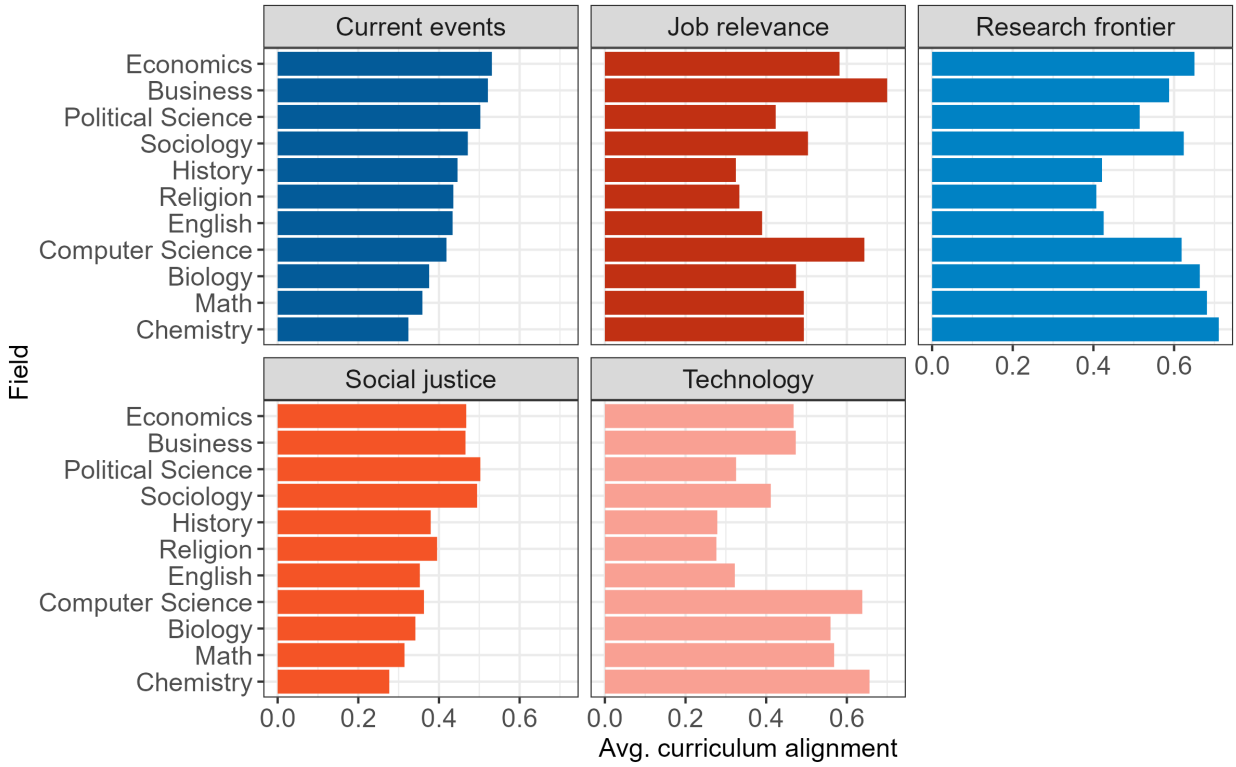
Notes: This figure contrasts the distinctive words of courses from 2013-14 to those of 2022-23. "Older courses" refer to those offered in 2013-14 but discontinued by 2022-23, while "newer courses" are those offered in 2022-23 but introduced after 2013-14. Descriptions are grouped by institution, field, and course age (older vs newer). 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	barack obama	0.85	0.00	0.29	0.71	0.01
	customer service	0.67	0.99	0.43	0.51	0.68
	research	0.41	0.70	0.83	0.60	0.33
	lgbtq	0.82	0.40	0.70	0.99	0.00
	invention	0.36	0.17	0.23	0.48	0.99
Pairs of similar words	king	0.32	0.03	0.02	0.09	0.01
	queen	0.59	0.05	0.01	0.06	0.01
	dog	0.66	0.08	0.09	0.13	0.19
	cat	0.55	0.14	0.13	0.07	0.24
	blackberry	0.86	0.68	0.00	0.40	0.53
	iphone	0.95	0.69	0.07	0.76	0.50
	global warming	0.94	0.07	0.90	0.38	0.71
	climate change	0.92	0.17	0.89	0.35	0.14

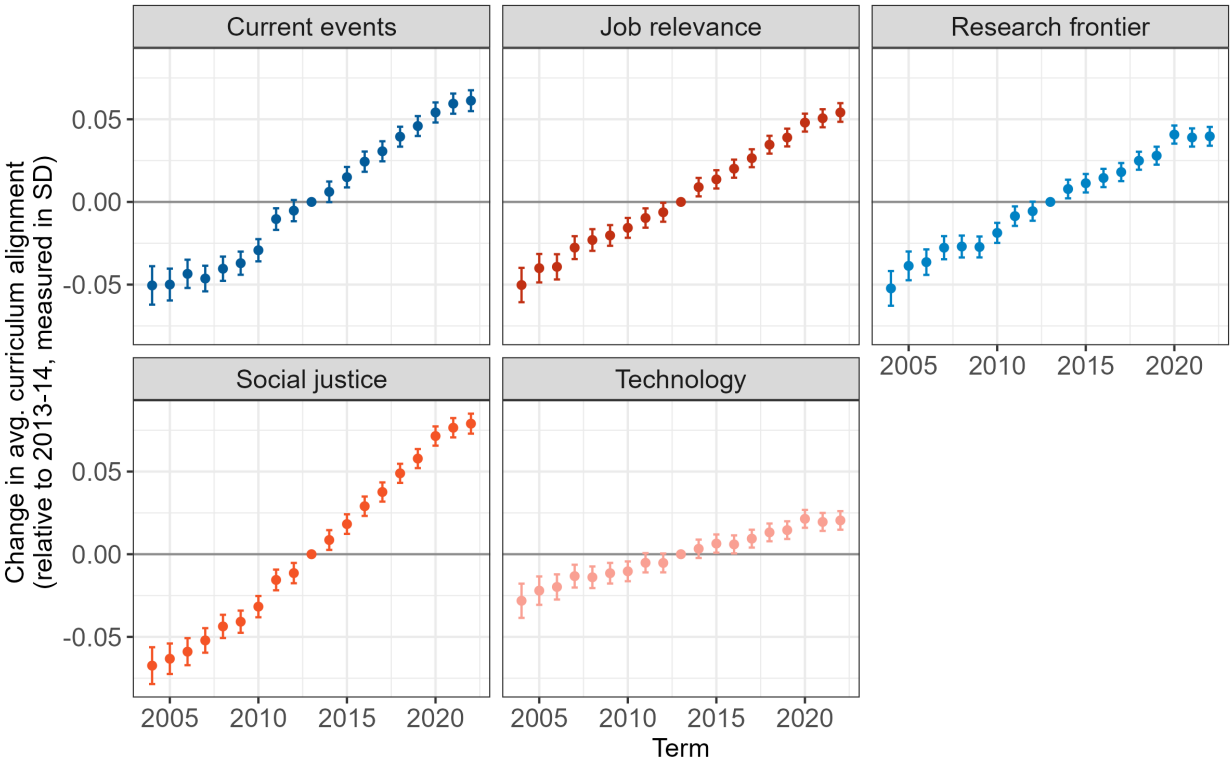
Notes: This table presents relevance weights of selected tokens. These weights measure a token's significance in a document related to a specific theme (e.g., a job description for job relevance) relative to its significance in a neutral text reference, such as the entirety of Wikipedia. Weights range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



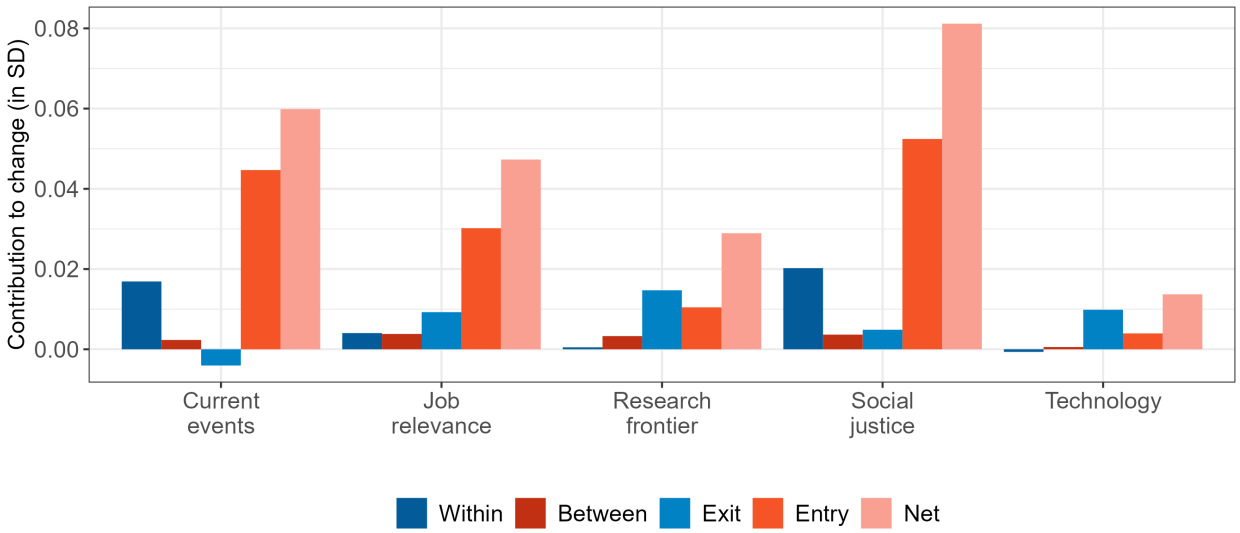
Notes: This figure displays the average curriculum alignment for selected fields. Each upper-level course from 2022-23 is scored for its curriculum alignment to each of the five themes. Within each theme, curriculum alignment scores are averaged within each field. Fields are sorted from highest to lowest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

Figure 7. Change in curriculum alignment: 2003-2022



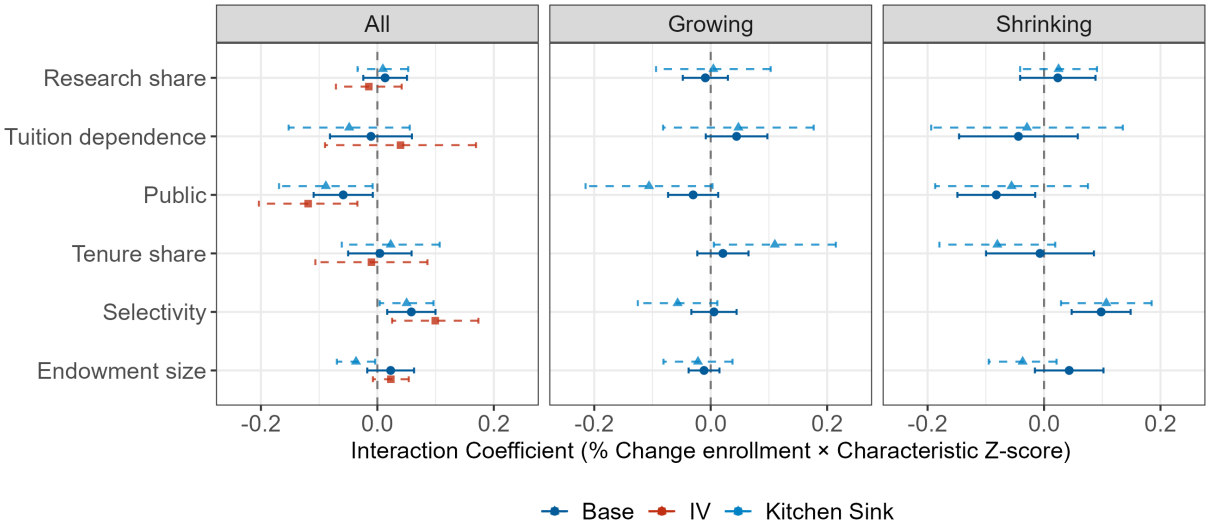
Notes: This figure plots the evolution of curriculum alignment scores for courses over two decades. Alignment estimates are estimated in separate course-level regressions of a course's curriculum alignment score for a given theme on a vector of year dummies, controlling for institution-by-field fixed 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



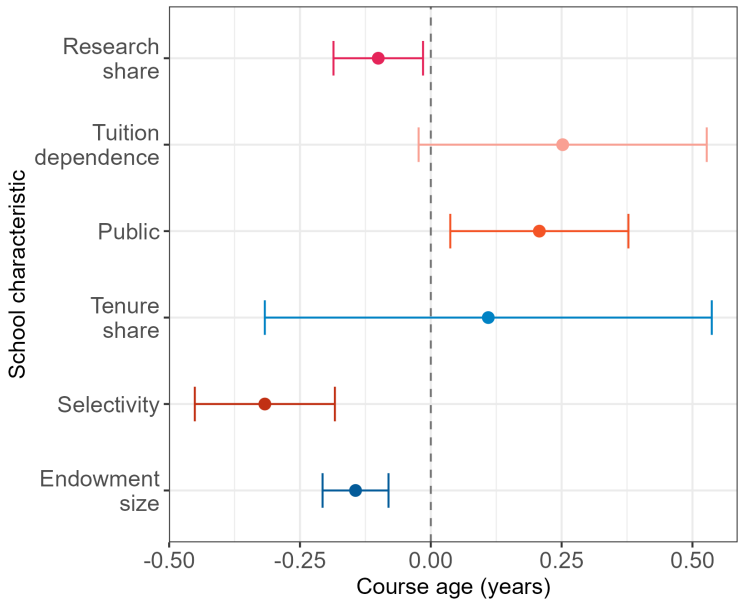
Notes: This figure decomposes down the shift in curriculum alignment between 2013-14 and 2022-23. Utilizing an approach based on Foster et al. (2001), the evolution in curriculum alignment at the institution-by-field level is decomposed into four components: updates within continuously-offered courses, 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



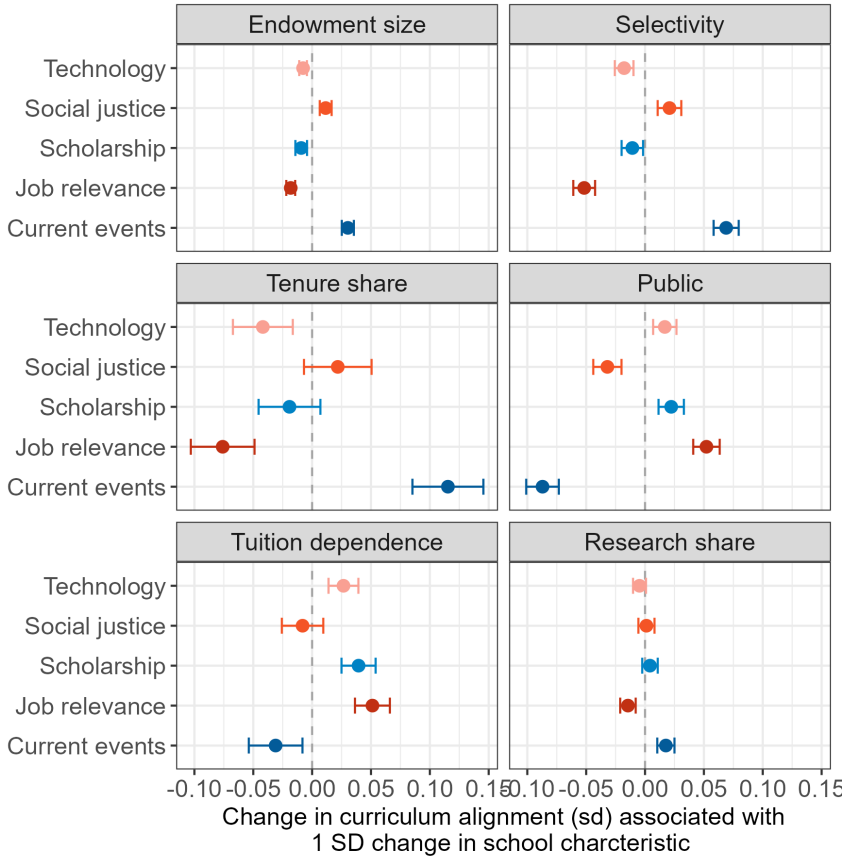
Notes: Using school data from IPEDS, this figure plots interaction term estimates of school characteristics with enrollment changes across three models: 'Base', 'Kitchen Sink', and 'IV'. The 'Base' specification estimates separate characteristic-changing enrollment interaction regressions for each characteristic. The 'Kitchen Sink' 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 field by Census division level.

Figure 10. Variation in average course age by school characteristics



Notes: Using school 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 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.[52]

[52]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.[53]

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.

[53] 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.[54]

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.[55]

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-6).

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

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

[55] 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 F.0.2 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:

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

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:

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

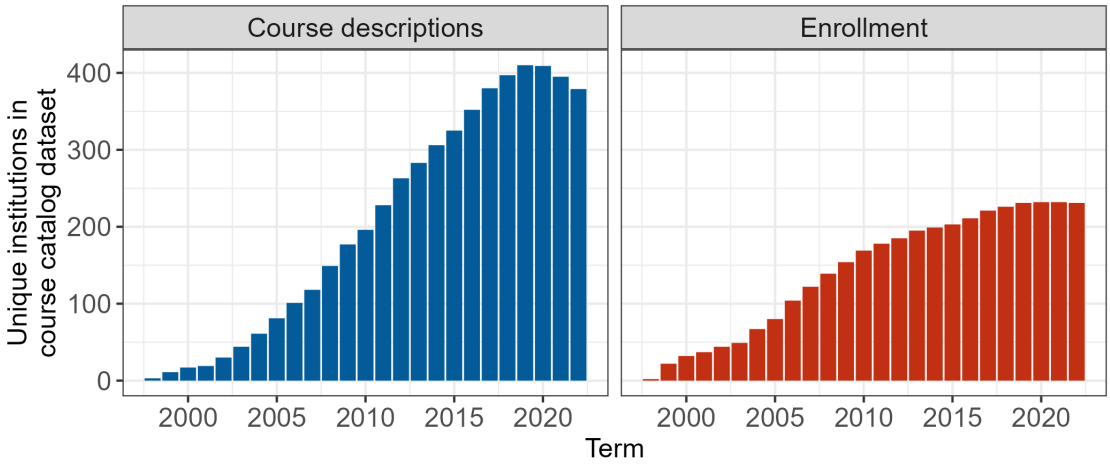
Where the coefficients θ^k represent the differential response of course supply to instrumented enrollment changes due to the specific university characteristic.

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).

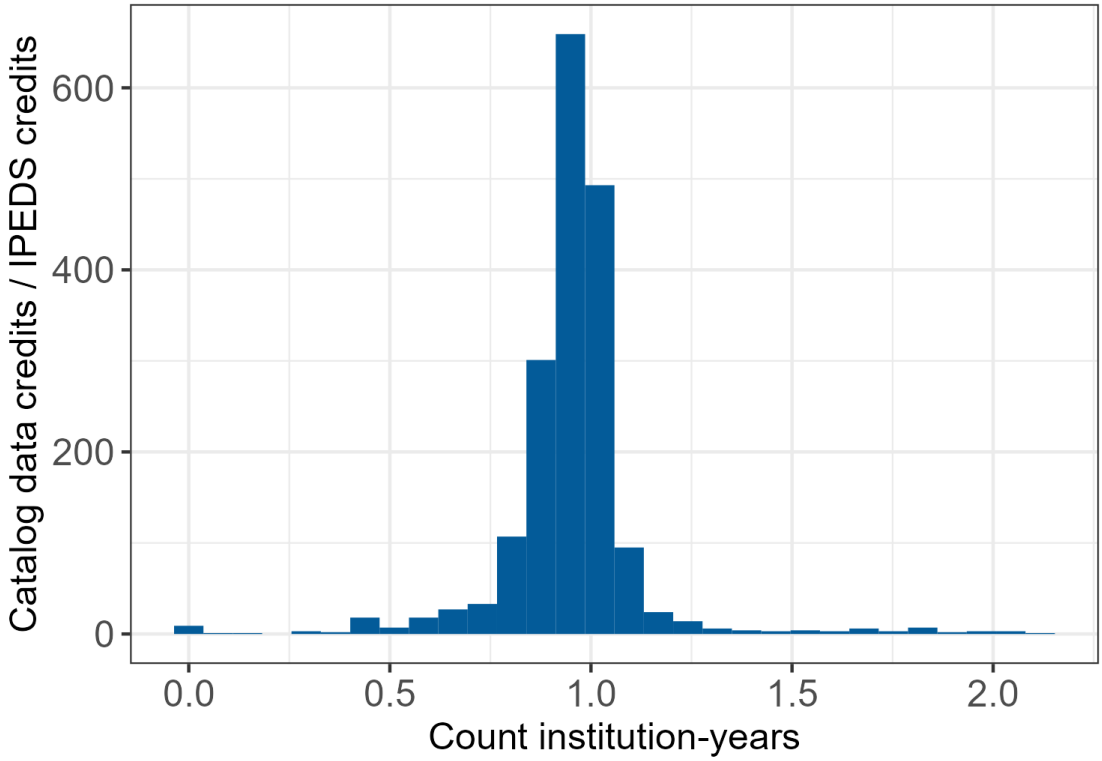
Data

Figure A-1. Annual coverage of course catalog data



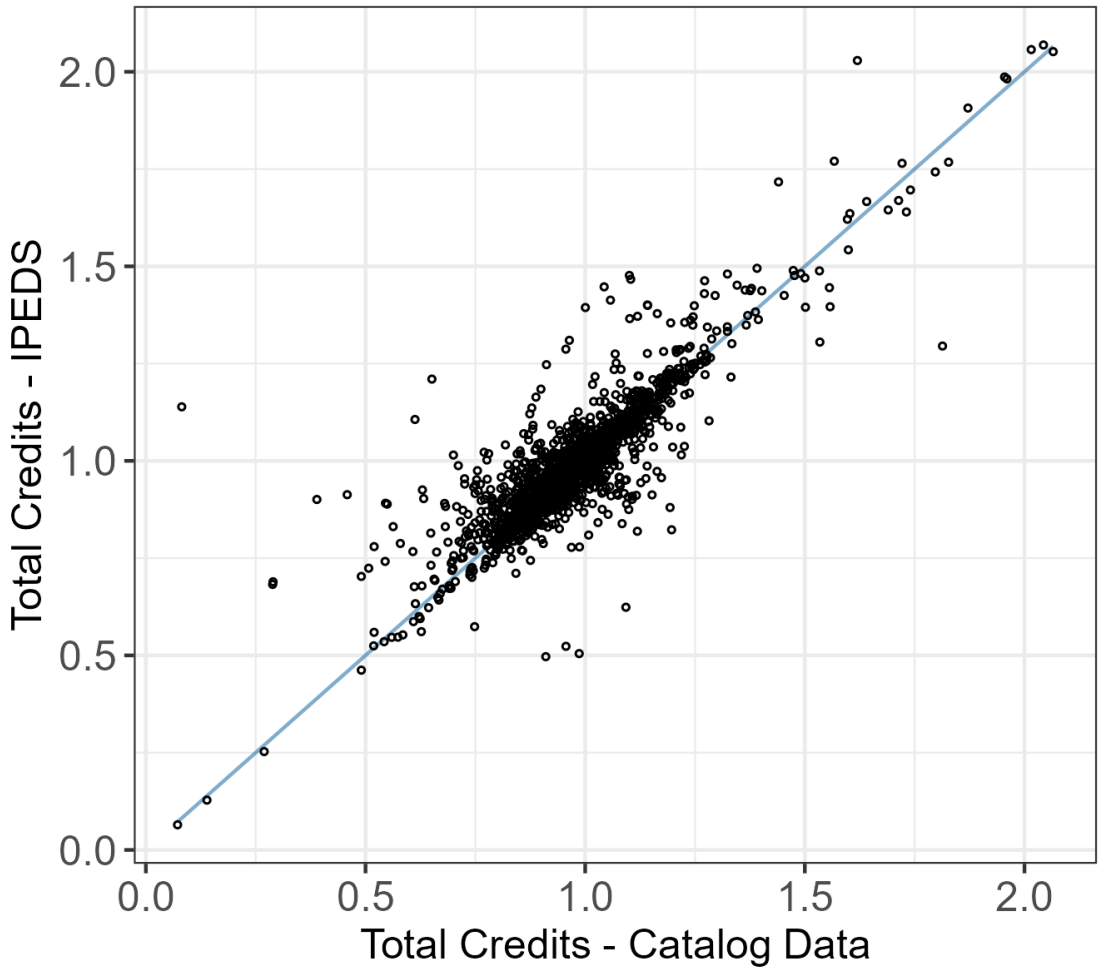
Notes: The figure counts the number of institutions in the course catalog dataset by year. The left panel counts the number of institutions with course description data; the right panel counts the number of institutions with enrollment data. For many institutions, the data record both enrollment and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

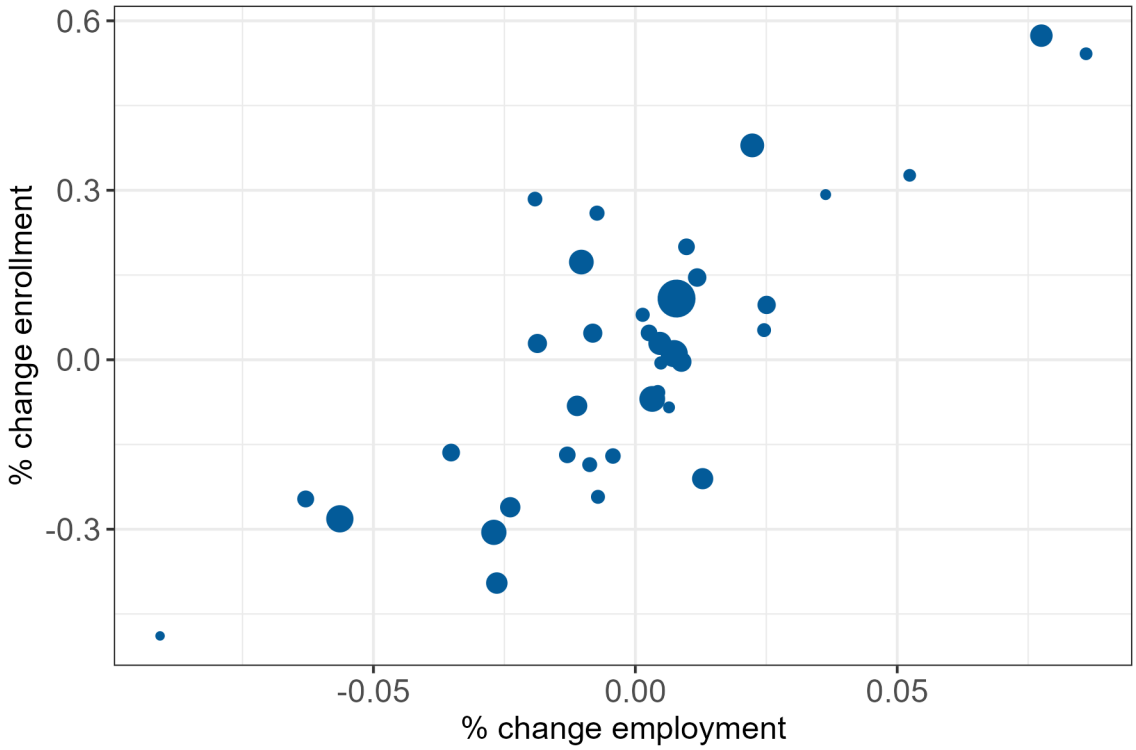


Table A-2. First-stage estimates

	All undergraduate (1)	Upper-level (2)	Completed degrees (IPEDS) (3)
Occupation growth	2.539***	4.611***	6.828***
	(0.3046)	(0.4033)	(0.6763)
Observations	3,825	3,540	3,135
R^2	0.38128	0.34688	0.26781
F-Stat	69.459	130.67	101.92
School fixed effects	✓	✓	✓

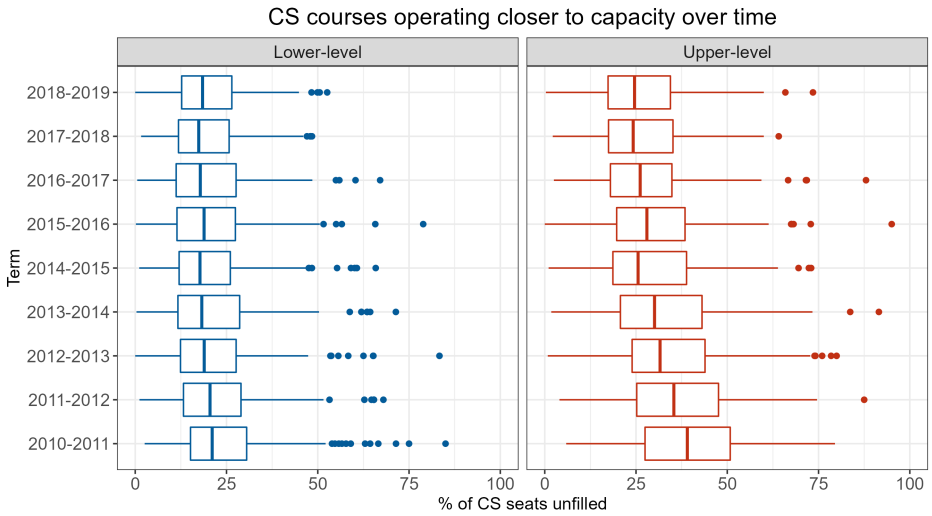
Notes: Observations are at the institution-by-field level. I regress the log change in enrollment on the shift-share instrument reflecting major-typical employment growth in the Census division where the institution is located. Columns 1-2 measure changing enrollment using the course catalog data; Column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

Table A-3. Reduced form

	# of Courses (1)	# of Sections (2)
shift_share_all	1.320	2.934
	(0.2006)	(0.3186)
Observations	3,540	3,540
R^2	0.16669	0.27230
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 subject level—the level of variation used for the instrument in the IV specification.

Figure A-5. 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. Estimates of course supply elasticity - all undergraduate courses

	# of Courses		# of Sections	
	OLS	IV	OLS	IV
	(1)	(2)	(3)	(4)
Course Enrollment	0.4246	0.3669	0.7657	0.5973
	(0.0209)	(0.0613)	(0.0142)	(0.0415)
Standard-Errors	School	Region x Field	School	Region x Field
Observations	3,825	3,825	3,825	3,825
R^2	0.39839	0.39400	0.78469	0.76197
School fixed effects	✓	✓	✓	✓

Notes: Observations are at the institution-by-field level. I regress the average annual change in the number of 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 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 subject level—the level of variation used for the instrument in the IV specification.

Table A-5. Asymmetry of course supply elasticity - all undergraduate courses

	# of Courses		# of Sections	
	OLS	IV	OLS	IV
	(1)	(2)	(3)	(4)
% change enrollment - growing	0.3980	0.2245	0.7121	0.3982
	(0.0342)	(0.1668)	(0.0273)	(0.1015)
% change enrollment - shrinking	0.4426	0.5596	0.8019	0.8669
	(0.0343)	(0.2695)	(0.0253)	(0.1401)
Observations	3,825	3,825	3,825	3,825
R^2	0.39873	0.38437	0.78553	0.76455
School fixed effects	✓	✓	✓	✓

Notes: Observations are at the institution-by-field level. I regress the average annual change in the number of courses on the average annual change in course enrollment. Separate regression terms for changing course enrollment are used to differentiate between increasing vs. decreasing enrollments. 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 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 institution level.

Table A-6. Elasticity regression with shorter duration - upper level courses only

	2010-2014 (1)	2014-2018 (2)	2018-2022 (3)	2010-2022 (4)
% change enrollment	0.3552	0.4344	0.3878	0.3921
	(0.0177)	(0.0214)	(0.0212)	(0.0131)
Observations	3,672	4,517	4,635	12,824
R^2	0.30372	0.34638	0.34967	0.34012
School-Year Range fixed effects	✓	✓	✓	✓

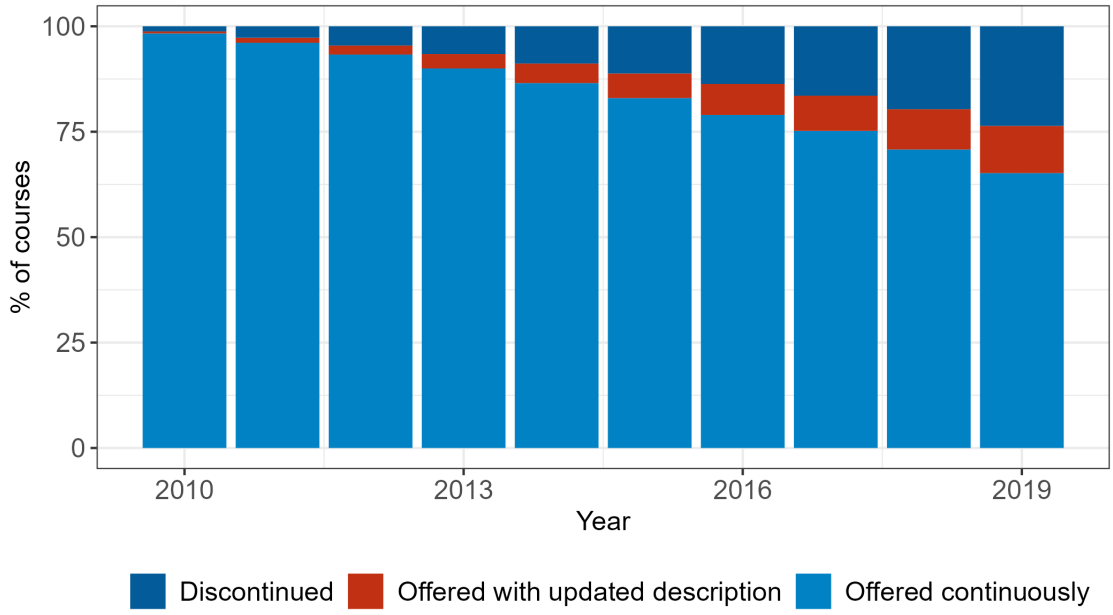
Notes: Observations are at the institution-by-field level. I regress the average annual change in the number of upper-level courses on the average annual change in course enrollment. The "number of courses" quantifies distinct courses taught in a year (e.g., Econ 101 and Econ 102 are separate courses). 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-7. Elasticity regression with shorter duration - all undergrad courses

	2010-2014 (1)	2014-2018 (2)	2018-2022 (3)	2010-2022 (4)
% change enrollment	0.3615	0.4013	0.4146	0.3934
	(0.0235)	(0.0187)	(0.0294)	(0.0170)
Observations	4,105	4,988	5,186	14,279
R^2	0.27713	0.25620	0.31679	0.29421
School-Year Range fixed effects	✓	✓	✓	✓

Notes: Observations are at the institution-by-field level. I regress the average annual change in the number of 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.

Figure A-6. 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.

Course	Type	High/Low	Description	Score
PHIL 102	BGT	Low	Major figures in early modern philosophy in epistemology, metaphysics, and philosophy of mind. Writings by Descartes, Leibniz, Hume, and Kant.	0.114
MS&E 175	BGT	High	Problem solving in organizations; creativity and innovation skills; thinking tools; creative organizations, teams, individuals, and communities. Limited enrollment.	0.867
SPECLANG 218B	ACA	Low	Grammatical structures, vocabulary, and sentence patterns through speaking, reading, writing, and listening. Urdu culture.	0.055
POLISCI 244U	ACA	High	The implications of social norms, preferences and beliefs for political and economic behavior and societal outcomes.	0.882
MATH 145	NYT	Low	An introduction to the methods and concepts of algebraic geometry. The point of view and content will vary over time, but include: affine varieties, Hilbert basis theorem and Nullstellensatz, projective varieties, algebraic curves. Required: 120. Strongly recommended: additional mathematical maturity via further basic background with fields, point-set topology, or manifolds.	0.2
POLSCI 420A	NYT	High	Theories of American politics, focusing on Congress, the presidency, the bureaucracy, and the courts.	0.696
AMSTUD 16N	PAT	Low	This course examines the January 6 storming of the US Capitol as a way to study and understanding religion and politics in contemporary America.	0.081
RAD 235	PAT	High	The focus of this course is on advanced ultrasound imaging techniques for medical imaging applications. Topics include beamforming, adaptive beamforming, Fourier beamforming, synthetic aperture techniques, speckle, speckle reduction, k-space, harmonic imaging, coherence imaging, phase aberration, radiation force imaging, elastography, quantitative ultrasound, Doppler and flow imaging, ultrasounds modeling and advanced ultrasound theory.	0.857

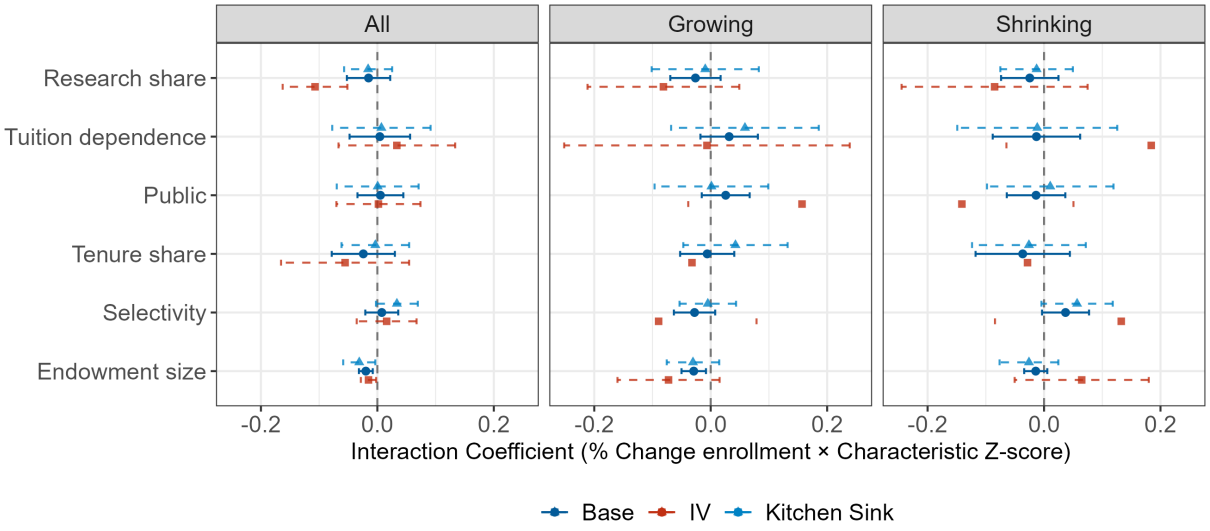
Source: Stanford University.

Table A-8. Correlation of school characteristics

char1	Selectivity	Endowment size	Tenure share	Public	Tuition dependence	Research sha
Selectivity	1.0	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

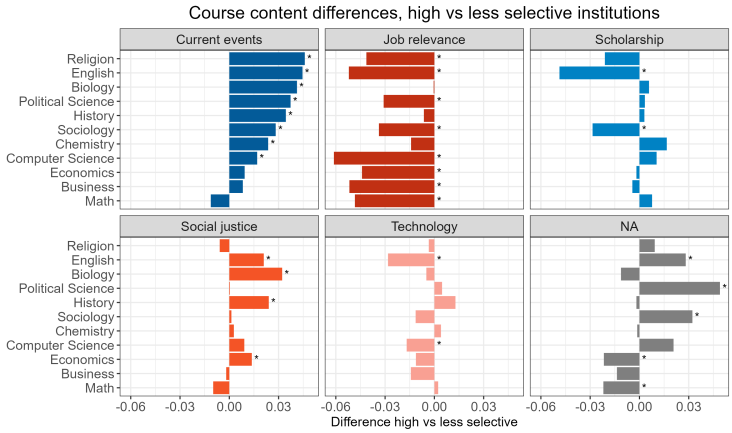
Notes: School characteristics from IPEDS, each normalized by the national distribution for degree-granting Title IV-elig non-profit institutions.

Figure A-7. Heterogeneity in extensive course section supply responsiveness



Notes: School characteristics from IPEDS, each normalized by the national distribution for degree-granting Title IV-eligible non-profit institutions. The "Base" points plot the point estimate on the interaction term of changing enrollment and the institution characteristic, estimated in separate regressions for each characteristic. The "Kitchen Sink" points plot point estimates from a single regression that contains changing enrollment-characteristic interaction terms for each characteristic. The "IV" points plot pint estimates from the changing enrollment-characteristic interaction terms estimated in separate IV regressions. Standard errors for the "Base" and "Kitchen Sink" models are clustered at the institution level; standard errors for the "IV" models are clustered at the field-by-Census region level. The "All" panel estimates a linear model of changing course supply on changing enrollment; the "Growing" and "Shrinking" panels plot estimates from a model that allows course supply to respond asymmetrically when enrollment is growing vs shrinking.

Figure A-8. Differences in curriculum alignment for highly selective vs less selective institutions



Notes: The figure splits institutions in my sample into highly selective (those with admit rates at or above the 90th percentile) and relatively less selective. The figure plots the difference in curriculum alignment scores for the average class at for each field between courses offered at highly selective vs less selective institutions. A * indicates that the difference is statistically significant at the 95% level.

Table A-9. Schools with the highest and lowest curriculum alignment scores

Theme	Rank	Highst	Lowest
	1	Middlebury College	Grambling State University
	1	Middlebury College	Texas Southern University
	2	Stanford University	Texas Southern University
	2	Stanford University	Grambling State University
	3	Princeton University	Chicago State University
	3	Princeton University	Chicago State University
Current events	1	Wesleyan University	Vincennes University
	2	Stanford University	East Carolina University
	3	Princeton University	Texas Southern University
Job relevance	1	Winthrop University	Middlebury College
	2	Vincennes University	Princeton University
	3	Fort Valley State University	Vassar College
Research frontier	1	Kettering University	Baylor University
	2	Fort Valley State University	University of Idaho
	3	University of California-Merced	Vassar College
Social justice	1	Stanford University	Auburn University Main Campus
	2	Northeastern University	Youngstown State University
	3	Fort Valley State University	East Carolina University
Technology	1	Fort Valley State University	Bucknell University
	2	University of the District of Columbia	Florida Atlantic University
	3	Kettering University	Vassar College

Notes: For each theme and each institution, I calculate the average curriculum alignment score for courses offered in 2022-23 controlling for field of study. The table lists the three institutions with top and bottom average curriculum alignment scores