The Education-Innovation Gap*

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Abstract

This paper documents differences across higher education courses in the coverage of frontier knowledge. Applying natural language processing (NLP) techniques to the text of 1.7M syllabi and 20M academic articles, we construct the "education-innovation gap," a syllabus's relative proximity to old and new knowledge. We show that courses differ greatly in the extent to which they cover frontier knowledge. Instructors play a big role in shaping course content; instructors who are active researchers teach more frontier knowledge. More selective and better funded schools, and those enrolling socio-economically advantaged students, teach more frontier knowledge. Students from these schools are more likely to complete a doctoral degree, produce more patents, and earn more after graduation.

JEL Classification: I23, I24, I26, J24, O33

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1 Introduction

The dissemination of up-to-date knowledge is key for innovation and economic growth (Jones, 2005; Goldin and Katz, 2010; Jones, 2009). Higher education (HE) plays a central role in this process. Through the teaching of their curricula, HE programs facilitate human capital accumulation and nurture future innovators (Biasi, Deming, and Moser, 2020). These programs might differ, however, in their ability to equip students with up-to-date knowledge.[1] These differences can have important implications for labor market outcomes, education choices, and technological progress. Yet, they have so far remained unexplored; very little is known on how the content of HE varies across and within schools, how it is shaped, and how it relates to students' outcomes.

This paper brings together new data and a novel methodology to measure the extent to which HE courses cover frontier, i.e., recently produced, knowledge. Applying natural language processing (NLP) techniques to textual information contained in course syllabi (the content of HE courses) and academic publications (the frontier of knowledge), we build a novel metric: the education-innovation gap, designed to capture the distance between education content and the knowledge frontier. Specifically, we define the gap as the ratio of the similarity between a course's content and knowledge from older vintages (covered by articles published decades ago) and the similarity between the course's content and new, frontier knowledge (covered by the most recent articles). For example, a Computer Science course that teaches *Visual Basic* (a relatively obsolete programming language) in 2020 would have a larger gap than a course that teaches *Julia* (a more recent programming language), because *Visual Basic* is mostly covered by old articles and *Julia* is mostly covered by recent articles.[2]

Using the education-innovation gap, we study the content of HE courses and discover four findings. First, HE courses differ greatly in their coverage of frontier knowledge, even conditioning on discipline and course level. Second, instructors play a big role in shaping the content of their courses, and research-active instructors teach more frontier knowledge, suggesting complementarities between teaching and research activities. Third, more selective and better funded institutions offer courses with lower gaps. These schools also enroll fewer disadvantaged students (Chetty

[1] Differences in HE programs attended have been associated with differences in earnings (Hoxby, 2020; Mountjoy and Hickman, 2020) and rates of invention (Bell et al., 2019).

[2] First released in 1991, *Visual Basic* is still supported by Microsoft in recent software frameworks, but it was discontinued in 2020 (https://visualstudiomagazine.com/articles/2020/03/12/vb-in-net-5.aspx, retrieved 9/30/2020). *Julia* is a general-purpose language initially developed in 2009. Constantly updated, it is among the best for numerical analyses and computational science and is used at over 1,500 universities (https://juliacomputing.com/blog/2021/08/newsletter-august/, retrieved 9/30/2021).

et al., 2020), which implies that access to frontier knowledge is highly unequal. Lastly, the dissemination of frontier knowledge through HE courses is strongly and positively related to students' labor market outcomes and their ability to innovate in the future.

Our empirical analysis uses a novel source of information: the text of a sample of 1.7 million college and university syllabi, including about 540,000 courses taught at 800 four-year US institutions between 1998 and 2018. This sample represents about 5% of all courses taught in this time window, and it covers nearly all fields. While the sample over-represents courses from very selective schools, it is representative of the population in terms of fields, course levels (basic, advanced undergraduate, and graduate), and a broad set of school characteristics.

To construct the education-innovation gap, we start by calculating measures of textual similarity between each syllabus and the title, abstract, and keywords of over 20 million academic articles published in top academic journals since the journals' creation.[3] Calculating pair-wise textual similarities involves three steps. First, we represent each document (a syllabus or an article) as a term frequency vector, projecting the text of the document on a comprehensive list of terms that refer to knowledge items. Each vector element is the frequency of a given term in the document, divided by the length of the document. Second, we use the "term-frequency-backward-inverse-document-frequency" (*TFBIDF*) approach (Kelly et al., 2021) to increase the importance of terms that are more informative of a document's content. This approach gives higher weights to more informative terms and de-emphasizes terms more commonly used across all documents at a certain point in time. Third, we use these reweighted term frequency vectors to compute the cosine similarity between each syllabus and each article.

Armed with these cosine similarities, we construct the education-innovation gap of a given syllabus as the *ratio* of its average similarities with (a) older knowledge vintages, i.e., all articles published 13-15 years prior to the syllabus's date and (b) frontier knowledge, i.e., all articles published 1-3 years prior.[4] Naturally, the gap is higher for syllabi that cover more knowledge that is older (rather than newer). By virtue of being constructed as a ratio of similarities, the gap is not affected by idiosyncratic attributes of a syllabus (such as length, structure, or writing style), which could introduce noise in cosine similarities as measures of content but would cancel out in a ratio measure.

The goal of our measure is to capture a syllabus's "true" knowledge content, and implementing

[3]Previous works have used academic publications to capture the research frontier (for example, see Angrist et al., 2017, for economics research).

[4]Our estimates are robust to small variations in the timing definition of old and new knowledge vintages.

the *TFBIDF*-adjustment helps us ensure that this is the case. First, this adjustment implies that the gap does not penalize syllabi for covering "classic" or "fundamental" knowledge. Although they belong to older knowledge vintages, terms related to classic topics are still widely taught. Therefore, they appear across many documents and receive a low weight. Similarly, the *TFBIDF*-adjustment minimizes the impact of academic "buzzwords," which are also widely used and receive a low weight. To demonstrate empirically that our measure captures "real" knowledge content, we show that the education-innovation gap for courses in STEM fields is very similar when we use patents (instead of academic publications) to capture the knowledge frontier.

A few empirical regularities confirm the ability of our measure to capture the distance between course content and the knowledge frontier. First, the gap is lower for syllabi that reference more recent articles and books in their lists of recommended readings. Second, the gap varies reasonably across course levels: It is the largest for basic undergraduate courses (taught in the first two years of a bachelor's degree and more likely to cover the fundamentals of a discipline) and smallest for graduate-level courses (master's and PhD). Third, using a simulation exercise, we show that gradually replacing "older" knowledge in a syllabus with "newer" knowledge (i.e., words most frequently appearing in old and new articles, respectively) progressively reduces the gap.

We begin our analysis by documenting significant differences in the gap across syllabi. To move a syllabus from the 25th to the 75th percentile of the gap distribution, approximately half of its content would have to be replaced with newer knowledge. A small share of this variation can be attributed to differences across fields and course levels. To account for these differences, the rest of our analysis compares syllabi within each field, course level, and year. Most of the observed variation in the education-innovation gap (about a quarter) occurs within schools, across courses taught by different instructors. The impact of instructors can also be seen from the fact that the gap of the typical course remains stable over time, but it declines significantly when the instructor of a course changes.

Most higher education instructors split their time and effort between teaching and research, reflecting the dual mission of universities to produce and disseminate knowledge. As time is scarce, these tasks are often seen as competing (Hattie and Marsh, 1996; Courant and Turner, 2020). The nature of higher education, though, could also create complementarities between the two (Becker and Kennedy, 2005; Arnold, 2008). Our findings support the latter hypothesis. The education-innovation gap is significantly lower for courses taught by instructors who are more active in producing research (i.e., they publish more, are cited more, and receive more grants). The gap is in-

stead higher for non-ladder faculty who specialize in teaching. The gap is also lower when the instructor's own research is closer to the topics of the course. These findings highlight that a proper deployment of faculty across courses can bring the content of education closer to the knowledge frontier. They also suggest that investments in faculty research (both public, in the form of government grants, and made by each institution) can generate additional returns in the form of more updated instruction.

Next, we explore differences in the gap across schools. Although explaining a small fraction of the total variance, these differences are useful for understanding how the content of higher education is shaped and how the access to frontier knowledge varies across students from different socioeconomic backgrounds. The gap is smaller in schools with a stronger focus on research (ranked as R1 in the Carnegie classification) and with more resources (higher endowment and spending on instruction and research). The gap is also smaller in more selective schools (for example the "Ivy-Plus," including the eight Ivy League colleges plus Stanford, MIT, Duke, and the University of Chicago) compared to non-selective schools. The magnitude of this difference is such that, in order to make the average syllabus in a non-selective school comparable to the average syllabus in an Ivy-Plus school, 8 percent of its content would have to be replaced with newer knowledge.

Importantly, differences across schools translate into disparities in access to up-to-date knowledge across students with different backgrounds. Since wealthier and more selective schools enroll more socio-economically advantaged students (Chetty et al., 2020), the education-innovation gap is significantly higher in schools enrolling students with lower median parental income and those with a higher share of Black or Hispanic students.

In principle, part of these differences could be due to a "vertical differentiation" of educational content across schools. If students with greater ability enroll in more selective or better funded schools and are more capable of absorbing up-to-date content, cross-school differences in the gap might simply reflect schools' efforts to provide students with better tailored educational content. We do not find evidence supporting this hypothesis: The negative correlation between the gap and parental income remains when we control for student ability by using the SAT and ACT scores of admitted students.

Our results so far unveil differences in the coverage of frontier knowledge across HE courses. Do these differences matter for the production of innovation and for students' outcomes? To answer this question, the ideal experiment would randomly allocate students to courses with different gaps and measure differences in outcomes. In the absence of this random variation, we settle on the

more modest goal of characterizing the empirical relationship between the education-innovation gap and students' graduation rates, incomes, and measures of innovation, measured at the school level. In an attempt to account for students' selection into each school and other determinants of student outcomes related to instruction, we control for a large set of school observables such as institutional characteristics, expenditures, instructional characteristics, enrollment by demographic groups and major, selectivity, and parental background. We find that students in schools that offer courses with a lower gap are more likely to complete a doctoral degree, produce more patents, and earn more after graduation. They are also more likely to graduate from college; a possible explanation is that taking more up-to-date courses makes students more motivated and thus more likely to complete their education program. Although our approach is silent on what the "optimal" education-innovation gap for a certain type of school or students should be, these correlations suggest that, on average, exposure to frontier knowledge are associated with better student outcomes.

The education-innovation gap measures the academic content of each course. The richness of the information included in the syllabi allows us to go beyond academic content and explore the skills students develop in each course. Recent works have highlighted the increasing importance of soft skills—non-cognitive attributes that shape the way people interact with others—for students' success (Deming, 2017; Deming and Kahn, 2018). We measure the "soft-skills intensity" of each course as the extent to which evaluations are based on activities such as group projects, presentations, and surveys, which train soft skills. We find that courses with a lower education-innovation gap also tend to have a higher soft-skills intensity. More selective schools, those with more resources, and those serving more socio-economically advantaged students teach more soft-skills intensive courses. Within schools, research-active instructors are most likely to teach soft-skills intensive courses. Lastly, soft-skills intensity is strongly positively associated with student outcomes.

In the final part of the paper, we probe the robustness of our results to the use of alternative measures of frontier knowledge coverage. We consider three of them: the share of all "new" knowledge contained in a syllabus, designed not to penalize a syllabus that contains old and new knowledge compared with one that only contains new knowledge; a measure of "tail" knowledge, aimed at capturing the presence of the most recent content; and the education-innovation gap obtained using patent filings as a measure of frontier knowledge. All these alternative measures are strongly correlated with the education-innovation gap, and our main results are qualitatively unchanged when we use them in lieu of the gap.

The main contribution of our paper is to document differences in the coverage of frontier knowl-

edge across HE programs, a new and important dimension of heterogeneity. Analyzing the education-innovation gap, we shed new light on some of the most central questions related to innovation and higher education.

Several studies have characterized heterogeneity in the production of human capital, focusing on differences in the returns to educational attainment (Hanushek and Woessmann, 2012), majors (Altonji et al., 2012; Deming and Noray, 2020), college selectivity (Hoxby, 1998; Dale and Krueger, 2014), and the skill content of college majors (Hemelt et al., 2021; Li et al., 2021). Here, we take a novel approach: We directly examine curricula and educational content, among the most central components of higher education. With this approach, we document significant differences in the knowledge covered by each course, which could have important implications for students.

Our study is also related to the literature on education and the production of frontier knowledge and innovation. Earlier works (Nelson and Phelps, 1966; Benhabib and Spiegel, 2005) and more recent ones (Akcigit et al., 2020; Bloom et al., 2021) have highlighted an important role for human capital and education—and education programs in particular—for the diffusion of ideas and technological advancements. Other studies have emphasized the importance of specific fields, such as STEM (Baumol, 2005; Toivanen and Väänänen, 2016; Bianchi and Giorcelli, 2019).[5] Our findings highlight differences in the ability of HE programs to equip students with the knowledge necessary to innovate, which originate from heterogeneous course content. Importantly, these differences confirm a "lack of democratization" in access to valuable knowledge. US inventors have been shown to come from a small set of schools, enrolling very few low-income students (Bell et al., 2019). We find that these schools provide the most up-to-date educational content, which in turn suggests that access to frontier knowledge is highly unequal.

Lastly, we provide direct evidence on the importance of instructors in shaping the content of higher education. While some studies have found important effects on student outcomes (Hoffman and Oreopoulos, 2009; Carrell and West, 2010; Braga et al., 2016; Feld et al., 2020), much less is known on why and how instructors impact students (De Vlieger et al., 2020). We study instructors' contributions to the production of educational content and carefully characterize differences across instructor types. Crucially, our findings highlight complementarities between teaching and research activities.

[5]The literature on the effects of education on innovation encompasses studies of the effects of the land grant college system (Kantor and Whalley, 2019; Andrews, 2017) and, more generally, of the establishment of research universities (Valero and Van Reenen, 2019) on patenting and economic activity. Educational institutions also play a crucial role in fostering entrepreneurship (Tartari and Stern, 2021).

2 Data

Our empirical analysis combines data from multiple sources. These include the text of course syllabi; the abstract of academic publications; job titles, publications, and grants of each instructor; characteristics of US higher education institutions; and labor market outcomes and innovation activities of the students at these institutions. More detail on the construction of our final data set can be found in Appendix B.

2.1 College and University Course Syllabi

We obtained the raw text of a large sample of college and university syllabi from Open Syllabus (OSP), a non-profit organization that collects these data by crawling publicly accessible university and faculty websites to support educational research and its applications. The initial sample contains more than seven million English-language syllabi of courses taught in over 80 countries between 1990 and 2018.

Most syllabi share a standard structure. The standard syllabus begins with basic details of the course (such as title, code, and the name of the instructor). It proceeds with a short description of its content, followed by a more detailed list of topics and required or recommended readings for each class session. Most syllabi contain information on evaluation criteria, such as assignments and exams; some also include general policies regarding grading, absences, lateness, and misconduct. Following this general structure, we parse each syllabus and extract four sets of information, which we describe in detail below: (i) basic course details, (ii) the course's content, (iii) the list of required and recommended readings, and (iv) a description of evaluation methods.[6]

Basic course details These include the name of the institution, the title and code of the course, the name of the instructor, the quarter or semester, and the academic year in which the course is taught. Course titles and codes allow us to classify each syllabus into one of three course levels: basic undergraduate, advanced undergraduate, or graduate. OSP assigns each syllabus to one of 69 detailed fields. We use this classification throughout the paper. For some tests, we further aggregate fields into four macro-fields: STEM, Humanities, Social Sciences, and Business.[7]

[6] Angrist and Pischke (2017) use hand-coded syllabi of undergraduate econometrics classes from 38 universities to study the evolution of econometrics education, leveraging the usefulness of syllabi as a data source for educational content.

[7] The field taxonomy used by OSP draws extensively from the 2010 Classification of Instructional Programs of the Integrated Postsecondary Education Data System, available at https://nces.ed.gov/ipeds/cipcode/default.aspx?y=55. Appendix Table BV lists all 69 fields and shows the correspondence between fields and macro-fields.

Course content We identify the portion of a syllabus that contains a description of the course's content by searching for section titles such as "Summary," "Description," and "Content."[8] Typically, this portion describes the basic structure of the course, the key concepts that are covered, and (in most cases) a timeline of the content and the materials for each lecture.

Reference list We compile a list of bibliographic information for the required and recommended readings of each course by combining the list provided to us by OSP with all other in-text citations that we could find, such as "Biasi and Ma (2022)." We are able to compile a list of references for 71 percent of all syllabi. We then collect bibliographic information on each reference from Elsevier's SCOPUS database (described in more detail in Section 2.2); this includes title, abstract, journal, keywords (where available), and textbook edition (for textbooks).

Methods of evaluation To gather information on the methods used to evaluate students and the set of skills trained in the course, we use information on exams and other assignments. We identify and extract the relevant portion of the syllabus by searching for sections titled "Exam," "Assignment," "Homework," "Evaluation," and "Group." Using the text of these sections, we distinguish between hard skills (assessed through exams, homework, assignments, and problem sets) and soft skills (assessed through presentations, group projects, and teamwork). We were able to identify this information for 99.9 percent of all syllabi.

Sample restrictions and description To maximize consistency over time, we focus our attention on syllabi taught between 1998 and 2018 in four-year US institutions with at least 100 syllabi in our sample. We remove universities which exclusively or primarily focus on online instruction. We also exclude 35,917 syllabi (1.9 percent) with fewer than 20 words or more than 10,000 words (the top and bottom 1 percent of the length distribution).

Our final sample, described in panel (a) of Table 1, contains about 1.7 million syllabi of 542,251 courses at 767 institutions. Thirty-three percent of all syllabi cover STEM courses, ten percent cover Business, 30 percent cover Humanities, and 24 percent cover Social Science. Basic courses represent 39 percent of all syllabi, and graduate courses represent 33 percent. A syllabus contains an average of 2,226 words in total, with a median of 1,778. Our textual analysis focuses on "knowledge" words, i.e., words that belong to a dictionary, a list of words compiled to capture a document's academic content (defined in greater detail in Section 3). The average syllabus contains 420 unique knowledge words, with a median of 327.

[8] The full list of section titles used to identify each section is shown in Appendix Table BIV.

Table 1: Summary Statistics: Syllabi, Instructors, and Schools

Panel (a): Syllabi Characteristics

	count	mean	std	25%	50%	75%
Education-innovation gap	1,706,319	95.3	5.8	91.6	94.9	98.8
# Words	1,706,319	2226	1987	1068	1778	2796
# Knowledge words	1,706,319	1011	1112	349	656	1236
# Unique knowledge word	1,706,319	420	327	203	330	535
Soft skills	1,703,863	33.4	22.9	14.0	30.5	50.0
STEM	1,706,319	0.326	0.469	0	0	1
Business	1,706,319	0.103	0.304	0	0	0
Humanities	1,706,319	0.299	0.457	0	0	1
Social science	1,706,319	0.240	0.427	0	0	0
Basic	1,706,319	0.393	0.488	0	0	1
Advanced	1,706,319	0.275	0.446	0	0	1
Graduate	1,706,319	0.332	0.471	0	0	1

Panel (b): Instructors' Research Productivity

	count	mean	std	25%	50%	75%
Ever Published?	332,064	0.41	0.49	0	0	1.00
# Publications per year	135,364	1.51	1.94	1.00	1.00	1.38
# Publications, last 5 years	111,404	6.01	14.89	0	1.00	5.42
# Citations per year	135,364	29.22	105.92	0	1.85	17.92
# Citations, last 5 years	111,404	172.46	887.99	0	0	54.32
Ever Grant?	332,064	0.18	0.38	0	0	0
# Grants	58,136	10.14	19.96	2.00	4.00	10.00
Grant amount ($1,000)	54,462	4,023	19,501	236	912	3,201

Panel (c): Students' Characteristics and Outcomes at the School Level

	count	mean	std	25%	50%	75%
Median parental income ($1,000)	767	97,917	31,054	78,000	93,500	109,900
Share parents w/income in top 1%	767	0.030	0.041	0.006	0.013	0.033
Share minority students	760	0.221	0.166	0.116	0.166	0.267
Graduation rates (2012–13 cohort)	758	0.614	0.188	0.473	0.616	0.765
Income (2003–04, 2004–05 cohorts)	762	45,035	10,235	38,200	43,300	49,800
Intergenerational mobility	767	0.294	0.138	0.182	0.280	0.375
Admission rate	715	0.642	0.218	0.533	0.683	0.800
SAT score	684	1104.4	130.5	1011.5	1079.5	1182.0

Note: Summary statistics of the variables used in the analysis.

2.2 Academic Publications

We use information from Elsevier's SCOPUS database and compile the list of all peer-reviewed articles that appeared in the top academic journals of each field since the journal's foundation. Top journals are defined as those ranked among the top 10 by Impact Factor (IF) in any of SCOPUS's

191 fields at least once since 1975 (or the journal's creation, if it occurred after 1975).[9] Our final list of publications includes 20 million articles, corresponding to approximately 100,000 articles per year. For each article, we extract information on its title, abstract, keywords, authors, and authors' affiliations.

2.3 Alternative Data Source to Capture Knowledge: Patents

An alternative way to measure the knowledge frontier is to use the text of patents, rather than academic publications. To this purpose, we collect the text of more than six million patents issued since 1976 from the US Patents and Trading Office (USPTO) website. We capture the content of each patent with its title and abstract.

2.4 Instructors: Research Productivity, Funding, and Job Titles

Nearly all course syllabi report the name of the course instructor. Using this information, we collect data on instructors' research productivity (publications and citations) and the receipt of public research funding. For a subset of instructors, we also collect information on job titles.

Research productivity Individual-level publications and citations data are from Microsoft Academic (MA). One of the world's top academic search engines, MA listed publications, working papers, other manuscripts, and patents for each researcher, together with citation counts for these documents, until its discontinuation in December 2021. We link MA records to syllabi via fuzzy matching based on instructor name and institution (details on this procedure are in Appendix B). We are able to successfully find 41 percent of all instructors, and we assume that instructors without a MA profile never published any article (Table 1, panel (b)).

Using data from MA, we measure each instructor's research quantity and quality with the number of articles published and citations received in the previous five years.[10] On average, instructors published 6 articles in the previous five years, with a total of 172 citations (Table 1, panel (b)). The distributions of citation and publication counts are highly skewed: The median instructor in our sample only published one article in the previous five years and received no citations.

Funding We also collect information on US government grants received by each instructor, which allows us to measure public investment in academic research. We focus on two of the main funding agencies of the US government: the National Science Foundation (NSF) and the National Institute

[9] Even if a journal appeared only once in the top 10, we collect all articles published since its foundation.

[10] Using citations and publications in the previous five years helps address issues related to the life cycle of publications and citations, with older instructors having a higher number of citations and publications per year even if their productivity declines with time.

of Health (NIH).[11] Our grant data include 480,633 NSF grants active between 1960 and 2021 (with an average size of $582K in 2019 dollars) and 2,566,358 NIH grants active between 1978 and 2021 (with an average size of $504K). We link grants to instructors via fuzzy matching between the name and institution of the investigator and those of the instructor (more details can be found in Appendix B). Eighteen percent of all syllabi instructors are linked to at least one grant. Among these, the average instructor receives ten grants, with a combined size of $4,023K (Table 1, panel (b)).

Job titles In many US states, information on public college and university employees is disclosed online, to comply with state regulations on transparency and accountability. These records usually contain each employee's name and job title. We are able to collect information on job titles for 32,090 instructors in our syllabi sample (9.7 percent of all instructors and 13 percent of public-sector instructors), employed in 278 public institutions in 13 states. We are able to observe instructors' titles for the most recent years (the modal year is 2017; we detail the coverage of these data in Appendix B). Among all syllabi instructors for which we have job title information, 42 percent are ladder faculty (including 11 percent who are assistant professors, 13 percent who are associate professors, and 18 percent who are full professors; Appendix Figure AI).

2.5 Information on US Higher Education Institutions

The last component of our data set includes information on all US colleges and universities of the syllabi in our data. Our primary source is the Integrated Postsecondary Education Data System (IPEDS), maintained by the National Center for Education Statistics (NCES).[12] For each school, IPEDS reports a set of institutional characteristics (such as name and address, public or private sector, affiliation, and Carnegie classification); the types of degrees and programs offered; expenditure and endowment; characteristics of the student population, such as the distribution of SAT and ACT scores of all admitted students, enrollment figures for different demographic groups, completion rates, and graduation rates; and faculty composition (ladder and non-ladder). We link each syllabus to the corresponding IPEDS record via a fuzzy matching algorithm based on school names. We are able to successfully link all syllabi in our sample.

We complement data from IPEDS with information on schools and students from three additional sources. The first one is the school-level data set assembled and used by Chetty et al. (2020), which includes a school's selectivity tier (defined using Barron's scale), the incomes of students and

[11] These data are published by each agency, at https://www.nsf.gov/awardsearch/download.jsp and https://exporter.nih.gov/ExPORTER_Catalog.aspx. We accessed these data on May 25, 2021.

[12] IPEDS includes responses to surveys from all postsecondary institutions since 1993. Completing these surveys is mandatory for all institutions that participate, or apply to participate, in any federal financial assistance programs.

parents, the number of patents obtained by all students, and a measure of intergenerational mobility (the share of students with parental income in the bottom quintile who reach the top income quintile as adults). These data are calculated using data on US tax records for a cross-section of cohorts who graduated between 2002 and 2004. The second is the Survey of Earned Doctorates, conducted by the NSF, which reports characteristics of all doctoral degree recipients in US institutions each year. We use information on students' graduating cohort and bachelor's institution to construct the share of undergraduate students in each school and graduation year who eventually complete a doctoral degree for the years 1998-2018.[13] The third is the College Scorecard Database of the US Department of Education, an online tool designed to help users compare costs and returns of attending various colleges and universities in the US. This database reports the earnings of graduates ten years after the start of the program. We use these variables, available for the academic years 1997-98 to 2007-08, to measure student outcomes for each school.

Panel (c) of Table 1 summarizes the sample of colleges and universities for which we have syllabi data. On average, the median parental income of all students at each school is $97,917. Across all schools, three percent of all students have parents with incomes in the top percentile. The share of minority students equals 0.22. Graduation rates average 61.4 percent in 2018, whereas students' incomes ten years after school entry, for the 2003–04 and 2004–05 cohorts, are equal to $45,035. Students' average intergenerational mobility is equal to 0.29.

2.6 Data Coverage and Sample Selection

Our syllabi sample only covers a small fraction of all courses taught in US schools between 1998 and 2018. The number of syllabi increases over time, from 17,479 in 2000 to 68,792 in 2010 and 190,874 in 2018 (Appendix Figure AII).

To more accurately interpret our empirical results, it is crucial to clarify patterns of selection into the sample. To do so, we compile the full list of courses offered between 2010 and 2019 in a subsample of 161 US institutions (representative of all institutions included in IPEDS) using course catalogs in the archives of each school.[14] This allows us to compare our sample to the population of all courses for these schools and years.

[13]The Survey of Earned Doctorates has been conducted since 1957. To assign a doctoral degree recipient to their undergraduate institution, we use information on the institution where they obtained their bachelor's degree; to assign the recipient to a bachelor's degree cohort, we subtract six from their year of doctoral degree completion.

[14]We begin by randomly selecting 200 schools among all four-year IPEDS institutions. Among these, we were able to compile course catalogs for 161 institutions. These look very similar in terms of observables to all schools in our sample (Appendix Table AI). We focus our attention on years 2010 onward to maximize our coverage. For an example of a course catalog, see https://registrar.yale.edu/course-catalogs.

This exercise does not reveal stark patterns of selection based on observables. The share of catalog courses covered by the syllabi sample remains stable over time, at 5 percent (Appendix Figure AIII). This suggests that, among these randomly selected schools, the increase in the number of syllabi over time is driven by an increase in the number of courses that are offered, rather than an increase in sample coverage. Our syllabi sample is also similar to the population in terms of field and course level composition. Between 2010 and 2018, STEM courses represent 33 percent of syllabi in our sample and 24 percent of courses in the catalog; Humanities represent 30 and 32 percent, and Social Sciences represent 24 and 20 percent, respectively (Appendix Figure AIV). Similarly, basic undergraduate courses represent 39 percent of syllabi in our sample and 31 percent of courses in the catalog; advanced undergraduate courses represent 28 and 30 percent, and graduate courses represent 33 and 38 percent (Appendix Figure AV). These shares are fairly stable over time.

In addition, a school's portion of the catalog that is included in our sample and the change in this portion over time are unrelated to school observables. We show this in panel (a) of Table 2 (column 1), where we regress a school's share of courses included in our sample in 2018 on the following variables, one at the time and also measured in 2018: financial attributes (such as expenditure on instruction, endowment per capita, sticker price, and average salary of all faculty), enrollment, the share of students in different demographic categories (Black, Hispanic, alien), and the share of students graduating in Arts and Humanities, STEM, and Social Sciences. We also test for the joint significance of all these variables. We find that these variables are individually and jointly uncorrelated with the share of courses in the syllabi sample, with an F-statistic close to one. In column 2 we repeat the same exercise, using the 2015-2018 change in the share of courses included in the syllabi as the dependent variable. Our conclusions are unchanged.

The only dimension in which our syllabi sample appears selected is school selectivity. Relative to non-selective institutions (for whom the share of courses in the sample is less than 0.1 percent), Ivy-Plus and Elite schools have a 2.4 percentage point higher share of courses included in the syllabi sample, and selective public schools have a 4.0 percentage point higher share. Taken together, these tests indicate that our syllabi sample does not appear to be selected on the basis of observable characteristics of schools and fields, although it does over-represent Ivy-Plus, Elite, and selective public schools. By construction, though, we cannot test for selection based on unobservables. Our results should therefore be interpreted with this caveat in mind.

Table 2: Selection into the Sample: Share of Syllabi Included in the Sample and Institution-Level Characteristics

Panel (a): Share and Δ Share, Correlation w/ School Characteristics

	Share in OSP, 2018		ΔShare in OSP, 2008-18	
	(1)	(2)	(3)	(4)
	Corr.	SE	Corr.	SE
ln Expenditure on instruction	0.002	(0.005)	0.015	(0.010)
ln Endowment per capita	-0.001	(0.002)	-0.001	(0.002)
ln Sticker price	0.003	(0.007)	0.007	(0.010)
ln Avg faculty salary	0.016	(0.020)	0.049	(0.024)
ln Enrollment	0.018	(0.009)	0.019	(0.011)
Share Black students	-0.030	(0.038)	0.035	(0.060)
Share Hispanic students	0.171	(0.145)	0.161	(0.115)
Share Asian students	0.186	(0.214)	0.324	(0.239)
Share grad in Arts & Humanities	0.159	(0.168)	0.189	(0.179)
Share grad in STEM	-0.001	(0.028)	0.064	(0.056)
Share grad in Social Sciences	0.014	(0.024)	0.104	(0.056)
Share grad in Business	0.037	(0.065)	0.116	(0.065)
F-stat	1.015		1.376	

Panel (b): Share and Δ Share, By School Tier

	Share in OSP, 2018		ΔShare in OSP, 2008-18	
	(1)	(2)	(3)	(4)
	Mean	SE	Mean	SE
Ivy Plus/Elite	0.024	(0.008)	0.022	(0.009)
Highly Selective	0.003	(0.003)	0.006	(0.004)
Selective Private	0.029	(0.018)	0.001	(0.029)
Selective Public	0.040	(0.023)	0.009	(0.029)
F-stat	3.677		1.806	

Note: The top panel shows OLS coefficients ("Corr.") and robust standard errors ("SE") of univariate regressions of each listed dependent variable on the corresponding independent variable. The bottom panel shows OLS coefficients ("Mean") and syllabus-clustered standard errors ("SE") of a regression of each dependent variable on indicators for school tiers. The dependent variables are the school-level share of syllabi contained in the OSP sample in 2018 (columns 1-2) and the change in this share between 2008 and 2018 columns (3-4). The F-statistics refer to multivariate regressions that include all the listed independent variables and test for the joint significance of these variables.

3 Measuring the Education-Innovation Gap

This section describes the construction of the education-innovation gap. We first explain how we measure textual similarities between course syllabi and academic publications. Then, we define and construct the gap using measures of similarity, implementing a series of adjustments to better describe each syllabus's content. Lastly, we validate our measure and describe its variation. Appendix

C provides additional details on the construction of the measure.

3.1 Measuring The Similarity Between Syllabi and Academic Publications

3.1.1 Constructing Term Frequency Vectors

We start by representing each document d (a syllabus or an article) as a term-frequency vector TF_d. Each element TF_{dw} of TF_d represents the frequency of term w in d:

$$TF_{dw} \equiv \frac{c_{dw}}{\sum_{k \in W} c_{dk}},$$

where, in the numerator, c_{dw} counts the number of times term w appears in d and the denominator is the total number of terms in d. To maximize our ability to capture the knowledge content of each document, we construct TF vectors focusing exclusively on terms related to knowledge concepts and skills, belonging to a dictionary W with $|W|$ terms (as a result, each term vector contains $|W|$ elements). Our primary dictionary is the list of all unique terms ever used as keywords in academic publications from the beginning of our publication sample until 2019.[15]

3.1.2 Adjusting for Term Relevance

When constructing similarity metrics, it is crucial to ensure that each term receives a weight proportional to its importance in capturing a document's content. TF vectors give more weight to terms with a higher document frequency. However, terms that are very common across *all* documents receive more weight regardless of their ability to capture the content of a given document. For example, holding term frequency fixed, terms such as "Programming" or "Animals"—very common among Computer Science and Biology syllabi, respectively—are usually less informative of content than terms such as "Natural Language Processing" or "CRISPR."[16]

To this purpose, we use a leading approach in the text analysis literature called "term-frequency-inverse-document-frequency" (TFIDF, Kelly et al., 2021). This approach assigns each term a weight inversely proportional to the frequency of the term across all documents, underweighting terms that are not diagnostic of a document's content. We implement this approach by constructing an

[15] We have also used the list of all terms that have an English Wikipedia webpage as of 2019. Our results are robust to this choice.

[16] Clustered Regularly Interspaced Short Palindromic Repeats (CRISPR) is a family of DNA sequences found in the genomes of prokaryotic organisms such as bacteria and archaea. The term also refers to a recent technology that can be used to edit genes.

inverse-document frequency vector IDF (of length $|W|$) with elements defined as

$$IDF_w \equiv \ln\left(\frac{|D|}{\sum_{n\in D}\mathbb{1}(c_{nw}>0)}\right),$$

where D is the set of all documents (syllabi *and* articles). The denominator in parentheses is the total number of documents that contain word w. IDF_w is thus the inverse of the share of all documents containing word w. Using IDF, we can then transform TF_d into a term-frequency-inverse-document-frequency vector $TFIDF_d$, with elements equal to

$$TFIDF_{dw} = TF_{dw} \times IDF_w. \tag{1}$$

Accounting for changes in term relevance over time The TFIDF approach calculates the relative importance of each term for a given document pooling together documents published in different years. This is not ideal for our analysis, because we are interested in the novelty of the content of a syllabus d relative to research published in the years *prior* to d. Consider, for example, course CS229 at Stanford University, taught by Andrew Ng in the early 2000s and one of the first that entirely focused on *Machine Learning*. The term "machine learning" term has become very popular in later years, so its frequency across all documents is very high and its IDF_w very low. Pooling together documents from different years would thus result in a very low $TFIDF_{dw}$ for the term "machine learning" in the course's syllabus, failing to recognize the course's novelty as of early 2000s. Generally, not accounting for changes in term frequency over time would lead us to severely mischaracterize a course's path-breaking content.

To overcome this issue, we modify the traditional $TFIDF$ and construct a retrospective or "point-in-time" version of IDF, meant to capture the inverse frequency of a term among all documents published *prior to* d. We call this vector "backward-IDF," or $BIDF_t$. It is indexed by t because it varies over time. We define the set of documents published prior to t as D_t; the elements of $BIDF_t$ can be defined as

$$BIDF_{tw} \equiv \log\left(\frac{|D_t|}{\sum_{n\in D_t}\mathbb{1}(c_{nw}>0)}\right).$$

The use of this weighting approach allows us to give a temporally appropriate weight to each term in a document. Using $BIDF_t$, we can then calculate a "backward" version of $TFIDF_d$—called

$TFBIDF_d$—whose elements are

$$TFBIDF_{dw} = TF_{dw} \times BIDF_{t(d)w}, \tag{2}$$

where $t(d)$ is the publication year of document d.

3.1.3 Building Textual Similarities Between Syllabi and Articles

Armed with weighted term vectors, we can now construct measures of textual similarities between syllabi and articles. For simplicity, we denote $TFBIDF_d$ as V_d for each d. The measure of similarity we use is the cosine similarity, defined for two documents d and d' as

$$\rho_{d,d'} = \frac{V_d}{\|V_d\|} \cdot \frac{V_{d'}}{\|V_{d'}\|} \tag{3}$$

where $\|V_d\|$ is the Euclidean norm of V_d. Since each element of V_d is non-negative, ρ lies in the interval $[0, 1]$. If d and d' use the exact same set of terms with the same frequency, $\rho_{d,d'} = 1$; if they have no terms in common, $\rho_{d,d'} = 0$.

3.2 Calculating the Education-Innovation Gap

We capture the similarity between each syllabus d and different vintages of knowledge using the average similarity of d with all the articles published in a three-year time period ending τ years before $t(d)$:

$$S_d^\tau = \frac{\sum_{n \in \Omega_\tau(d)} \rho_{dn}}{|\Omega_\tau(d)|}$$

where ρ_{dk} is the cosine similarity between syllabus d and an article k, $\Omega_\tau(d)$ is the set of all articles published in the three-year time interval $[t(d) - \tau - 2, t(d) - \tau]$, and $|\Omega_\tau(d)|$ is the total number of these articles.[17]

We construct the education-innovation gap as the ratio between the average similarity of a syllabus with older technologies (published in $t - \tau$) and the similarity with more recent ones (published in $t - \tau'$, where $\tau' < \tau$):

$$Gap_d \equiv \left(\frac{S_d^\tau}{S_d^{\tau'}} \right) \tag{4}$$

Given this definition, the syllabus of a course taught in t has a lower education-innovation gap if its text is more similar to more recent research (published in $t - \tau'$) than to older research (published

[17] Our main analysis uses three-year intervals; our results are robust to the use of one-year or two-year intervals.

in $t - \tau$). For our analysis, we set $\tau = 13$ ($[t - 15, t - 13]$ vintage) and $\tau' = 1$ ($[t - 3, t - 1]$ vintage). We multiply the gap by 100 for readability.

Our measure features two attractive properties. First, being constructed as a ratio, the gap is not affected by syllabus-specific attributes such as style, format, or length, which could introduce noise when measuring a syllabus's similarity to knowledge. For example, two courses covering the same materials could have different similarities to research publications if one syllabus is more detailed or uses more academic terms. We illustrate this point with a simulation exercise in Appendix C.[18]

Second, our measure does not heavily penalize syllabi for covering "classic" topics in the literature, as long as these are widespread across courses. This is guaranteed by the use of a $TFBIDF$ approach, which reduces the impact on the gap of terms—such as those pertaining to classics—frequently used across all documents. For example, the term "Ordinary Least Squares" ("OLS") refers to a relatively old but very common concept taught in most econometrics and statistics courses. As such, it will receive a low weight, and syllabi will not be penalized much by covering it.

3.3 Validating The Measure and Interpreting Its Magnitude

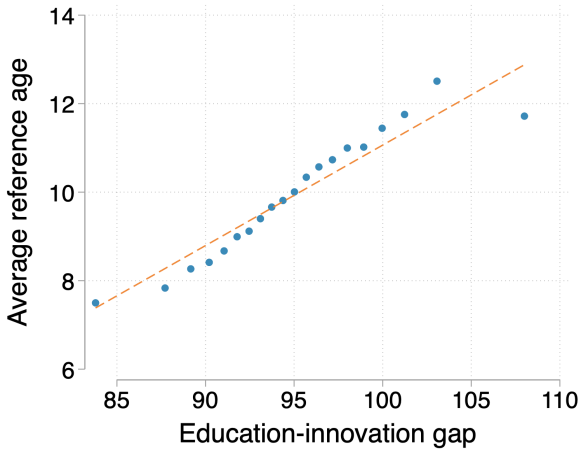
We perform a series of tests to validate our measure's ability to capture the distance between the content of a course and the research frontier. First, we show that the relationship between the gap and the average age of its reference list (defined as the average difference between the year of the syllabus and the publication year of each reference) is positive and significant (Figure 1, panel (a)). While the average reference age is easy to calculate, our text-based measure is available for all syllabi (including those for which the reference list is unavailable) and is more accurate in capturing the content of courses that only rely on very few bibliographic sources (for example, a textbook).

Second, we show that the gap varies reasonably across course levels. More advanced undergraduate courses and graduate-level courses have lower gaps than basic undergraduate courses. Controlling for field-by-year effects, basic undergraduate courses have a gap of 95.7, advanced undergraduate courses have a gap of 95.3, and graduate courses have a gap of 94.7 (Figure 1, panel (b)). This confirms the intuition that more advanced courses cover content that is closer to the knowledge frontier.

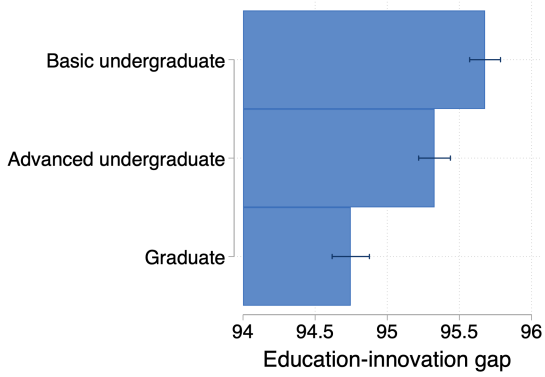
[18] We manually create a sample of 1.7 million simulated syllabi, for which we know ex ante the ratio between "old" knowledge terms (more popular among old publications) and "new" knowledge terms (more popular among recent publications). In the presence of syllabi idiosyncracies, the education-innovation gap performs significantly better at recovering a syllabus's knowledge content (the ex ante ratio between old and new knowledge terms) than a simple measure of similarity with new terms (Appendix C).

Figure 1: Validating the Education-Innovation Gap

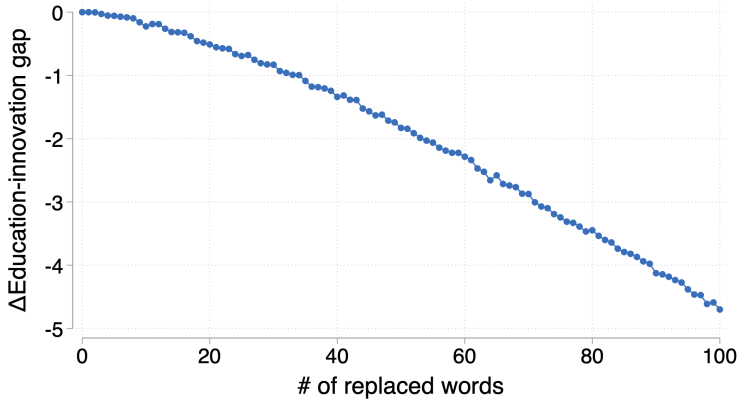
(a) Gap and Average Reference Age



(b) Gap by Course Level



(c) Change in Gap as Old Words are Replaced with New Words



Note: Panel (a) shows a binned scatterplot of the education-innovation gap and the average age of a syllabus's references (required or recommended readings), in which age is calculated as the difference between the year of the syllabus and the year of publication of each reference. Panel (b) shows the mean and 95-percent confidence intervals of the gap by course level, controlling for field-by-year effects. Panel (c) shows the change in the gap for a subsample of 100,000 syllabi, in which we progressively replace "old" words with "new" words.

Third, we use a simulation exercise to confirm that our measure responds to even small changes in a syllabus's similarity to different knowledge vintages. Specifically, we randomly draw a subsample of 100,000 syllabi. Then, we progressively replace terms that are more frequent in older knowledge vintages ("old words") with terms more frequent in newer vintages ("new words"), and we re-calculate the gap as we replace more words. Old words are those in the top 5 percent in terms of frequency in the old publication corpus between $t-15$ and $t-13$ or in the old publication corpus between $t-15$ and $t-13$ but not in the new publication corpus between $t-3$ and $t-1$

(where t is the year of the syllabus); new words as those in the top 5 percent in terms of frequency in the new publication corpus between $t-3$ and $t-1$ or in the new publication corpus between $t-3$ and $t-1$ but not in the old publication corpus between $t-15$ and $t-13$. The gap monotonically decreases as we replace more old words with new ones (Figure 1, panel (c)). This simulation is also useful for gauging the economic magnitude of changes in the gap. In particular, a unit change in the gap is equivalent to the replacement of 10 percent of a syllabus's old words (or 34 old words out of 327 words for the median syllabus).

3.4 The Education-Innovation Gap: Variation and Variance Decomposition

The average course has a gap of 95.3, with a standard deviation of 5.8, a 25th percentile of 91.6, and a 75th percentile of 98.8 (Table 1, panel (a) and Appendix Figure AVI). To give an economic meaning to this variation, we use the relationship illustrated in panel (c) of Figure 1. In order to move a syllabus from the 75th to the 25th percentile of the distribution (a 7.2 change in the gap), we would have to replace approximately 200 of its words, or 61 percent of the content of the median syllabus.

To better understand what drives variations in the gap, we calculate the contribution of each of five attributes to the total variance: year, field, school, course, and instructor. We do this by means of a Shapley-Owen decomposition (Israeli, 2007; Huettner et al., 2012), which proceeds in three steps. We first estimate OLS regressions of the gap on fixed effects for all possible combinations of the five attributes.[19] Second, for each of these regressions, we compute by how much the adjusted R^2 declines if we exclude the fixed effects for a specific attribute j. Lastly, we calculate the average decline for each j across all these regressions, which we denote as the *partial-R^2* of attribute j, or R^2_j. This quantity, which is analogous to the Shapley value used in game theory, represents the portion of total variance in the education-innovation gap that can be attributed to j. Analytically, it is equal to

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

where $R^2(S)$ is the adjusted R^2 of a regression of the gap on fixed effects for a set of factors S, V is the set of all attributes considered, $|T|$ is the number of attributes in set T, and $K \equiv |V| = 5$ is the

[19] Since school effects are subsumed by course effects (each course is taught only at one school), school effects are not separately identified in a regression that also contains course fixed effects. Our method, however, still allows us to quantify the contribution of school effects to the total variation in the education-innovation gap out of the regressions of those combination of the five attributes that do not include course effects.

total number of attributes considered. The use of adjusted R^2 accounts for the fact that the various sets of fixed effects have different numbers of categories (using the standard R^2, larger categories would mechanically explain a larger portion of the variance).[20]

Table 3: Decomposing the Variation in the Gap: Schools, Years, Fields, Courses, and Instructors

Variable	Partial R^2	
Year	0.169	0.180
Field	0.039	0.056
School	0.021	0.028
Course level	.	0.008
Course	0.330	.
Instructor	0.248	0.346
Total	0.807	0.772

Note: The table shows a decomposition of the adjusted R^2 of a regression of the education-innovation gap on all sets of listed fixed effects into the contribution of each set of fixed effects. This is done using a Shapley-Owen decomposition, described in details in Section 3.4. Column 1 includes course fixed effects; column 2 only includes course level fixed effects. *Total* reports the R^2 of a regression with all sets of fixed effects included. We use adjusted R^2 in lieu of R^2 to account for the large number of fixed effects.

This decomposition exercise indicates that differences across fields explain 4 percent of the total variation in the gap, while differences across schools explain 2 percent (Table 3, column 1). Courses explain a large 33 percent, indicating a great deal of persistence in the content of a course over time. Importantly, differences across instructors explain a large 25 percent. Results are similar when we replace courses with course levels; the latter explain less than 1 percent of the total variation (column 2).

4 The Role of Instructors

Instructors are considered one of the most important inputs for the production of student learning and one of the most costly for schools (De Vlieger, Jacob, and Stange, 2020). In line with this, our data show that most of the variation in the gap occurs within schools and across courses taught by different people. Motivated by these findings, we begin our analysis by investigating in depth the

[20]We perform a placebo test to demonstrate that the large variation explained by courses and instructors is not just an artifact of the large number of categories in these attributes. In this test, we randomly scramble the course codes in the data. In this way, the number of course indicators remain the same, but scrambled course codes do not bear any economic meaning. We replicate the Shapley-Owen decomposition shown in column (1) of Table 3. If the large portion of explained variance were solely driven by the large number of indicators, even scrambled course codes should explain some variance. Instead, we find that they explain less than 1% of the total variation in the education-innovation gap.

role of instructors and their characteristics in shaping the content of higher education.

4.1 Persistence in a Course's Content over Time and Changes in Instructors

We start by studying how the education-innovation gap of a course varies when the course instructor changes. This allows us to measure the direct role of instructors in shaping course content. We estimate an event study of the gap in a $[-4, 4]$ year window around the time of an instructor change:

$$\text{Gap}_i = \sum_{k=-4}^{4} \delta_k \mathbb{1}(t(i) - T_{c(i)} = k) + \gamma_{c(i)} + \phi_{f(i)t(i)} + \varepsilon_i, \tag{5}$$

where i, f, and t denote a syllabus, field, and year respectively. The subscript c denotes a specific course within each school (for example, Econ 101 at Yale University); the variable T_c represents the first year in our sample in which the instructor of course c changes.[21] To more precisely capture the impact of an instructor change, we restrict our attention to courses taught by a maximum of two instructors in each year and set the indicator function to zero for all courses without an instructor change, which serve as the comparison group. We cluster standard errors at the course level. After normalizing δ_{-1} to be 0, the parameters δ_k capture the differences between the gap k years after an instructor change relative to the year preceding the change.

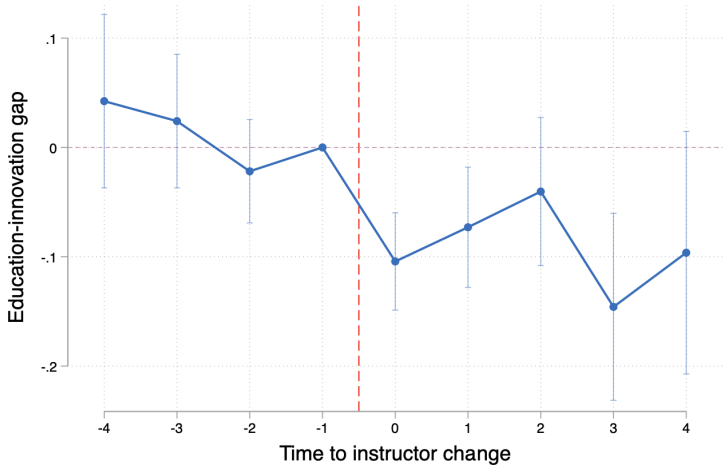
OLS estimates of δ_k, shown in Figure 2, indicate that a change in a course's instructor is associated with an immediate decline in the education-innovation gap. Estimates are indistinguishable from zero and on a flat trend in the years leading to an instructor change; in the year of the change, the gap declines by 0.1. In order to quantify the economic magnitude of these differences, we can use the simulation results in Figure 1 (panel (c)). These indicate that this decline is equivalent to replacing 2 percent of the content of the median syllabus. The decline is also robust to the presence of plausible deviations from the standard parallel trends assumption of event studies (Rambachan and Roth, 2019).[22]

In Table 4 we re-estimate equation (5) for different subsamples of syllabi, pooling together years preceding and following an instructor change. After a change, the gap declines for all fields and course levels by about 0.1 on average (2 percent of a course's content, column 1, significant at 1 percent). The decline is largest for Humanities and STEM courses (-0.14 and -0.11, columns 3 and 4, respectively) and for graduate courses (-0.12, column 8).

[21] Our results are robust to using the median or the last year with an instructor change.

[22] In Appendix Figure AVII we test the robustness of the statistical significance of δ_0 in equation (5), by implementing the test proposed by (Rambachan and Roth, 2019). Estimates of δ_0 remain distinguishable from zero even under plausible violations of the parallel trends assumption, which indicates that the measured decline in the gap is not due to differential trends.

Figure 2: Event Study: The Education-Innovation Gap Around An Instructor Change



Notes: Estimates and confidence intervals of the parameters δ_k in equation (5), representing an event study of the education-innovation gap around an instructor change and controlling for course and field-by-year fixed effects. Observations are at the course-by-year level; we focus on courses with at most two episodes of instructor changes. Standard errors clustered at the course level.

These results indicate that course updating is not a gradual process taking place over time. Instructors who teach the same course for many years tend to leave content unchanged. Instead, instructors who take over a course from someone else significantly update its content, bringing it closer to the knowledge frontier. This is also consistent with the interpretation that instructors play a crucial role in shaping the content of the courses they teach, particularly for advanced courses.

Table 4: The Education-Innovation Gap Around An Instructor Change

		Field				Course level		
	All	Business	Humanities	STEM	Soc. Sci.	Basic	Advanced	Grad
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
After change	-0.1021***	-0.1009	-0.1417***	-0.1060***	-0.0289	-0.0897**	-0.0875*	-0.1152***
	(0.0244)	(0.0683)	(0.0464)	(0.0399)	(0.0416)	(0.0456)	(0.0450)	(0.0374)
N (Course*yr)	379482	36325	105316	152974	95223	125493	112206	137721
# Courses	126343	11775	35947	45982	31805	43530	35395	46213
Course FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Field*yr FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Note: OLS estimates; one observation is a course in a given year. The dependent variable is the education-innovation gap. The variable *After change* is an indicator for years following an instructor change for courses with only one instructor and at most two instructor changes over the observed time period. All specifications control for course and field-by-year fixed effects. Standard errors in parentheses are clustered at the course level. $^{*} \leq 0.1$, $^{**} \leq 0.05$, $^{***} \leq 0.01$.

4.2 The Education-Innovation Gap and Instructors' Characteristics

The decline in the gap that follows an instructor change indicates that instructors are crucial drivers of differences in course content. We next explore differences in the education-innovation gap among instructors with different characteristics. We are particularly interested in the relationship between instructors' research activity and the education-innovation gap of the courses they teach. This relationship is not clear ex ante: On the one hand, research-active faculty members are better informed on the frontier of knowledge and thus are better able to design more updated courses. On the other hand, research may demand more time and attention, limiting an instructor's ability to invest in the design of their courses.

Research productivity We test this hypothesis directly by exploring the relationship between a course's gap and the research productivity of the instructor, measured using individual counts of citations and publications in the previous five years. We estimate the following equation:

$$\text{Gap}_i = \sum_{n=1}^{4} \beta^n q^n_{k(it(i))} + \gamma_{c(i)} + \phi_{f(i)t(i)} + \varepsilon_i \tag{6}$$

where q^n_k equals one if instructor k's measure of research productivity (publications or citations) is in the nth quartile of the distribution (the omitted category is courses with instructors whose measure k equals zero). Course fixed effects γ_c and field-by-year fixed effects ϕ_{ft} control for unobserved determinants of the gap that are specific to a course in a given field and year. Estimates of β^n capture the difference in the gap between courses taught by faculty with productivity in the nth quartile and those taught by faculty with no citations or publications, and they are identified using changes of instructors for the same course over time.

Estimates of β^n, shown in Table 5, indicate that the gap progressively declines as the research productivity of the instructor increases. In particular, a switch from an instructor without publications to one with publication counts in the top quartile of the field distribution is associated with a 0.11 decline in gap (equivalent to updating 3 percent of a course's syllabus; Table 5, panel (a), column 1, significant at 1 percent). Similarly, a switch from an instructor without citations to one with citations in the top quartile is associated with a 0.07 lower gap (panel (b), column 1, significant at 5 percent). These relationships are stronger for Social Sciences courses (column 5) and for courses at the graduate level (column 8).[23]

[23] Appendix Figure AVIII shows a binned scatterplot of the gap and either citations (panel (a)) or publications (panel (b)) in the prior five years, controlling for field effects. In this figure, the horizontal axis corresponds to quantiles of each productivity measure; the vertical axis shows the average gap in each quantile.

Table 5: The Education-Innovation Gap and Instructors' Research Productivity: Publications and Citations

	Field					Course level		
	All	Business	Humanities	STEM	Soc. Sci.	Basic	Advanced	Grad
Panel (a): #publications	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
1st quartile	-0.0219	0.0485	-0.0815**	0.0556	-0.0641**	-0.0099	-0.0277	-0.0308
	(0.0178)	(0.0472)	(0.0328)	(0.0367)	(0.0291)	(0.0298)	(0.0324)	(0.0300)
2nd quartile	-0.0151	0.0138		0.0309	-0.0418	-0.0207	0.0224	-0.0366
	(0.0298)	(0.0729)		(0.0462)	(0.0425)	(0.0531)	(0.0543)	(0.0471)
3rd quartile	-0.0045	0.0596	-0.0387	0.0953*	-0.1057**	0.0374	-0.0115	-0.0356
	(0.0302)	(0.0712)	(0.0694)	(0.0563)	(0.0459)	(0.0574)	(0.0540)	(0.0462)
4th quartile	-0.1103***	0.0220	-0.1184	-0.0638	-0.1817***	-0.0448	-0.0927	-0.1711***
	(0.0376)	(0.0894)	(0.0797)	(0.0699)	(0.0621)	(0.0742)	(0.0698)	(0.0551)
Panel (b): #citations	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
1st quartile	0.0288	-0.0097	0.0313	0.1068**	-0.0469	0.0438	0.0543	-0.0031
	(0.0248)	(0.0667)	(0.0636)	(0.0437)	(0.0361)	(0.0427)	(0.0450)	(0.0409)
2nd quartile	0.0194	0.0050	0.0106	0.0827*	-0.0413	0.0271	0.0276	0.0059
	(0.0282)	(0.0675)	(0.0682)	(0.0499)	(0.0431)	(0.0508)	(0.0508)	(0.0448)
3rd quartile	-0.0658**	-0.0464	-0.0919	-0.0355	-0.1056**	0.0011	-0.0965	-0.0961**
	(0.0324)	(0.0775)	(0.0782)	(0.0584)	(0.0491)	(0.0625)	(0.0600)	(0.0477)
4th quartile	-0.0713*	0.0667	-0.1090	-0.0151	-0.1305**	-0.0200	-0.0497	-0.1385**
	(0.0412)	(0.0946)	(0.1056)	(0.0722)	(0.0655)	(0.0799)	(0.0775)	(0.0601)
N (Course x year)	579622	60953	156970	195375	150731	209190	170946	199228
# Courses	153392	15156	43067	51873	39169	55444	43320	54557
Course FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Field*yr FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Note: OLS estimates; one observation is a course in a given year. The dependent variable is the education-innovation gap; the independent variables are indicators for quartiles of the number of publications (panel (a)) and citations (panel (b)) of a course's instructors in the previous five years, within each macro field. The omitted category is courses with instructors with no publications or citations. For courses with more than one instructor, we consider the mean number of publications and citations across all instructors. All specifications control for course and field-by-year fixed effects. Standard errors in parentheses are clustered at the course level. $^{*} \leq 0.1$, $^{**} \leq 0.05$, $^{***} \leq 0.01$.

Table 6: The Education-Innovation Gap and the Fit Between Instructors' Research and Course Content

	Field					Course level		
	All	Business	Humanities	STEM	Soc. Sci.	Basic	Advanced	Grad
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Fit w/top course (sd)	-0.0877**	0.1638	0.0017	-0.0756	-0.0845	-0.0637	-0.1428*	-0.0611
	(0.0398)	(0.0997)	(0.1728)	(0.0559)	(0.0656)	(0.0832)	(0.0790)	(0.0558)
N (Course x year)	54591	3293	2270	35859	12626	16743	16224	21139
# Courses	17077	1040	781	11166	3923	5208	4833	6883
Course FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Field x Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Note: OLS estimates; one observation is a course in a given year. The dependent variable is the education-innovation gap. The variable *Fit w/top course* is a measure of fit between the instructor's research and the content of the course, defined as the cosine similarity between the instructor's research in the previous five years and the content of the course with the smallest education-innovation gap among all courses with the same topic across all schools. All specifications control for course and field-by-year fixed effects. Standard errors in parentheses are clustered at the course level. $^{*} \leq 0.1$, $^{**} \leq 0.05$, $^{***} \leq 0.01$.

Table 7: The Education-Innovation Gap and Instructors' Research Resources: NSF/NIH Grants

	Field					Course level		
	All	Business	Humanities	STEM	Soc. Sci.	Basic	Advanced	Grad
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
At least one grant	-0.0453**	0.0045	-0.0649	-0.0316	-0.0596*	-0.0476	-0.0324	-0.0567*
	(0.0199)	(0.0571)	(0.0400)	(0.0367)	(0.0330)	(0.0327)	(0.0370)	(0.0336)
N (Course x year)	581995	60953	156970	195375	150731	210121	171867	199735
# Courses	153809	15156	43067	51873	39169	55594	43474	54663
Course FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Field*yr FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Note: OLS estimates; one observation is a course in a given year. The dependent variable is the education-innovation gap. The variable *At least one grant* equals one if the course's instructor (or at least one of the course's instructors in the case of multiple instructors) has received at least one NSF or NIH grant. All specifications control for course and field-by-year fixed effects. Standard errors in parentheses are clustered at the course level. $^{*} \leq 0.1$, $^{**} \leq 0.05$, $^{***} \leq 0.01$.

Fit with the course A natural explanation for this finding is that research-active instructors are better informed about the research frontier. If this is the case, we should expect the relationship between productivity and the gap be stronger for courses whose topics are more similar to the instructor's own research. To test for this possibility, we construct a measure of "fit" between the course and the instructor's research. This measure is defined as the cosine similarity between the instructor's research in the previous five years and the most updated course on the same topic across *all* schools (for example, Introductory Econometrics).[24] Estimates of equation (6), obtained using this measure as the explanatory variable, indicate that a one-standard deviation higher instructor-course fit is associated with a 0.09 lower gap (Table 6, significant at 5 percent). This relationship is particularly strong for Social Sciences and STEM courses (columns 4 and 5) and for courses at the advanced undergraduate level (column 7).

Research funding In Table 7, we use data on the number of NSF and NIH grants received by each instructor and test whether the same relationship holds between the gap and research inputs, such as government grants. As before, we control for course and field-by-year effects. A switch from an instructor who never received a grant to one with at least one grant is associated with a 0.05 reduction in the gap (column 1, significant at 5 percent).[25] This suggests that public investments in academic research can yield additional private and social returns in the form of more updated instruction.[26]

Ladder vs non-ladder faculty These results presented so far carry implications for how the education-innovation gap may co-vary with faculty ranks and tracks (tenure-track vs. non-tenure-track), due to differences in their research activities. Ladder (i.e., tenure-track or tenured) faculty are generally more focused on research compared with non-ladder faculty, whose primary job is to teach. In recent years, universities have started to increasingly rely on non-ladder faculty to meet a rapid rise in enrollment (Goolsbee and Syverson, 2019).[27] Ex ante, one could argue that—by virtue of being specialized in teaching—non-ladder faculty might be better at keeping educational content updated.

[24] An attractive property of this measure is that it does not uniquely reflect the instructor's own syllabus; rather, it aims to capture the content of all courses on the same narrowly defined topic. To construct this measure, we obtained a unique identifier for courses in the same field or topic (e.g., Machine Learning) across schools. Appendix B describes the procedure used to do this.

[25] A binned scatterplot reveals a negative relationship between the gap and the number of NSF and NIH grants (Appendix Figure AVIII, panel (d)).

[26] For a review of the role of grant funding as a tool to promote innovation, see Azoulay and Li (2020).

[27] Colleges have monopsony power on tenure-track (but not ladder) faculty, as these earn substantially lower wages and have a much higher elasticity of labor supply. This implies that, when enrollment increases, schools can avoid increasing wages for tenure-track faculty by hiring more non-ladder faculty (Goolsbee and Syverson, 2019).

Comparing the education-innovation gap across job titles and controlling by field-by-course level-by-year effects, we find that non-ladder faculty (such as adjunct professors, lecturers, professors in the practice, and visiting professors) have the largest gap, at 95.8 (Figure 3). Tenure-track assistant professors, on the other hand, have the lowest gap at 95. The difference between assistant professors and non-ladder faculty is equivalent to 7 percent of a syllabus's content. One possible explanation for this finding is that assistant professors are more recently trained and therefore better updated about frontier knowledge. Furthermore, they often have the strongest incentives to be active in research.

Notably, the gap is almost as high for full (tenured) professors as it is for adjuncts, at 95.6. Associate professors have a slightly smaller gap than full at 95.5, but still significantly higher than assistant professors. Junior faculty on the tenure track thus appear to teach the courses with the most updated content.

Taken together, these findings indicate that instructors play a crucial role in shaping course content. They also reveal some complementarities between research and teaching: Research-active instructors are more likely to cover frontier knowledge in their courses, especially when teaching advanced courses and courses closest in topic to their own research agendas. Our results suggest that a proper deployment of faculty across courses can have important impacts on the content of education, and that investments in faculty research (both public, in the form of government grants, and institution-specific) can generate additional returns in the form of more updated instruction.

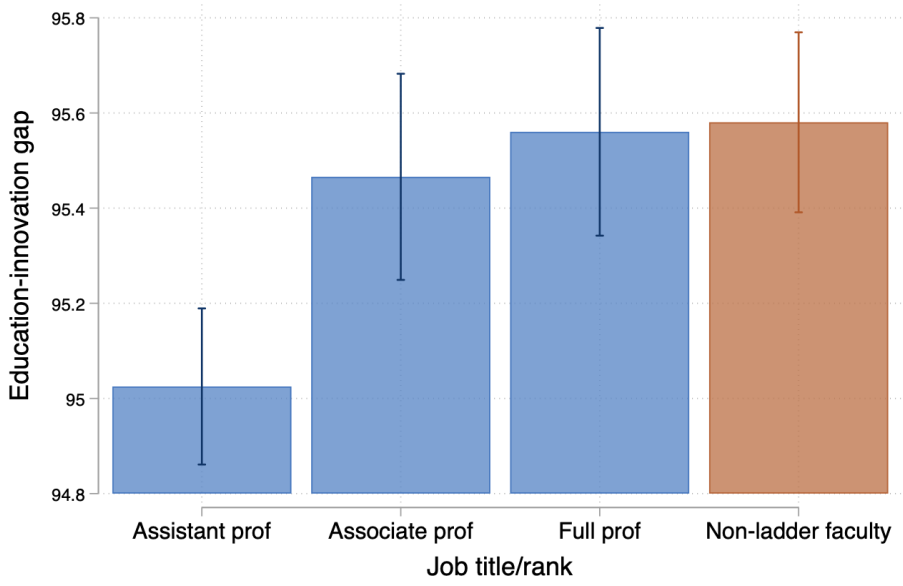
5 The Education-Innovation Gap Across Schools

Next, we explore differences in the education-innovation gap across schools. Examining these differences is helpful to understand how institutional characteristics relate to educational content. This analysis also allows us to study how access to low-gap content varies across students from different socio-economic backgrounds, which tend to enroll in schools with different characteristics (Chetty et al., 2020).

5.1 School Characteristics

We begin by testing how the education-innovation-gap relates to three sets of school attributes: (i) institutional, such as sector (public or private), research intensity (distinguishing between schools classified as R1—"Very High Research Intensity"—according to the Carnegie classification, and all other schools), and emphasis on liberal arts and sciences relative to other subjects (distinguishing between Liberal Arts Colleges (LAC) and all other schools); (ii) financial, such as endowment and

Figure 3: Gap by Job Titles



Notes: Mean education-innovation gap by job title, along with 95-percent confidence intervals. Means are obtained as OLS coefficients from a regression of the gap on indicators for the job title of the instructor and field-by-course level-by-year fixed effects. Estimates are obtained by pooling data for multiple years. Standard errors are clustered at the school level.

spending on instruction, faculty salaries, and research; and (iii) faculty composition and productivity, such as the share of non-ladder faculty, the share of tenure-track (non-tenured) faculty, and the number of academic publications per faculty member.

We estimate pairwise correlations between the gap and these attributes controlling for field, course level, and year of the syllabus. These correlations are captured by β in the following equation:

$$\text{Gap}_i = \beta X_{s(i)} + \psi_{f(i)l(i)t(i)} + \varepsilon_i \tag{7}$$

where Gap_i measures the education-innovation gap of syllabus i, taught in school $s(i)$ and year $t(i)$; the variable X_s is the institutional characteristic of interest in school s; and field-by-level-by-year fixed effects ψ_{flt} control for systematic differences in the gap, common to all syllabi in the same field (f) and course level (l), that vary over time (t). We cluster standard errors at the institution level.

Institutional and financial characteristics Estimates of β for each school characteristic are shown in Figure 4. Public schools have a slightly larger gap compared with private schools, but this difference is indistinguishable from zero. No differences emerge between LACs and other schools. R1

schools have a 0.2 smaller gap compared to schools with a lower research intensity. These estimates imply that, in order to close the difference in the gap between R1 and other schools, we would have to replace approximately 2 percent of the knowledge content of the median syllabus (7 terms).

The education-innovation gap is also significantly related to schools' financial characteristics, such as endowment and spending on instruction, faculty salary, and research. For example, a 10 percent increase in instructional spending is associated with a 3.5 lower gap, or a 35 percent change in the syllabus; a 10 percent increase in research spending is associated with a unit lower gap, or a 10 percent change in the syllabus.

Selectivity Next, we test whether the gap differs across schools with different selectivity. Following Chetty et al. (2020), we group schools in four "tiers" according to their selectivity in admissions, measured with Barron's 2009 ranking. "Ivy Plus" include Ivy League universities and the University of Chicago, Stanford, MIT, and Duke. "Elite" schools are all the other schools classified as tier 1 in Barron's ranking. "Highly selective" schools include those in tiers 2 and 3, while "Selective" schools are those in tiers 4 and 5. Lastly, "Non-selective" schools include those in Barron's tier 9 and all four-year institutions not included in Barron's classification.

To compare the gap across different school tiers, we use the following equation:

$$\text{Gap}_i = \mathbf{S}_i'\boldsymbol{\beta} + \phi_{f(i)l(i)t(i)} + \varepsilon_i \tag{8}$$

where the vector $\mathbf{S}_i'$ contains indicators for selectivity tiers (we omit non-selective schools), and everything else is as before.

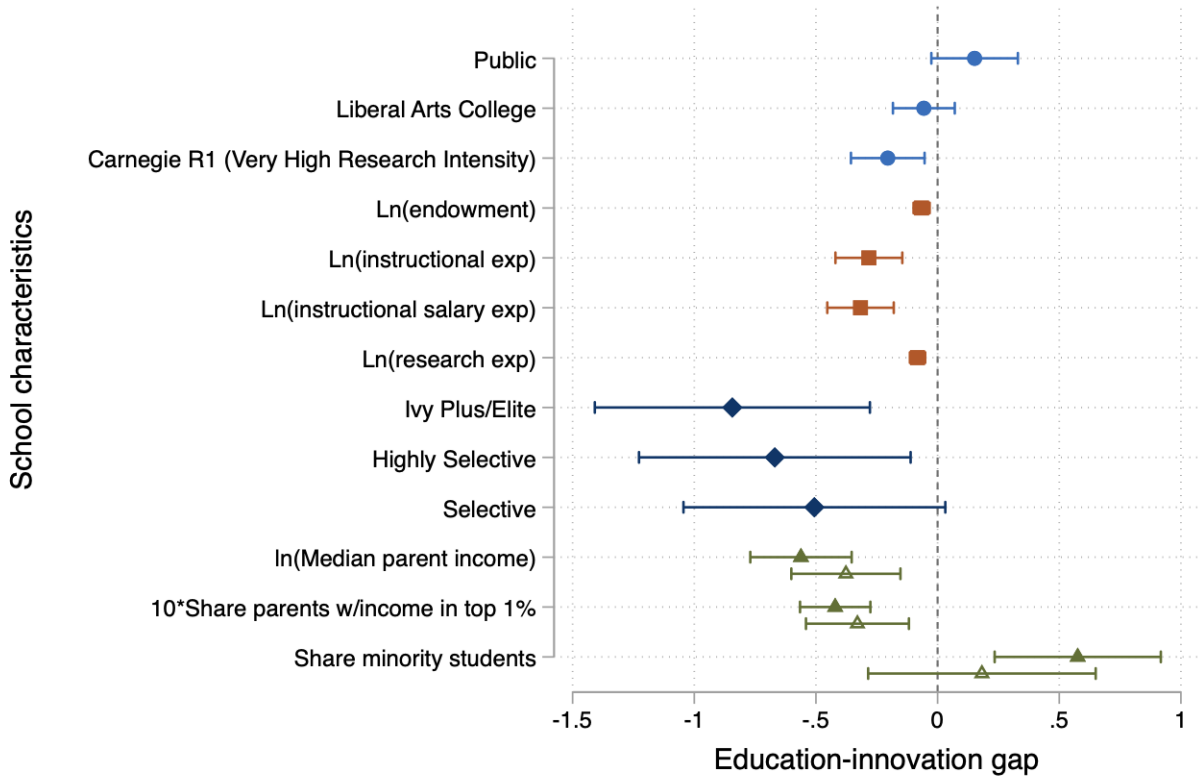
Point estimates of the coefficients vector $\boldsymbol{\beta}$ in equation (8), shown as diamonds in Figure 4, indicate that more selective schools offer content that is closer to the research frontier. Ivy Plus and Elite schools have the smallest gap, 0.84 smaller than non-selective schools (corresponding to an 8 percent difference in the median syllabus). Highly selective schools have a 0.67 smaller gap and selective schools have a 0.51 smaller gap (5 percent). One interpretation for these differences is that more selective schools offer higher-quality education. However, if higher-ability students are better able to absorb frontier knowledge, another possibility is that schools tailor instruction to the abilities of their students. We attempt to test this hypothesis in the next section and in Section 6, where we relate the education-innovation gap to student outcomes.

5.2 Students' Characteristics

Schools with different characteristics serve different populations of students. For example, Ivy Plus and Elite schools are disproportionately more likely to enroll students from wealthier families (Chetty et al., 2020). Cross-school differences might therefore translate into significant disparities in access to up-to-date knowledge among students with different backgrounds. Here, we focus on two dimensions of socio-economic background: parental income and race and ethnicity.

Parental income We re-estimate equation (7) using two measures of parental income as the explanatory variable: median parental income and the share of parents with incomes in the top percentile of the national distribution, constructed using tax returns for the years 1996 to 2004 (Chetty

Figure 4: The Education-Innovation Gap and School Characteristics



Notes: OLS point estimates and 95-percent confidence intervals of β in equation (7), i.e., the slope of the relationship between each reported variable and the education-innovation gap controlling for field-by-course level-by-year fixed effects. Each estimate is obtained from a separate regression, with the exception of selectivity tiers (Ivy Plus/Elite, Highly Selective, Selective) which are jointly estimated. Endowment, expenditure, and share minority refer to the year 2018 and are taken from IPEDS. Estimates are obtained by pooling syllabi data for the years 1998 to 2018. Standard errors are clustered at the school level.

et al., 2020). These estimates, shown as the full triangles in Figure 4, indicate that schools serving more economically disadvantaged students offer courses with a higher gap. Specifically, a one percent higher median parental income is associated with a 0.56 lower gap, which corresponds to a 5 percent difference in the median syllabus. Similarly, a 10 percentage point higher share of students with parental income in the top percentile is associated with a 0.42 lower gap (4 percent).

In principle, part of these differences could be due to a "vertical differentiation" of educational content across schools. If students with greater ability are better able to absorb more up-to-date content, cross-school differences in the gap might reflect schools' efforts to provide students with appropriate educational content. Our data, however, do not support this hypothesis. Controlling for the average SAT score of the students admitted at each school (a proxy for their ability) yields only slightly smaller estimates compared with the baseline (Figure 4, hollow triangles). This rules out vertical differentiation as an explanation for cross-school differences in the gap.

Students' race and ethnicity Schools that enroll a higher share of minority students (Black or Hispanic) also offer courses with a higher gap. Using the share of minority students as the explanatory variable in equation (7) reveals that a one percentage point higher share is associated with a 0.58 higher gap, equivalent to a 6 percent change in the average syllabus. This relationship holds (but becomes less precise) if we control for average student ability.

In line with existing evidence on disparities in access to selective schools among more and less advantaged students, our results document a new dimension of inequality: access to educational content that is close to the research frontier. Importantly, this inequality cannot be explained by differences in student ability.

6 The Education-Innovation Gap and Students' Outcomes

Our findings so far reveal significant differences in access to up-to-date knowledge, both within and across schools. Do these differences matter for students' outcomes and for the production of innovation? As an attempt to answer this question, we now explore the relationship between the gap and a) measures of students' innovation activities, such as a school's share of undergraduate students who complete a doctoral degree and the number of patents produced by students, and b) labor-market outcomes, such as graduation rates, earnings, and intergenerational mobility.

All these outcomes are measured at the school level or at the school-by-cohort level (with the exception of the share of students who attend graduate school, available separately by macro-field). To match this feature of the data, we follow the school value-added literature (Deming, 2014) and

estimate the school component of the gap using the following model:

$$\text{Gap}_i = \theta_{s(i)} + \phi_{f(i)l(i)t(i)} + \varepsilon_i. \tag{9}$$

In this equation, the quantity θ_s captures the school component of the education-innovation gap for school s, accounting for flexible time trends that are specific to the level l and field f of the course. Because outcome measures refer to students who complete undergraduate programs at each school, we construct θ_s using only undergraduate syllabi; our results are robust to the use of all syllabi. Appendix Figure AXI shows the distribution of $\hat{\theta}_s$; its standard deviation is 0.85, corresponding to a 10 percent change in the average syllabus.

In the remainder of this section, we present estimates of the parameter δ in the following equation:

$$Y_{st} = \delta\hat{\theta}_s + X_{st}\Gamma + \tau_t + \varepsilon_{st} \tag{10}$$

where Y_{st} is the outcome for students who graduated from school s in year t; $\hat{\theta}_s$ is the school-level component of the gap (estimated from equation (9) and standardized to have mean zero and variance one); X_{st} is a vector of school observables; and τ_t are year fixed effects. We report bootstrapped standard errors, clustered at the level of the school, to account for the fact that $\hat{\theta}_s$ is an estimated quantity.

It should be stressed that the parameter δ does not necessarily capture the causal effect of the gap on outcomes. There might be school and student attributes related to both the content of a school's courses and student outcomes. To account for as many of these attributes as is possible, we control for a rich set of school observables. We include seven groups of controls, including institutional characteristics (private-public, selectivity tiers, and an interaction between selectivity tiers and an indicator for R1 institutions according to the Carnegie classification); instructional characteristics (student-to-faculty ratio and the share of ladder faculty); financials (total expenditure, research expenditure, instructional expenditure, and salary instructional expenditure per student); enrollment (share of undergraduate and graduate enrollment, share of white and minority students); selectivity (indicator for institutions with admission share equal to 100, median SAT and ACT scores of admitted students in 2006, indicators for schools not using either SAT or ACT in admission); major composition (share of students with majors in Arts and Humanities, Business, Health, Public and Social Service, Social Sciences, STEM, and multi-disciplinary fields); and family background, measured as the natural logarithm of median parental income.

6.1 Innovation Measures

Obtaining a doctoral degree We begin by studying the relationship between the gap and the share of students who obtain a doctoral degree. We construct this variable using data from the NSF Survey of Doctorate Recipients (SDR), separately for five macro-fields: STEM, Health, Business, Social Science, and Humanities. To match the level of aggregation of this variable, we aggregate the education-innovation gap at the school-by-macro field level, rather than just at the school level, and we modify equation (10) so that one observation in our data is a school and by macro-field in a year. The quantity θ_s is also estimated separately for each macro field. In column 1 of Table 8 (panel (a)), we pool data across all macro-fields. The unconditional correlation between the gap and the share of students who obtain a doctoral degree is negative and statistically significant: A one-standard deviation lower gap is associated with a 0.44 percentage point higher share, or 15 percent compared with an average of 2.69 percent. The correlation is particularly strong for Social Science (-0.0124) and Health (-0.0074), while it is small and indistinguishable from zero for STEM, Business, and Humanities. These correlations remain remarkably robust when we control for school characteristics (Table 8, panel (b)).

Invention Next, we test whether students at schools that offer courses with a lower gap produce more inventions later in their lives, in the form of patents. We do so by using the total number of patents received after graduation by students at each school as the dependent variable in equation (10). Unconditionally, a one-standard deviation decline in the gap is associated with 27 additional patents at a given school, or 20 percent compared with an average of 130 patents per school (Table 8, panel (a), column 7, p-value equal to 0.11). The relationship remains robust and even becomes more precise controlling for school observables (Table 8, column 7, panel (b)). These results indicate that, although students in schools with a lower gap are not more likely to complete a STEM doctorate (as shown in column 2), they produce significantly more innovation in the form of patents.

6.2 Labor Market Outcomes

Graduation rates Next, we examine the relationship between the education-innovation gap and labor market outcomes. We begin with graduation rates, an outcome that immediately precedes entry in the labor market. Graduation is in part also a function of choices made by the students, which could be impacted by the content of the courses they took.

Column 1 of Table 9 shows the relationship between the gap (measured in standard deviations) and graduation rates. An estimate of -0.05 in panel (a), significant at 1 percent, indicates that

a one-standard deviation decline in the gap (or a 10 percent change in the content of a syllabus) is associated with a 5 percentage point higher graduation rate. Compared with an average of 57 percent, this corresponds to a 9 percent increase in graduation rates.

The estimate of δ declines as we control for observable school characteristics, indicating that part of this correlation can be explained by other differences across schools. However, it remains negative and significant at -0.007, indicating that that a one-standard deviation reduction in the gap is associated to a 1.3 percent increase in graduation rates (panel (b), column 1, significant at 5 percent).

Table 8: The Education-Innovation Gap and Innovation Measures: Share of Undergraduate Students Who Obtain a Doctoral Degree and Total Number of Patents

	Share of students who obtain a doctoral degree, by field						Nr
	All	STEM	Health	Business	Soc. Sci.	Humanities	Patents
Panel (a): no controls	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Gap (sd)	-0.0044**	-0.0010	-0.0074**	-0.0003	-0.0124**	0.0054	-26.8006
	(0.0018)	(0.0022)	(0.0033)	(0.0005)	(0.0051)	(0.0076)	(16.6213)
Mean dep. var.	0.0265	0.0452	0.0249	0.0021	0.0335	0.0228	129.7813
N	65755	14714	9218	12698	14657	14468	1715
Panel (b): w/ controls	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Gap (sd)	-0.0046**	0.0002	-0.0066**	-0.0003	-0.0101**	0.0061	-21.8882*
	(0.0021)	(0.0019)	(0.0030)	(0.0005)	(0.0046)	(0.0074)	(12.5836)
Mean dep. var.	0.0269	0.0461	0.0257	0.0021	0.0342	0.0228	131.0248
N	47723	10673	6656	9243	10645	10506	1610

Note: OLS estimates of the coefficient δ in equation (10). In columns 1-6, the variable *Gap (sd)* is a school-by-macro field-level education-innovation gap (estimated as $\theta_{s(i)}$ in equation (9), separately for each macro-field), standardized to have mean zero and variance one. In column 7, *Gap (sd)* is estimated at the school level pooling data from all fields. In columns 1-6, the dependent variable is the share of undergraduate students at each institution-field who eventually complete a doctoral degree (from the NSF Survey of Doctorate Recipients, year 2000); in column 7, it is the total number of patents filed by students at each school, from Chetty et al. (2020). All columns in panel (b) control for sector (private or public), selectivity tiers, and an interaction between selectivity tiers and an indicator for R1 institutions according to the Carnegie classification; student-to-faculty ratio and the share of ladder faculty; total expenditure, research expenditure, instructional expenditure, and salary instructional expenditure per student; the share of undergraduate and graduate enrollment and the share of white and minority students; an indicator for institutions with admission share equal to 100, median SAT and ACT scores of admitted students in 2006, and indicators for schools not using either SAT or ACT in admission; the share of students with majors in Arts and Humanities, Business, Health, Public and Social Service, Social Sciences, STEM, and multi-disciplinary fields; and the natural logarithm of parental income. Columns 1-6 control for year effects. Column 1 also controls for macro field fixed effects. Bootstrapped standard errors in parentheses are clustered at the school level. $^{*} \leq 0.1$, $^{**} \leq 0.05$, $^{***} \leq 0.01$.

Students' income and intergenerational mobility We next examine the relationship between the education-innovation gap and students' economic success after they leave college. In columns 2-8 of Table 9 we estimate the relationship between the gap and various income statistics.

Column 2 shows estimates of the correlation between the gap and the natural logarithm of median student earnings 10 years after graduation, from the College Scorecard. Controlling for the full set of observables, a one-standard deviation lower gap is associated with a 0.9 percent higher earnings (column 2, panel (b), significant at 5 percent). The College Scorecard also reports mean earnings, overall and for students with parental incomes in the bottom tercile of the distribution. Overall, the correlation between the gap and mean earnings equals 0.7 percent (column 3, significant at 10 percent). For students with parental income in the bottom tercile, it is slightly larger at 0.8 percent (column 4, panel (b), significant at 10 percent).

Information on mean student earnings at the school level is also reported by Chetty et al. (2020), who calculate it using tax records for two cohorts of students. Unconditional estimates (which omit year effects due to the cross-sectional structure of the data) indicate that a one-standard deviation in the gap is associated with a 7 percent increase in students' mean earnings (panel (a), column 5, significant at 1 percent). This estimate is smaller, at 1.4 percent, when controlling for institutional characteristics (panel (b), column 5, significant at 1 percent).

In columns 6 through 8 of Table 9 we investigate the relationship between the gap and the probability that students' earnings reach the top echelons of the distribution. Estimates with the full set of controls indicate that a one-standard deviation decline in the gap is associated with a 0.84 percentage point increase in the probability of reaching the top 20 percent (2.2 percent, panel (b), column 6, significant at 1 percent), a 0.53 percentage point increase in the probability of reaching the top 10 percent (2.5 percent, column 7, significant at 5 percent), and a 0.31 percentage point increase in the probability of reaching the top 5 percent (2.7 percent, column 8, significant at 10 percent). Taken together, these results indicate a positive relationship between the school-level education-innovation gap and students' average and top earnings.

Lastly, in column 9 of Table 9 we study the association between the gap and intergenerational mobility. The unconditional correlation between these two variables is equal to -0.0293, indicating that a one-standard deviation lower gap is associated with a 2.9 percentage point increase in intergenerational mobility (9.9 percent, panel (a), column 9, significant at 1 percent). This correlation becomes smaller at -0.0047 when we control for school observables (column 9, panel (b), significant at 10 percent).

Table 9: The Education-Innovation Gap and Student Outcomes

		Earnings (College Scorecard)			Earnings (Chetty et al., 2020)				
	Grad rate	Median	Mean		Mean	P(earnings in top...)			P(top20%
			Overall	$P_y \leq 33$ pctile		top 20%	top 10%	top 5%	|$P_y$bottom 20%)
Panel (a): no controls	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Gap (sd)	-0.0513***	-0.0512***	-0.0555***	-0.0645***	-0.0722***	-0.0333***	-0.0265***	-0.0187***	-0.0293***
	(0.0068)	(0.0088)	(0.0104)	(0.0106)	(0.0124)	(0.0057)	(0.0046)	(0.0036)	(0.0053)
Mean dep. var.	0.5692					0.3694	0.2082	0.1143	0.2945
N	15683	3793	3793	3566	763	763	763	763	763
# schools	761	760	760	734					
Panel (b): w/ controls	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Gap (sd)	-0.0073**	-0.0090**	-0.0067	-0.0083*	-0.0137***	-0.0084***	-0.0053**	-0.0031**	-0.0047*
	(0.0030)	(0.0045)	(0.0041)	(0.0050)	(0.0048)	(0.0025)	(0.0021)	(0.0015)	(0.0028)
Mean dep. var.	0.5816	10.7096	10.8281	10.7605		0.3710	0.2100	0.1159	0.2957
N	11471	1996	1996	1843	718	718	718	718	718
# schools	733	727	727	701					

Note: OLS estimates of the coefficient δ in equation (10). The variable *Gap (sd)* is the school-level education-innovation gap (estimated as $\theta_{s(i)}$ in equation (9)), standardized to have mean zero and variance one. The dependent variables are graduation rates (from IPEDS, years 1998-2018, column 1); the log of median student earnings 10 years after graduation, from the College Scorecard (column 2); the log of mean earnings 10 years after graduation, also from the College Scorecard, for all students (column 3) and for students with parental income in the bottom tercile (column 4); the log of mean earnings for students who graduated between 2002 and 2004 (from Chetty et al. (2020), column 5); the probability that students have earnings in the top 20, 10, and 5 percent of the national age-specific income distribution (from Chetty et al. (2020), columns 6-8); and the probability that students with parental income in the bottom quintile reach the top quintile during adulthood (column 9). Columns 1-4 in panels (a) and (b) control for year effects. All columns in panel (b) control for sector (private or public), selectivity tiers, and an interaction between selectivity tiers and an indicator for R1 institutions according to the Carnegie classification; student-to-faculty ratio and the share of ladder faculty; total expenditure, research expenditure, instructional expenditure, and salary instructional expenditure per student; the share of undergraduate and graduate enrollment and the share of white and minority students; an indicator for institutions with admission share equal to 100, median SAT and ACT scores of admitted students in 2006, and indicators for schools not using either SAT or ACT in admission; the share of students with majors in Arts and Humanities, Business, Health, Public and Social Service, Social Sciences, STEM, and multi-disciplinary fields; and the natural logarithm of parental income. Bootstrapped standard errors in parentheses are clustered at the school level. $^{*} \leq 0.1$, $^{**} \leq 0.05$, $^{***} \leq 0.01$.

Summary Our findings indicate that students at schools offering courses with a lower education-innovation gap at the school level produce more innovation and have better academic and economic student outcomes. The lack of experimental variation in the gap across schools prevents us from estimating a causal relationship. Yet, our results are robust to the inclusion of controls for a large set of school and student characteristics, indicating that these correlations are unlikely to be driven by cross-school differences in spending, selectivity, major composition, or parental background. These findings point to the potentially important role of up-to-date instruction in determining future innovation levels and the outcomes of students as they exit college and enter the labor market.

7 Alternative Measures of Course Content

In this section, we explore alternative measures to describe a course's content and examine the sensitivity of our results to the use of these measures.

7.1 Soft Skills in Course Content

The education-innovation gap focuses on the *academic* content of a course. However, academic content might not be the only thing that matters for students. Recent works have highlighted the importance of *skills* for students' later life outcomes. In particular, soft skills—defined as non-cognitive abilities that define how a person interacts with their colleagues and peers—are increasingly in high demand in the labor market and associated with better outcomes (Deming, 2017).

The richness of the syllabi data allows us to examine differences across syllabi in the extent to which they cover soft skills. We do so by focusing on each course's evaluation scheme. Specifically, we consider a course to be more soft-skills intensive if the assignments portion of the syllabus has a higher share of words that refer to soft-skills training, including "group", "team", "presentation", "essay", "proposal", "report", "drafting", and "survey", relative to hard-skill assignments such as "homework", "exam", and "quiz". In the average syllabus, 33 percent of the words in the assignment portion of the syllabus refer to soft skills (Table 1, panel (a)).

This measure of soft-skills intensity is negatively correlated with the education-innovation gap (with a correlation of -0.14, Figure 5, panel (a)). Soft-skills intensity varies across schools in a similar pattern as the education-innovation gap: It is higher in schools with higher expenditure on instruction and salaries, in more selective schools, and in those with a higher median parental income and with a lower share of minority students (Figure AIX, panel (a)). Soft-skills intensity is higher for courses taught by more research-productive instructors (Figure AX, panel (a)).

Soft-skills intensity is also positively related to student outcomes. Controlling for the full set of school observables used in Tables 8 and 9, a one-standard deviation higher soft-skills intensity of a school's courses is associated with a 1.2 percentage point higher graduation rate (2 percent, Table AII, panel (h), column 1, significant at 1 percent), 1.7 percent higher mean earnings (column 2, significant at 1 percent), and a 1.2 percent higher chance of reaching the top earnings quintile for students with parental income in the bottom quintile (18 percent, column 9, significant at 1 percent).

Taken together, these findings indicate that differences across and within schools in course content are not limited to the extent to which content is updated with respect to the knowledge frontier, but also extend to the skills that are trained. We interpret this as additional evidence for the importance of accounting for differences in content across courses when characterizing the heterogeneity of educational experiences for students at different schools.

7.2 Alternative Measures of The Education-Innovation Gap

In spite of its desirable properties, our measure of the education-innovation gap has some limitations. For example, it penalizes courses for including old content. This implies that, among two courses that cover the exact same new content, the one that *also* covers older knowledge will have a higher gap. In addition, our measure is designed to capture the "average" knowledge vintage a course's content resembles to; it is thus unable to identify courses with extremely novel content among those with the same gap. Lastly, the gap relies on academic publications to capture knowledge frontier. In some fields, such as STEM, frontier knowledge could also be disclosed in other forms, such as patents for new technologies.

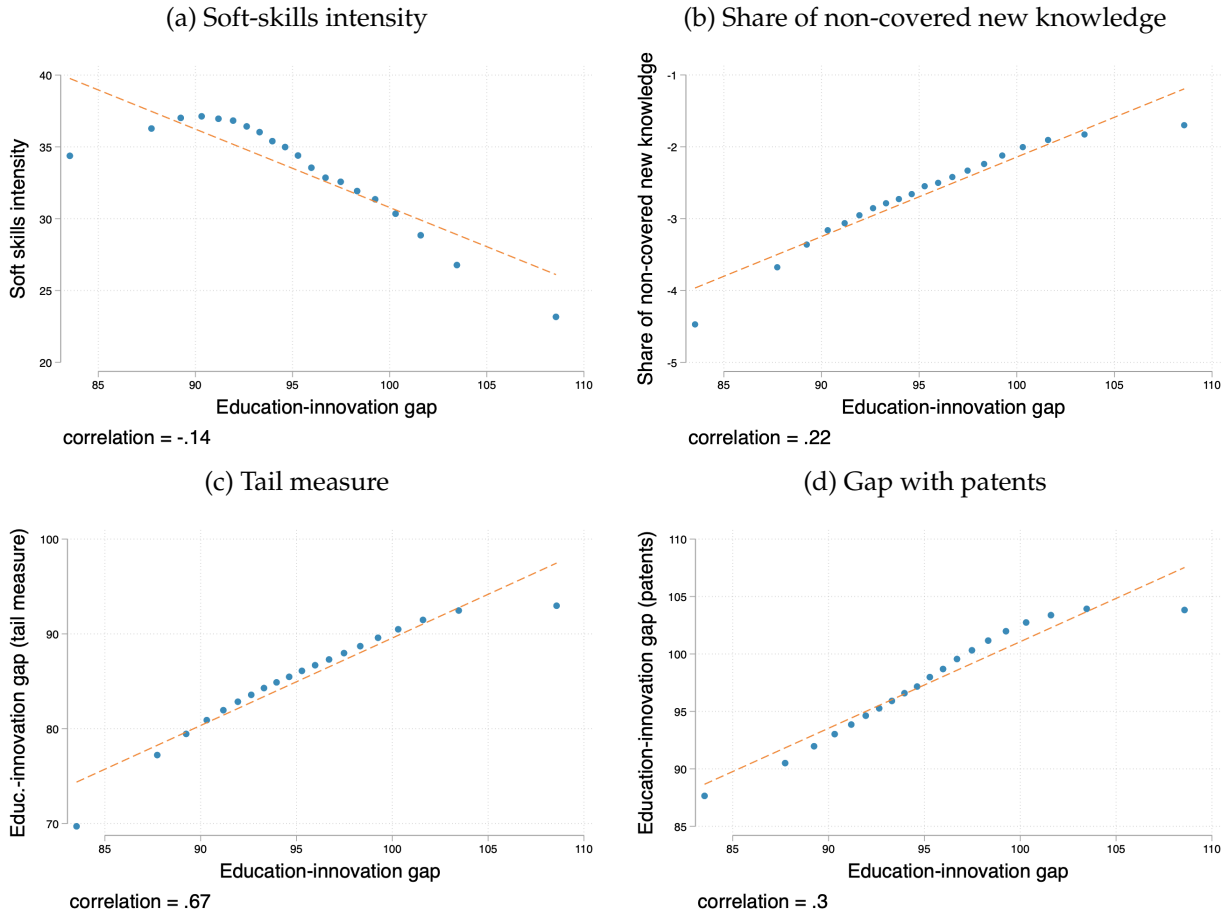
In this subsection, we probe the robustness of our results using alternative measures of a course's content, designed to address these issues.

Presence of old vs new knowledge The education-innovation gap measures the presence of new content relative to old content. Consider two syllabi that cover the *same amount* of frontier research; the first syllabus only contains this new content, while the second one also contains some old content. Our measure would assign a larger gap to the second syllabus compared to the first due to the presence of old content, even though both do an equal job in covering frontier knowledge.

To address this limitation, we construct an alternative metric: the share of new knowledge covered by a course, defined as the ratio between the number of "new words" in each syllabus and the number of all new words. New words are defined as knowledge words that are (a) in the top 5 percent of the word frequency among articles published between $t-3$ and $t-1$ or (b) used in articles published between $t-3$ and $t-1$ but not in those published between $t-15$ and $t-13$. Intuitively,

this measure captures the portion of all new knowledge covered by the course, regardless of the presence of old knowledge. For clarity, we show our results using one minus the share of covered new knowledge, which we refer to as the *share of non-covered new knowledge*. This allows us to work with a metric that, like the education-innovation gap, is larger when the content of a course is more distant from frontier knowledge. The correlation between the share of non-covered new knowledge and the education-innovation gap is 0.22 (Figure 5, panel (b)), and our main results hold if we use

Figure 5: The Education-Innovation Gap and Alternative Measures of Novelty: Binned Scatterplots



Notes: Binned scatterplots of the education-innovation gap and four alternative measures of novelty of each syllabus: a measure of soft-skills intensity, defined as the share of words in the assignment portion of a syllabus that refer to soft skills (panel (a)); the share of non-covered new knowledge, defined as one minus the share of all new words contained by each syllabus (where new words are knowledge words that are (i) in the top 5 percent of the word frequency among articles published between $t-3$ and $t-1$ or (ii) used in articles published between $t-3$ and $t-1$ but not in those published between $t-15$ and $t-13$ (panel (b)); a "tail measure," calculated for each syllabus by (i) randomly selecting 100 subsamples containing 20 percent of the syllabus's words, (ii) calculating the gap for each subsample, and (iii) selecting the 5th percentile of the corresponding distribution (panel (c)); and the education-innovation gap calculated using the text of all patents as a benchmark for frontier knowledge, instead of academic articles (panel (d)).

this alternative metric to capture the novelty of a syllabus's content (see panel (b) of Figure AIX for the correlation with school-level characteristics, panel (b) of Figure AX for the correlation with instructors' research productivity, and panels (a) and (b) of Table AII for the relationship with student outcomes).

Right tail of academic novelty The education-innovation gap captures the "average" novelty of a syllabus. It is possible for two syllabi to have the same gap when one of them only covers content from five years prior, while the other covers mostly material from fifteen years prior but also a small amount of material from the previous year. To construct a measure that captures the presence of "extremely" new material in a syllabus, we proceed as follows. First, we draw 100 "sub-syllabi" from each syllabus, defined as random subsets of 20 percent of the syllabus's words, and calculate the corresponding education-innovation gap. The gaps of these 100 sub-syllabi form a distribution; we use the 5th percentile of this distribution for each syllabus as a tail measure of new content.[28] We refer to this as a "tail measure" of novelty.

The tail measure is positively correlated with the education-innovation gap, with a correlation of 0.67 (Figure 5, panel (c)). All our results hold when we use the tail measure as a metric for syllabus novelty (see panel (c) of Figure AIX for the correlation with school-level characteristics, panel (c) of Figure AX for the correlation with instructors' research productivity, and panels (c) and (d) of Table AII for the relationship with student outcomes).

Gap with patents The education-innovation gap is defined using new academic publications as the frontier of knowledge. For STEM fields, knowledge advancements are also documented in the form of patents. To incorporate this information in our analysis, we construct a version of the education-innovation gap for STEM courses that uses patents in lieu of academic publications. This measure is positively correlated with the standard education-innovation gap (Figure 5, panel (d)), and our main results hold when we use the patent-based gap (see panel (d) of Figure AIX for the correlation with school-level characteristics, panel (d) of Figure AX for the correlation with instructors' research productivity, and panels (e) and (f) of Table AII for the relationship with student outcomes).

Taken together, these results indicate that our main conclusions regarding the content of higher-education courses across schools, and the way the content relates to instructors' characteristics and student outcomes, are not dependent on the specific way in which we measure up-to-date content.

[28] Our results are robust to the use of the top 10 and one percent.

8 Conclusion

This paper uses the text of HE course syllabi to quantify the distance between the content of each course and frontier knowledge. Our approach centers around a new measure, the "education-innovation gap," defined as the textual similarity between course syllabi and knowledge from older vintages, relative to newer ones. We construct this measure by applying NLP techniques to the full text of 1.7 million syllabi and 20 million academic publications. Our empirical approach combines a large-scale novel data source with textual analysis to shed new light on some key aspects of higher education.

Using our measure, we document a set of new findings about the dissemination of frontier knowledge across HE programs. Across and within schools, significant differences exist in the extent to which frontier knowledge is taught to students. Instructors play the largest role in shaping the content of the courses they teach. Courses taught by more research-active instructors have lower gaps. More selective schools and those with more resources offer courses with a smaller gap. Since these schools enroll a lower portion of socio-economically disadvantaged students, access to updated knowledge is highly unequal across students from different backgrounds. The education-innovation gap is strongly correlated with students' innovation and labor-market outcomes. In schools offering courses with lower gaps, students are more likely to graduate, earn a PhD, and produce patents. They also earn more once they enter the labor market. Taken together, our findings indicate that the education-innovation gap can be an important metric for quantifying how frontier knowledge is produced and disseminated, and they could help shed new light on the way in which schools and instructors impact students' lives.

For future research, a careful analysis of the causal impacts of a low-gap education on students' later life outcomes represents an important and fruitful avenue. The use of novel alternative data, such as the text of various documents, could open the opportunity for researchers to investigate questions related to higher education which would otherwise be difficult to study.

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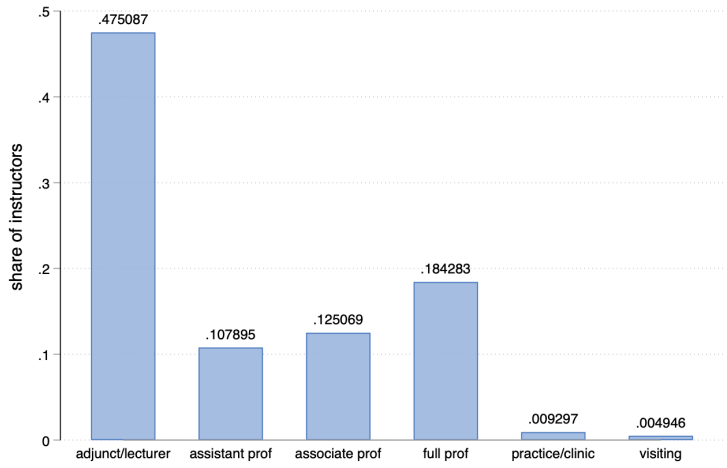
Appendix

For online publication only

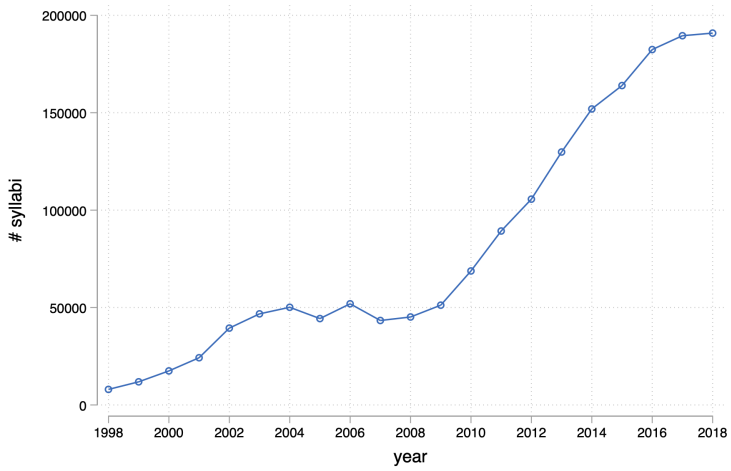
Appendix A Additional Tables and Figures

Figure AI: Distribution of Instructor Job Titles



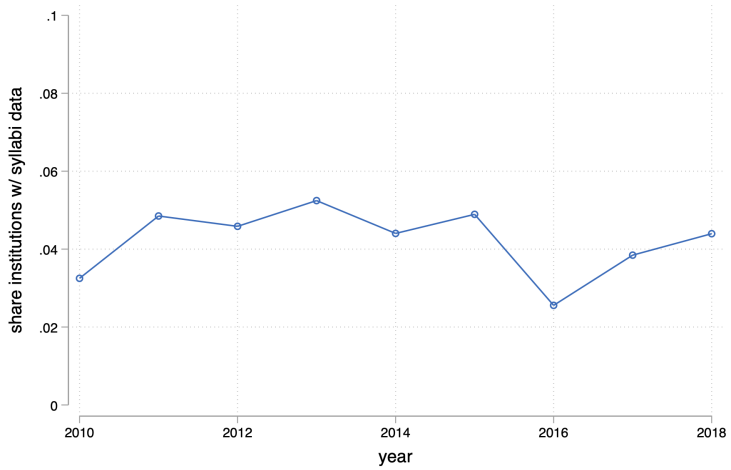
Note: Share of syllabi instructors by job title. The sample is restricted to 32,090 instructors in public institutions for whom title information is available.

Figure AII: Number of Syllabi in the Sample, By Year



Note: Number of syllabi included in final sample, by year.

Figure AIII: Share of Catalog Courses in the Syllabi Sample

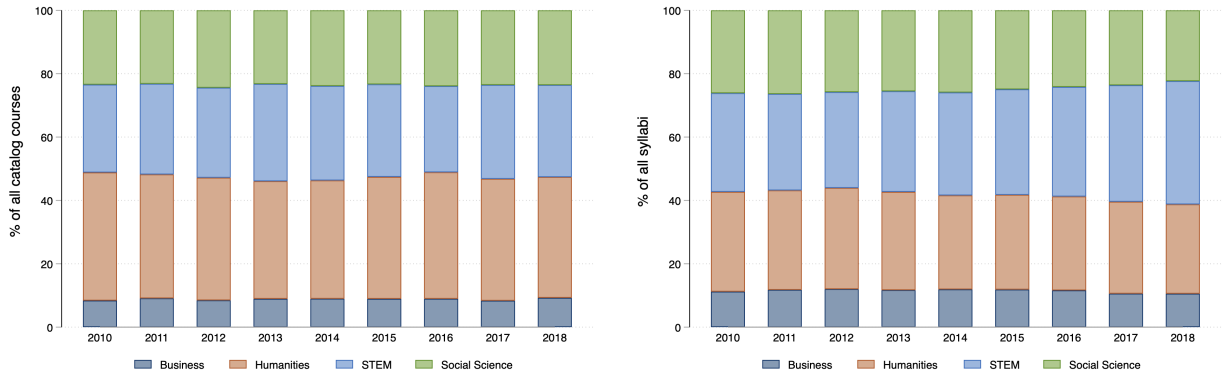


Note: Share of courses from full course catalogs whose syllabi are included in the syllabi sample.

Figure AIV: Macro-Field Coverage, Course Catalogs, and Syllabi Sample

(a) Course Catalog

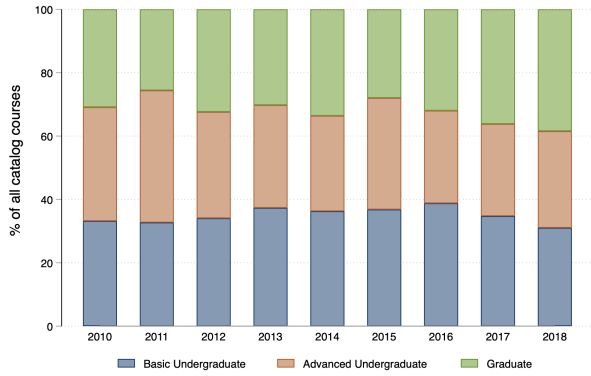
(b) Syllabi Sample



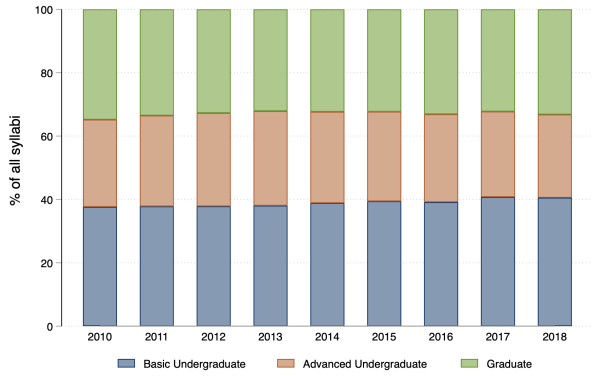
Note: Composition across macro fields, for all courses included in a sample of school catalogs (panel (a)) and for courses included in the syllabi sample (panel (b)).

Figure AV: Course Level Coverage, Course Catalogs, and Syllabi Sample

(a) Course Catalog

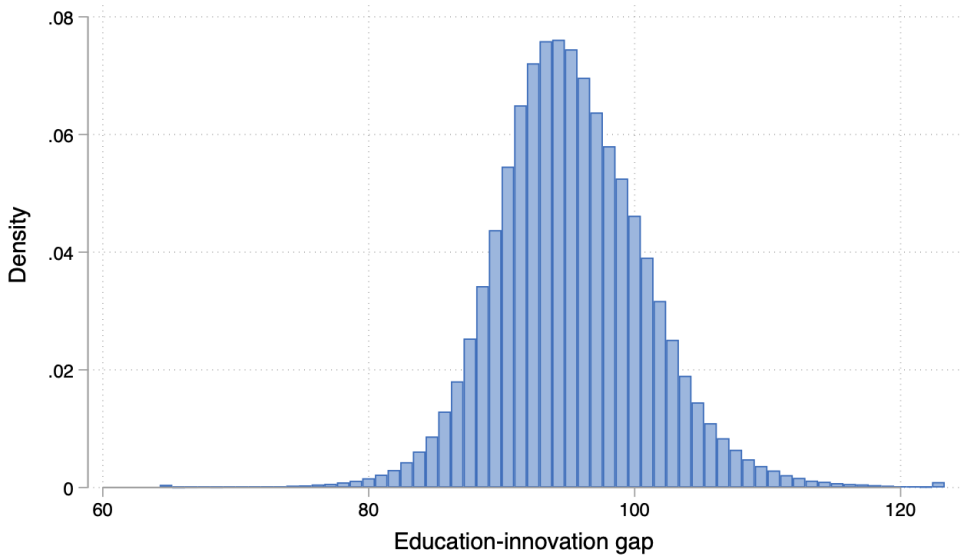


(b) Syllabi Sample



Note: Composition across course levels, for all courses included in a sample of school catalogs (panel (a)) and for courses included in the syllabi sample (panel (b)).

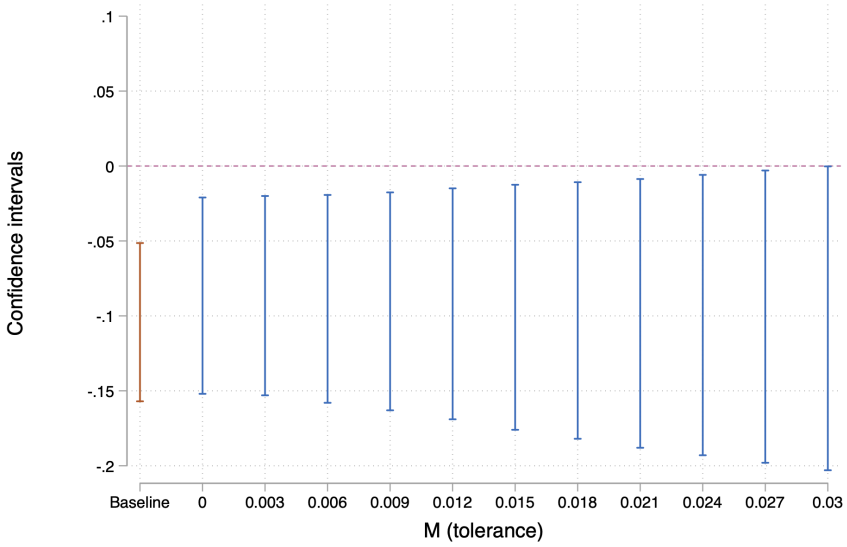
Figure AVI: Education-Innovation Gap: Distribution



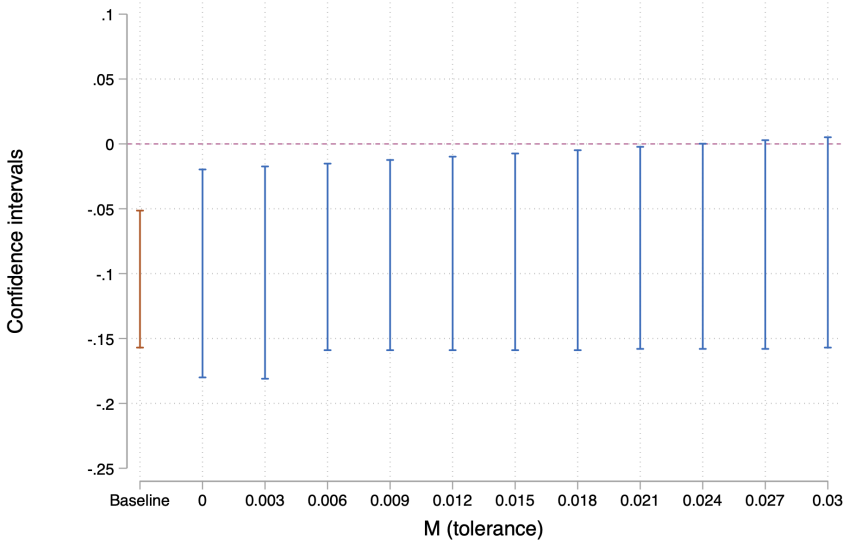
Notes: Histogram of the education-innovation gap.

Figure AVII: Event Study of The Gap Around an Instructor Change: Rambachan and Roth (2019) Test for Parallel Trends

(a) Without monotonicity ($\Delta^{SD}(M)$)



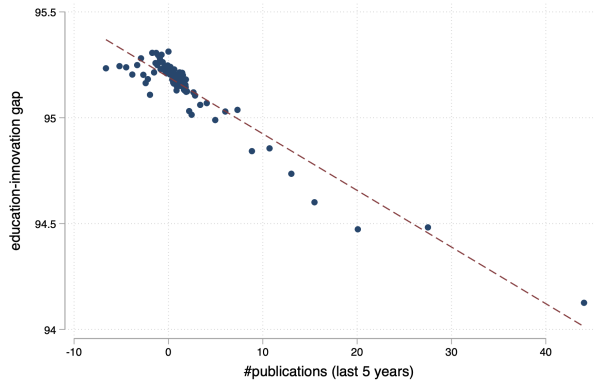
(b) With monotonicity ($\Delta^{SDD}(M)$)



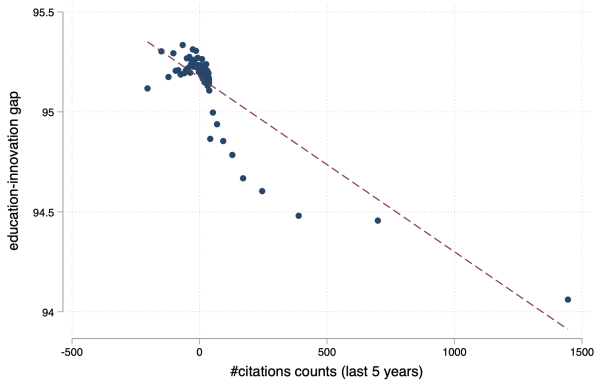
Notes: Sensitivity plots of the confidence intervals of δ_0 in equation (5), constructed following the approach of Rambachan and Roth (2019). The approach tests for violations of the parallel trends assumption and studies their impacts on the point estimates and confidence intervals of interest. Specifically, their proposed test consists in (a) constructing a set Δ of possible deviations from the parallel trends assumption, and (b) constructing the confidence intervals associated with these deviations. In panel (a) we adopt Rambachan and Roth (2019)'s main robustness test, which involves constructing confidence intervals that allow for deviations from linearity up to a tolerance parameter M: defining δ as the trend, $\Delta^{SD}(M) := \{\delta : |(\delta_{t+1} - \delta_t) - (\delta_t - \delta_{t-1})| \leq M, \forall t\}$. In panel (b) we also show confidence intervals for deviations in $\Delta^{SDD}(M)$, analogous to $\Delta^{SD}(M)$ but with the additional assumption that the pre-trend be decreasing. In both panels, the orange series represents baseline OLS confidence intervals; the blue series show confidence intervals as M grows. We allow M to range from zero (linear pre-trends) to the standard error of the coefficient of interest.

Figure AVIII: Instructors' Research Productivity, Funding, and Fit with the Course and the Education-Innovation Gap

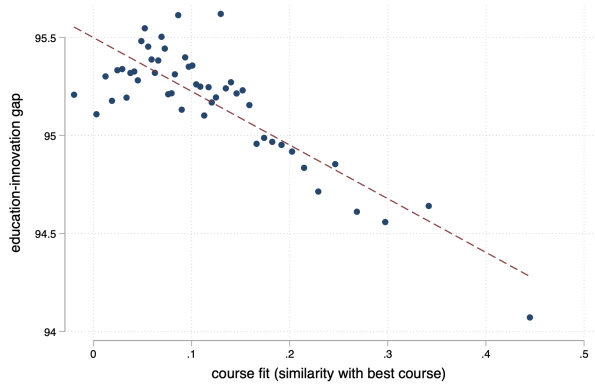
(a) Publications, Last 5 Years



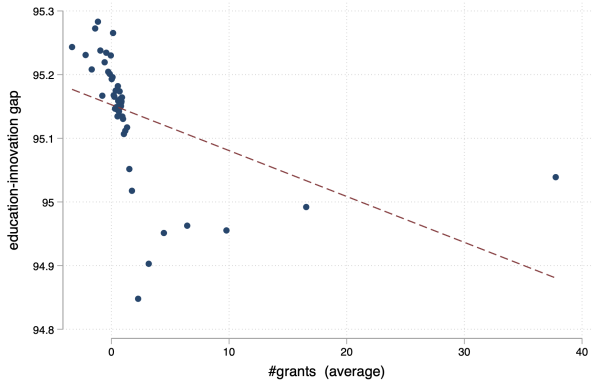
(b) Citations, Last 5 Years



(c) Fit Between Course Topic and Instructor's Research

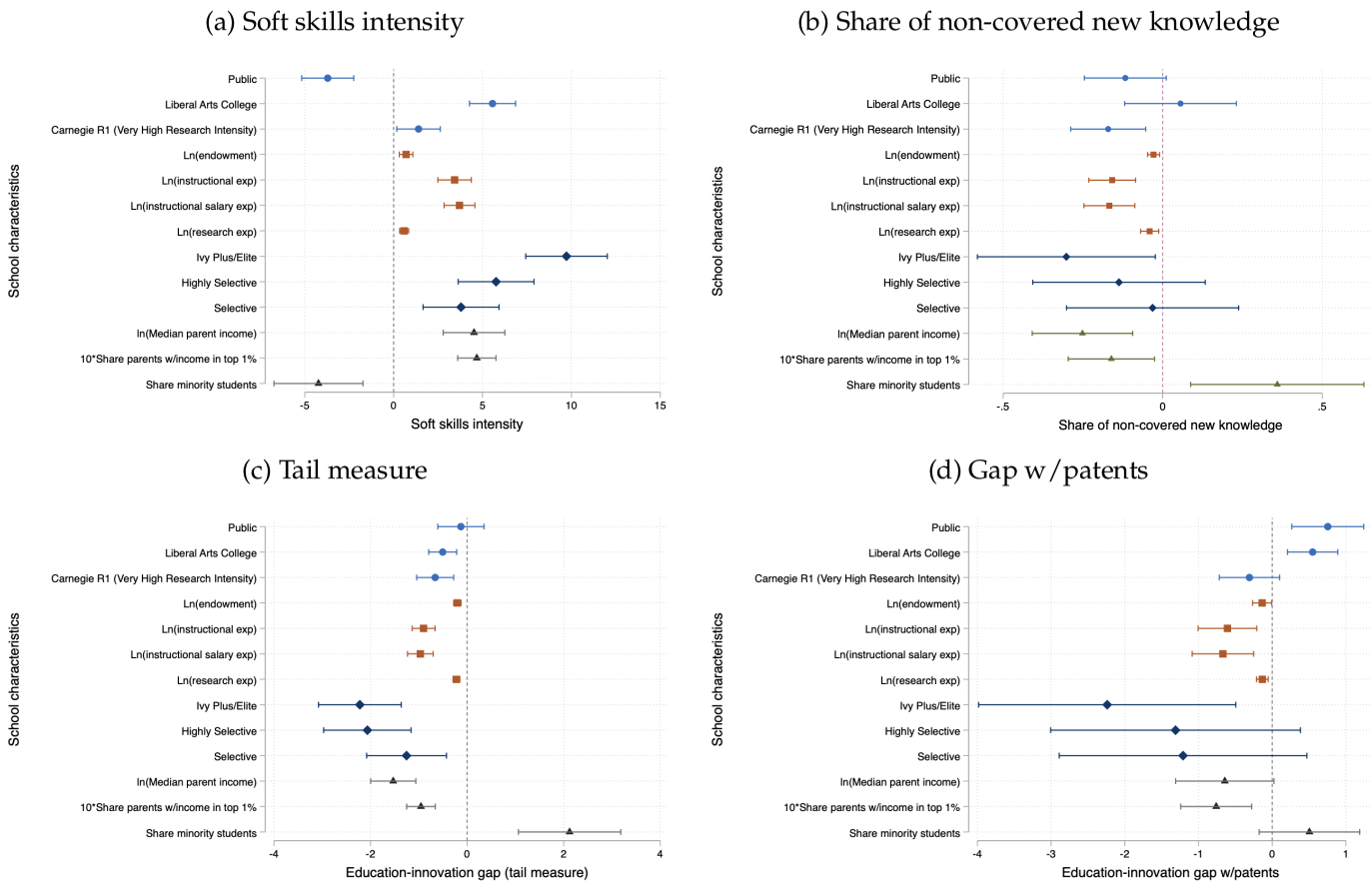


(d) Total #Grants



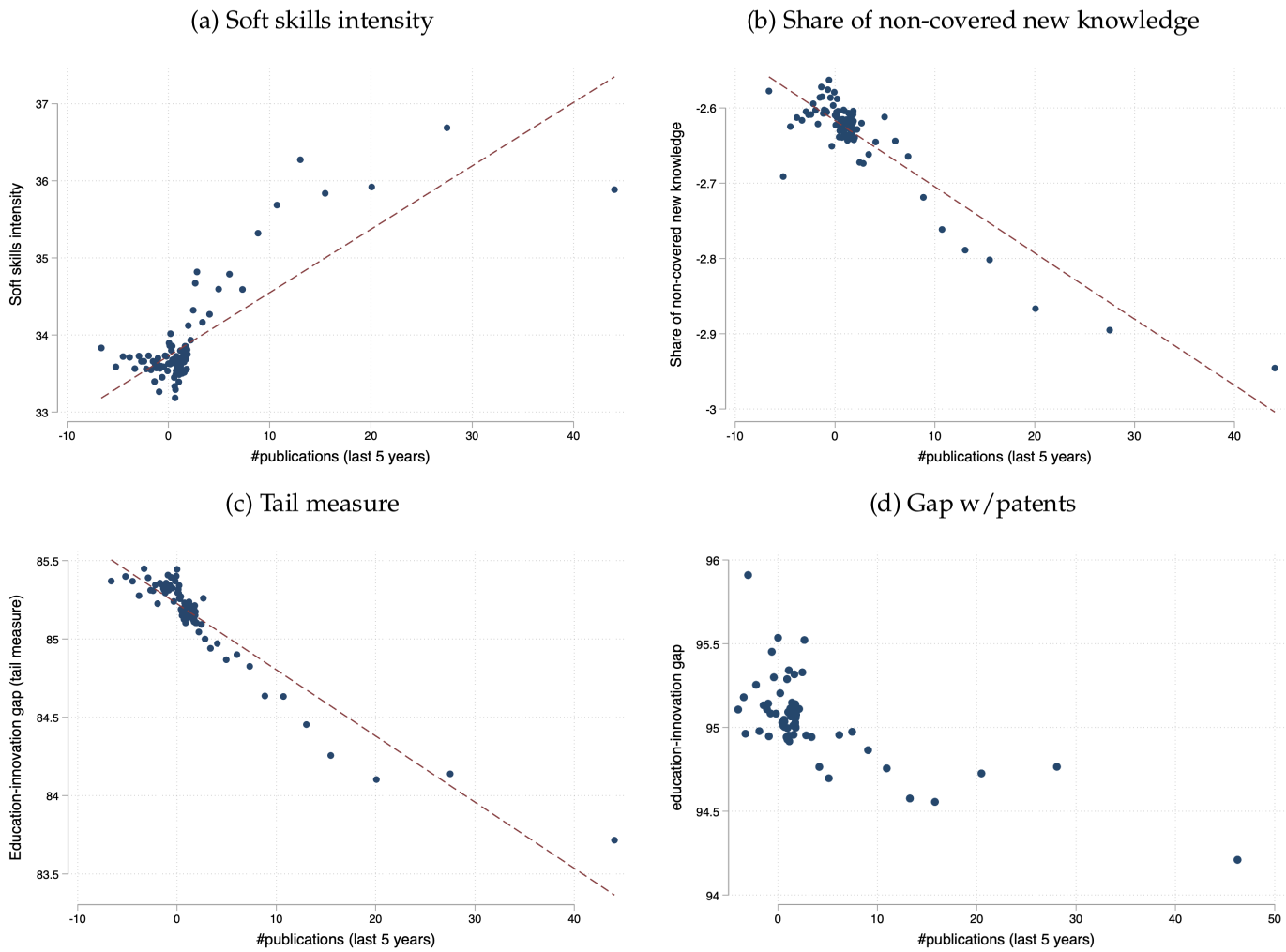
Notes: Binned scatterplots of the gap (vertical axis) and measures of research productivity, funding, and fit between the course topic and the research of the instructor. These measures are the number of publications in the last five years (panel a); the number of citations in the last five years (panel b); the fit between the instructor's research agenda and the course content, calculated as the cosine similarity between the instructor's publications and the syllabus of the course with the lowest gap among all courses on a given topic (for example, Advanced Microeconomics) across schools in each year (panel c); and the total number of NSF and NIH grants ever received (panel d). All graphs control for field fixed effects.

Figure AIX: School Characteristics and Alternative Measures of Course Novelty



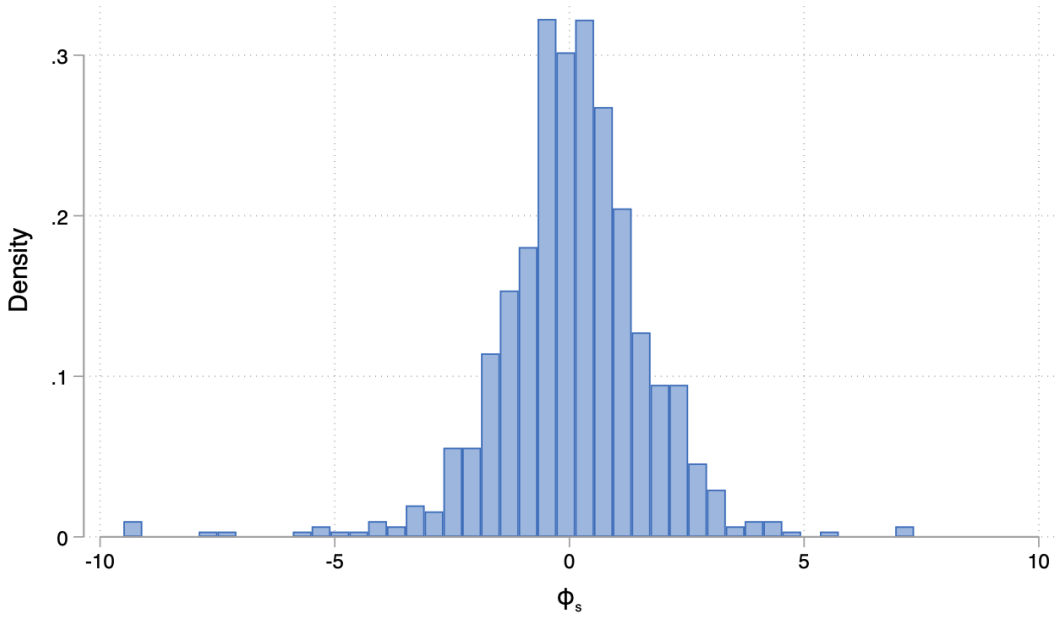
Notes: Point estimates and 95-percent confidence intervals of coefficient β in equation (7), using alternative measures of course novelty: a measure of soft skills intensity, defined as the share of words in the assignment portion of a syllabus that refer to soft skills (panel a); a measure of non-covered new knowledge, defined as one minus the share of all new words contained by each syllabus (where new words are knowledge words that are (a) in the top five percent of the word frequency among articles published between $t-3$ and $t-1$ or (b) used in articles published between $t-3$ and $t-1$ but not in those published between $t-15$ and $t-13$, panel b); a "tail measure," calculated for each syllabus by (a) randomly selecting 100 subsamples containing 20 percent of the syllabus's words, (b) calculating the gap for each subsample, and (c) selecting the 5th percentile of the corresponding distribution (panel c); and the education-innovation gap calculated using the text of all patents as a benchmark, instead of academic articles (panel d). Each coefficient is estimated from a separate regression, with the exception of selectivity tiers (Ivy Plus/Elite, Highly Selective, Selective) which are jointly estimated. Endowment, expenditure, and share minority information refers to the year 2018 and is taken from IPEDS. Estimates are obtained by pooling syllabi data for the years 1998 to 2018. Standard errors are clustered at the school level.

Figure AX: Instructor Productivity (# Publications) and Alternative Measures of Course Novelty



Notes: Binned scatterplots of a measure of instructor productivity (the number of publications in the prior five years) and four alternative measures of course novelty: a measure of soft skills intensity, defined as the share of words in the assignment portion of a syllabus that refer to soft skills (panel a); a measure of non-covered new knowledge, defined as one minus the share of all new words contained by each syllabus (where new words are knowledge words that are (a) in the top five percent of the word frequency among articles published between $t-3$ and $t-1$ or (b) used in articles published between $t-3$ and $t-1$ but not in those published between $t-15$ and $t-13$, panel b); a "tail measure," calculated for each syllabus by (a) randomly selecting 100 subsamples containing 20 percent of the syllabus's words, (b) calculating the gap for each subsample, and (c) selecting the 5th percentile of the corresponding distribution (panel c); and the education-innovation gap calculated using the text of all patents as a benchmark instead of academic articles (panel d). Relationships are plotted controlling for field effects.

Figure AXI: Distribution of School-Level Gap



Note: Distribution of the school-level component of the gap, denoted by $\theta_{s(i)}$ in equation (9).

Table AI: Characteristics of Schools Included and Not Included in the Random Catalog Sample

Schools:	In Sample N = 158	Out of Sample N = 1,956	t-stat	p-values
ln Expenditure on instruction (2013)	8.693	8.601	-1.725	0.085
ln Endowment per capita (2000)	6.857	6.483	-1.304	0.193
ln Sticker price (2013)	9.197	9.153	-0.520	0.603
ln Avg faculty salary (2013)	8.890	8.850	-1.897	0.058
ln Enrollment (2013)	8.708	8.634	-0.685	0.494
Share Black students (2000)	0.109	0.112	0.153	0.879
Share Hispanic students (2000)	0.063	0.065	0.183	0.855
Share alien students (2000)	0.025	0.022	-1.030	0.303
Share grad in Arts & Humanities (2000)	7.581	7.958	0.382	0.703
Share grad in STEM (2000)	14.861	14.050	-0.772	0.440
Share grad in Social Sciences (2000)	21.068	19.202	-1.342	0.180

Note: Balance test of universities included and not included in the catalog sample.

Table AII: Alternative Measures of Novelty and Student Outcomes

		Income (College Scorecard)			Income (Chetty et al., 2020)				
	Grad rate	Mean	$P_y \leq 33$ pctile	Median	Mean	P(top 20%)	P(top 10%)	P(top 5%)	P(top 20%| $P_y \leq 20$ pctile)
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Panel (a): Share of non-covered new knowledge, no controls									
Gap (sd)	-0.0424***	-0.0594***	-0.0678***	-0.0499***	-0.0755***	-0.0338***	-0.0303***	-0.0226***	-0.0310***
	(0.0078)	(0.0108)	(0.0113)	(0.0101)	(0.0131)	(0.0067)	(0.0052)	(0.0037)	(0.0062)
Mean dep. var.	0.5692					0.3694	0.2082	0.1143	0.2945
N	15683	3793	3566	3793	763	763	763	763	763
# schools	761	760	734	760					
Panel (b): Share of non-covered new knowledge, with controls									
Gap (sd)	-0.0040	-0.0034	-0.0027	-0.0018	-0.0109**	-0.0048	-0.0041*	-0.0032*	-0.0004
	(0.0033)	(0.0045)	(0.0058)	(0.0051)	(0.0052)	(0.0031)	(0.0023)	(0.0017)	(0.0033)
Mean dep. var.	0.5816	10.8281	10.7605	10.7096		0.3710	0.2100	0.1159	0.2957
N	11471	1996	1843	1996	718	718	718	718	718
# schools	733	727	701	727					
Panel (c): Tail measure, no controls									
Gap (sd)	-0.0503***	-0.0643***	-0.0714***	-0.0580***	-0.0882***	-0.0393***	-0.0336***	-0.0245***	-0.0385***
	(0.0090)	(0.0105)	(0.0119)	(0.0101)	(0.0125)	(0.0056)	(0.0050)	(0.0036)	(0.0056)
Mean dep. var.	0.5692					0.3694	0.2082	0.1143	0.2945
N	15683	3793	3566	3793	763	763	763	763	763
# schools	761	760	734	760					
Panel (d): Tail measure, with controls									
Gap (sd)	-0.0023	-0.0123***	-0.0166***	-0.0137***	-0.0194***	-0.0113***	-0.0089***	-0.0057***	-0.0121***
	(0.0034)	(0.0043)	(0.0047)	(0.0049)	(0.0048)	(0.0027)	(0.0023)	(0.0016)	(0.0030)
Mean dep. var.	0.5816	10.8281	10.7605	10.7096		0.3710	0.2100	0.1159	0.2957
N	11471	1996	1843	1996	718	718	718	718	718
# schools	733	727	701	727					
Panel (e): Gap w/patents, no controls									
Gap (sd)	-0.0232***	-0.0323***	-0.0434***	-0.0282***	-0.0404***	-0.0144**	-0.0140**	-0.0120***	-0.0146**
	(0.0068)	(0.0116)	(0.0122)	(0.0099)	(0.0138)	(0.0067)	(0.0059)	(0.0042)	(0.0064)
Mean dep. var.	0.5692					0.3694	0.2082	0.1143	0.2945
N	15683	3793	3566	3793	763	763	763	763	763

(Continued)

Table AII. Continued

	Grad rate	Mean	$P_y \leq 33$ pctile	Median	Mean	P(top 20%)	P(top 10%)	P(top 5%)	P(top 20%| $P_y \leq 20$ pctile)
# schools	761	760	734	760					
Panel (f): Gap w/patents, with controls									
Gap (sd)	-0.0049	-0.0003	-0.0023	-0.0007	-0.0039	0.0004	-0.0015	-0.0023*	-0.0014
	(0.0032)	(0.0038)	(0.0044)	(0.0042)	(0.0046)	(0.0025)	(0.0020)	(0.0012)	(0.0029)
Mean dep. var.	0.5816	10.8281	10.7605	10.7096		0.3710	0.2100	0.1159	0.2957
N	11471	1996	1843	1996	718	718	718	718	718
# schools	733	727	701	727					
Panel (g): Soft skills intensity, no controls									
Gap (sd)	0.0982***	0.0935***	0.0966***	0.0818***	0.1125***	0.0497***	0.0394***	0.0293***	0.0521***
	(0.0065)	(0.0091)	(0.0113)	(0.0085)	(0.0115)	(0.0052)	(0.0044)	(0.0035)	(0.0053)
Mean dep. var.	0.5692					0.3694	0.2082	0.1143	0.2945
N	15683	3793	3566	3793	763	763	763	763	763
# schools	761	760	734	760					
Panel (h): Soft skills intensity, with controls									
Gap (sd)	0.0116***	0.0172***	0.0096	0.0209***	0.0125**	0.0103***	0.0028	0.0007	0.0119***
	(0.0034)	(0.0052)	(0.0068)	(0.0058)	(0.0057)	(0.0031)	(0.0027)	(0.0020)	(0.0038)
Mean dep. var.	0.5816	10.8281	10.7605	10.7096		0.3710	0.2100	0.1159	0.2957
N	11471	1996	1843	1996	718	718	718	718	718
# schools	733	727	701	727					

Note: OLS estimates of the coefficient δ in equation (10). The variable *Gap (sd)* is a school-level alternative measure of the education-innovation gap (estimated as $\theta_{s(i)}$ in equation (9)), standardized to have mean zero and variance one. In panels (a) and (b), the alternative measure is the share of non-covered new knowledge; in panels (c) and (d) it is a "tail measure;" in panels (e) and (f) it is the education-innovation gap calculated using the text of all patents as a benchmark for frontier knowledge; and in panels (g) and (h) it is a measure of soft-skills intensity. The dependent variables are graduation rates (from IPEDS, years 1998-2018, column 1); the log of mean student incomes from the College Scorecard, for all students (column 2) and for students with parental income in the bottom tercile (column 3); the log of median income from the College Scorecard (column 4); the log of mean income for students who graduated between 2002 and 2004 (from Chetty et al. (2020), column 5); the probability that students have incomes in the top 20, 10, and 5 percent of the national distribution (from Chetty et al. (2020), columns 6-8); and the probability that students with parental income in the bottom quintile reach the top quintile during adulthood (column 9). Columns 1-4 in panels a and b control for year effects. All columns in panels b, d, f, and h control for sector (private or public), selectivity tiers, and an interaction between selectivity tiers and an indicator for R1 institutions according to the Carnegie classification; student-to-faculty ratio and the share of ladder faculty; total expenditure, research expenditure, instructional expenditure, and salary instructional expenditure per student; the share of undergraduate and graduate enrollment and the share of white and minority students; an indicator for institutions with admission share equal to 100, median SAT and ACT scores of admitted students in 2006, and indicators for schools not using either SAT or ACT in admission; the share of students with majors in Arts and Humanities, Business, Health, Public and Social Service, Social Sciences, STEM, and multi-disciplinary fields; and the natural logarithm of parental income. Bootstrapped standard errors in parentheses are clustered at the school level. $^{*} \leq 0.1$, $^{**} \leq 0.05$, $^{***} \leq 0.01$.

Appendix B Dataset Construction

B.1 Syllabi

We obtained data on the text of university and college syllabi from the Open Syllabus Project (OSP).[29] The dataset includes nearly 7 million syllabi, collected from 7,365 institutions across the world. OSP provided us with basic information on each syllabus, the full text, and the list of references (papers, textbooks, articles, etc.) included in each syllabus, for a total of 1.8 million unique titles.

We use the following variables from the OSP database:

- `id`: The unique identifier assigned to each syllabus.
- `text`: The text of the syllabus.
- `textmd5`: The md5sum of the text, which can also be used as a unique identifier.
- `language`: The language of the document.
- `year`: The academic year when the syllabus was taught.
- `fieldname`: The name of the academic field most associated with the syllabus.
- `institutionid`: The unique identifier for the institution of the course.
- `unitid`: The IPEDS identifier for the institution.
- `countrycode`: The ISO 3166-1 alpha-2 code of the country the syllabus was taught in.
- `institutionname`: The name of the institution of the course.

In the paper, we focus on syllabi that satisfy the following criteria:

(i) Taught in a four-year, non-online university based in the US (`countrycode` equal to "US") with at least 100 syllabi in the data;

(ii) Taught in English;

(iii) Taught between 1998 and 2018;

(iv) With a word length between 20 and 10,000.

[29] https://opensyllabus.org

The number of syllabi we keep in each step, and the associated syllabi characteristics, are shown in Table BIII.

Table BIII: Summary Statistics of Open Syllabus Project

	# of records	Syllabus word length (raw)	Syllabus word length ("knowledge content")
Original data	6,852,971		
Keep syllabus based in the United States (Syllabus language is English)	3,995,483		
Keep syllabus from four-year university	1,951,933	2,725.41	1,435.09
Year from 1998 to 2018	1,937,284	2,732.09	1,436.77
Extracted syllabus length must be in [20, 10000]	1,901,367	2,279.66	1,057.35
Number of syllabi per institution larger than 100	1,882,224	2,274.55	1,056.77
Remove syllabi from online-only universities	1,752,795	2,218.08	1,010.82

Note: Counts of syllabi, raw word length, and knowledge content (number of words remaining after the cleaning process is complete).

Course catalog data To complement the syllabi data and determine selection patterns into this sample, we also obtained the entire list of course offerings from university catalogs for a sample of US institutions. We begin by randomly selecting 10% of all universities in our sample (212 universities). Then, we manually search and download electronic copies (usually in the PDF format) of university catalogs for those universities for all years available, which list all courses offered in that institution and year. Out of the 212 universities selected, 161 have at least one catalog available. We downloaded and processed a total of 2,348 catalogs for these 161 universities (14.5 catalogs per university). Due to random selection, these schools are representative of the full sample on the basis of standard school-level characteristics. A balance test of characteristics between the full sample and the catalog sample is shown in Table AI.

University catalog data provide the following information: course code, course name, and course level (classified into Basic, Advanced, and Graduate). Some course catalogs also provide a brief course description.

B.1.1 Extracting A Course's Content From Its Syllabus

The full text of a syllabus is contained in the variable `text` of the OSP database. To transform text into usable content, we (i) clean it by removing html language left over from web scraping or correcting obvious errors from OCR procedures; (ii) identify the various sections of the syllabus in it; and (iii) remove text unrelated to content (e.g., course policy, absence policy, accommodation rules). We now explain these steps in more detail.

B.1.2 Cleaning The Raw Text

To clean the text of each syllabus, we proceed as follows:

(i) We use the Unidecode Python Package[30] to convert Unicode text into ASCII text. This includes legacy code that does not support Unicode, non-Roman names on a US keyboard, and ASCII approximations for symbols and non-Latin alphabets.

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

B.1.3 Identifying Syllabi Sections

Most syllabi contain a set of sections, only some of which are relevant for our analysis. The relevant sections include: instructor and course information (such as code, course level, and title); course description, requirements, and objectives; an outline; homework, exams, and other evaluation methods; and other policies. A syllabus often also includes other information that we do not use in the analysis and, as such, we want to remove. This includes the honor code, policies related to disability, classroom laptop and cellphone policies, and others.

To parse among sections, we developed a supervised algorithm based on a set of section title keywords. The algorithm identifies a section type by searching through a set of keywords belonging to each category. Table BIV provides section types along with the corresponding keywords.

Using these keywords, the algorithm separates the text into different sections of the syllabus by combining keywords with the formatting rules of each syllabus. In Figure BXII, we use part of a syllabus as an example to present our process step by step.

[30] https://pypi.org/project/Unidecode/

Table BIV: Section Title Keywords List

Section type	Keywords
Course Description	Syllabi, Syllabus, Title, Description, Method, Instruction, Content, Characteristics, Overview, Tutorial, Intro, Abstract, Methodologies, Summary, Conclusion, Appendix, Guide, Document, Module, Introduction, Approach, Lab, Background
Requirements	Requirement, Applicability, Required
Objectives	Objectives, Achievement, Outcome, Motivation, Purpose, Statement, Skill, Competency, Performance, Goal
Outline	Outline, Schedule, Timeline, Guideline
Materials	Text, Material, Resource, Recommend, Reference, Book, Calendar, Textbook, Guidebook
Instructor information	Instructor, About, Email, Phone, Contact, Professor, Staff, Faculty, Information
Projects, homwork, papers, and exams	Personal, Total, Individual, Exercise, Essay, Submission, Assign, Homework, Paper, Final, Examing, Midterm, Term, Semester, Proposal, Application, Demonstration, Program, Task, Report, Pracical, Drafting, Project, Plan, Deadline, Makeup, Advising, Advisor, Survey, Assignment, Planning, Practice, Group, Participation, Team, Research, Activity, Complaint, Design, Analysis, Strategy, Procedure, Working, Work, Exam, Examination, Training, Professional, Test, Case, Discussion, Grade, Presentation, Quiz, Essay, Layout, Sample, Rewrite
Grades	Assessment, Point, Scope, Evaluation, Record, Grading, Composition, Review
Other Policies	Academic, Justice, Administration, Rule, Discipline, Disclaimer, Regulation, Standard, Affair, Dishonesty, Plagiarism, Misconduct, Offence, Medical, Absent, Absence, Trip, Religious, Observance, Ttendance, Honesty, Origination, Originator, Help, Technology, Attendance, Accessing, Service, Oppotunity, Administrative, Accommodation, Support, Policy, Right, Responsibility, Disability, Weather, Integrity, Copyright
Notes	Remark, Notice, Additional, Acknowledgement, Absolutely, Absolute, Important, Note, Cannot, Can, Must, Should, Will, Please, No
Other Words	Course, Lecture, Catalog, Campus, Commuity, Class, Classroom, College, Univerity, Discussion, Seminar

Note: Keywords used to identify the corresponding section types of a syllabus. In the implementation, we use both the singular and plural versions of each term.

1. For each syllabus, we identify the section titles based on the word list described above and the formatting features. We mark all cases in which the section title phrases appear as all uppercase or consecutive initial capital letters using regular expressions.

    - In Figure BXII, underlined sentences satisfy the features of a section title, such as "Course Description".

2. We divide the syllabus into parts, and we use Arabic numerals to mark them out. Finally, we select sections with relevant titles and extract the cleaned text.

    - In Figure BXII, we focus on highlighted sections, such as "Course Objective," "Prerequisites," and "Text".

B.1.4 Extracting Additional Information

Instructor Names To extract the name of the instructor from each syllabus, we build a neural network model based on the BiLSTM-CNNs-CRF model for named entity recognition (NER).[31] The training/test dataset is built via the following three steps:

(i) We select syllabi that contain at least one keyword such as "Doctor", "Doctors", "Dr", "Professor", "Prof", "Instructor", "Instructors", "Tutor", "Tutors" in the first 3,500 characters.

(ii) We use the Spacy[32] package to identify whether the words following those keywords are names of people (entity label is "PERSON").

(iii) We process the syllabus text sentence by sentence as the training and test data of the model.

We also apply a few additional filters: (a) we remove single letter names; (2) all the words in the name are required to appear in the Python Library *English First and Last Names Data Set*[33]; (c) after the first two filters, we only keep the first instructor name. With this algorithm, we are able to assign an instructor name to 86.23% of all syllabi. The out-of-sample precision of this algorithm is 85.18%.

Course Level: Basic, Advanced, Graduate To assign a course level (basic undergraduate, advanced undergraduate, and graduate) to each syllabus, we trained a Natural Language Processing (NLP) algorithm. Our training sample consists of 56,831 syllabi taught in universities for which we

[31] BiLSTM-CNNs-CRF model for named entity recognition (NER), Ma and Hovy (2016).
[32] https://spacy.io/
[33] https://github.com/philipperemy/name-dataset

have catalog information and for which we can manually code the course levels. Specifically, in the catalog data, we label a course as basic undergraduate if the course belongs to the undergraduate catalog of a university and the course code starts with 1 or 2; we label the course as advanced undergraduate if the course belongs to the undergraduate catalog and the course code starts with 3 or 4; finally, we label the course as graduate if the course belongs to the graduate catalog or the first digit of the course code is larger than 4. We link syllabi to catalog information using institution and course code. Once we have obtained course levels for these syllabi, we use course levels as labels and the text of each syllabus as input in the training model. The model we use is Distilled BERT[34] (Sanh et al., 2019), accessed via the transformers library.[35] The out-of-sample prediction precision is 85.04%.

Course code Our data extraction process allows us to obtain the course code corresponding to each syllabus. However, these courses are institution-specific and often vary over time. To be able to identify courses of the same level (e.g., basic undergraduate) covering the same topic (e.g., Principles of Microeconomics), both within and across schools, we proceed as follows. First, we construct a unified within-school course code using the raw course code and the course name. We do so as follows: (a) we remove the punctuations and multiple whitespaces from codes and names; (b) for course names, we further remove stop-words and isolate the course stem name (the common base form of the words). We then consider two courses as sharing a course code if (a) they share the same name and code or (b) they share the same name, even if the course code changes over time. This procedure accounts for the possibility that the course code system might have changed within a school over time.

Once we have a disambiguated identifier for courses within the same school, we assign courses a cross-school identifier. Specifically, we assign two courses the same cross-school identifier if they share the same standardized course name.

B.2 References and Recommended Readings in Each Syllabus

In addition to syllabi text and metadata, OSP provided us with two additional datasets: "Matches" and "Catalog." "Matches" allows us to link syllabi to records in "Catalog." "Catalog" is the set of 1.8 million bibliographic records assigned to at least one syllabus. We use the following variables from the "Matched" dataset:

- `MatchID`: The unique identifier of the match

[34] https://arxiv.org/abs/1910.01108
[35] https://huggingface.co/transformers/index.html

- `ID`: The id of the syllabus
- `WorkID`: The id of the catalog record

We use the following variables from the "Catalog" dataset:

- `WorkID`: The id of the catalog record
- `Publicationtype`: The type of publication ("journal" or "book")
- `Publicationyear`: The year of publication

B.2.1 Syllabi Field

The OSP database classifies syllabi into one of 69 fields. For some of our analyses, we group these into macro-fields. The grouping is illustrated in Table BV.

Table BV: Categorization of Course (Macro-)Fields

Macro-field	Fields
Business	Business, Accounting, Marketing, Public Administration
Humanities	English Literature, Media / Communications, Philosophy, Theology, Criminal Justice, Library Science, Classics, Women's Studies, Journalism, Religion, Sign Language, Liberal Arts, Music, Theatre Arts, Fine Arts, History, Film and Photography, Dance, Anthropology, Japanese, French, Chinese, German, Spanish, Hebrew
Science	Mathematics, Biology, Chemistry, Physics, Earth Sciences, Astronomy, Atmospheric Sciences, Dentistry, Medicine, Nutrition, Nursing, Veterinary Medicine, Natural Resource Management
Engineering	Computer Science, Engineering, Architecture, Agriculture, Basic Computer Skills, Engineering Technician, Transportation
Social Sciences	Psychology, Political Science, Economics, Law, Social Work, Geography, Education, Linguistics, Sociology Education, Criminology
Other	Fitness and Leisure, Basic Skills, Mechanic / Repair Tech, Cosmetology, Culinary Arts, Health Technician, Public Safety, Career Skills, Construction, Military Science

Note: Mapping between the "macro-fields" used in our analysis and syllabi "fields" as reported in the OSP database.

Figure BXII: Dividing A Syllabus Into Sections: An Example

Econ 561a Yale University Fall 2005
Prof. Tony Smith (Part I) Prof. Michael Keane (Part II)
Syllabus for **COMPUTATIONAL METHODS FOR ECONOMIC DYNAMICS** ECON 561a

Course Objectives:
Most of the dynamic economic models used in modern quantitative research in economics do not have analytical (closed-form) solutions. For this reason, the computer has become an indispensable tool for conducting research in dynamic economics. The goal of this two-part course is precisely to teach students computational tools for conducting numerical analysis of dynamic economic models. The focus of the first half of the course, taught by Prof. Tony Smith, is on solving dynamic programming problems and on computing competitive equilibria of dynamic economic models. The first half of the course also provides an introduction to some of the basic tools of numerical analysis, including minimization, root-finding, interpolation, function approximation, and integration. The focus of the second half course, taught by Prof. Michael Keane, is on solving and estimating discrete-choice dynamic programming models of economic behavior. Taken together, the two halves of the course provide students with a thorough introduction to the numerical analysis of dynamic economic models in both microeconomics and macroeconomics.

Contact Information (Prof. Tony Smith)
Office: 28 Hillhouse, Room 306 Office phone: (203) 432-3583
Email address: tony.smith@yale.edu Course Web site: www.econ.yale.edu/smith/econ561a
Office hours: Thursdays from 10AM–noon, or by appointment

Class Meetings:
The course meets on Mondays and Wednesdays from 2:30PM to 3:50PM in a room to be determined.

Prerequisites:
This course is designed for graduate students in economics who have taken first-year graduate courses in microeconomics, macroeconomics, and econometrics. No prior knowledge of either numerical methods or computer programming is assumed, but some familiarity with a programming language would prove helpful.

Texts:
The required textbook for this course is:
Numerical Recipes in Fortran 77: The Art of Scientific Computing, Second Edition (Volume 1 of Fortran Numerical Recipes) by William H. Press, Saul A. Teukolsky, William T. Vetterling, and Brian P. Flannery (Cambridge University Press, 1992). This book, as well as its (optional) companion Numerical Recipes in Fortran 90: The Art of Parallel Scientific Computing, Second Edition (Volume 2 of Fortran Numerical Recipes), is available online at: www.library.cornell.edu/nr/.
Other (optional) books that students might find useful are:
- Numerical Methods in Economics by Kenneth L. Judd (MIT Press, 1998).
- Handbook of Computational Economics (Volume 1), edited by Hans M. Amman, David A. Kendrick, and John Rust (North-Holland, 1996).
- Computational Methods for the Study of Dynamic Economies, edited by Ramon Marimon and Andrew Scott (Oxford University Press, 1999).
- Dynamic Economics: Quantitative Methods and Applications by Jérôme Adda and Russell Cooper (MIT Press, 2003).
- Applied Computational Economics and Finance by Mario J. Miranda and Paul L. Fackler (MIT Press, 2002).

Grading:
The course grade will be based on two (equally-weighted) projects, one for the first part of the course and one for the second part of the course. Each project consists of writing a program in Fortran to solve an assigned problem. Students must submit their code as well as a brief (roughly five pages) description of their numerical findings. The first project will involve solving for the competitive equilibrium of a dynamic macroeconomic model; the second project will involve solving and estimating a discrete-choice dynamic programming model. Fortran is the language of choice for most researchers in computational economics; requiring that the code for the projects be written in Fortran will help students to become proficient in this powerful and useful language. The first project is due on Monday, November 14 and the second project is due at the end of the semester. Occasional short programming problems may also be assigned as the course proceeds. The purpose of these assignments is to help students develop the skills they need to complete the projects; these assignments will not be graded.

Approximate Schedule of Lectures (Part I)
I. **INTRODUCTION**
Lecture 1 Introduction to numerical dynamic programming (built around the stochasticgrowth model and the Aiyagari (1994) model). General considerations in numerical analysis: convergence, roundoff error, truncation error. Numerical differentiation.
Readings:
- Aiyagari, S.R. (1994), "Uninsured Idiosyncratic Risk and Aggregate Saving," Quarterly Journal of Economics 109, 659–684.
- Numerical Recipes: Chapters 1 and 5.7
- Judd: Chapters 1, 2, and 7.7

II. **BASIC NUMERICAL METHODS**
Lecture 2 Root-finding in one or more dimensions: bisection, secant method, Newton's method, fixed-point iteration, Gauss-Jacobi, Gauss-Seidel, Brent's method.
Readings:
- Numerical Recipes: Chapter 9

……

Note: Example of a syllabus from OSP, in its original format. Subsections are identified using the algorithm described in this appendix.

B.3 Academic Publications

To construct the education-innovation gap, we collect a large sample of academic articles from top journals. We describe here how this sample is defined, constructed, and collected.

B.3.1 List of Top Journals

noindent We begin by compiling a list of top academic journals within each discipline. Our starting point is the Journal Citation Reports (JCR), an annual report published by Thomson Reuters (formerly ISI) to provide citation and publication data of academic journals in the science and social science fields by means of the impact factor.[36] We consider as top journals those that were ranked within the top ten of their respective field at least once since their establishment. This leaves us with 3,962 journals in 223 fields.

B.3.2 Collecting Academic Articles

Having compiled a list of top journals, we collect information on all the articles ever published in these journals. These data come from Scopus, an Elsevier-owned database containing abstracts and citations of academic articles.[37] To extract the metadata of journal articles, we access Scopus's API and search for the ISSN of each journal ("ISSN(0022-1082)"). We then extract all the metadata of all articles of the relative journal for all available years. We focus our attention on the following variables:[38]:

- `EID`: electronic ID, used as the unique identifier of each article;
- `title`: title of the article;
- `ISSN`: ISSN of publisher;
- `coverdate`: publication date;
- `description`: abstract;
- `authkeywords`: keywords.

Our initial search yielded 20,779,713 articles, of which we discarded those without an abstract.

[36] https://jcr.clarivate.com/

[37] https://www.scopus.com

[38] The full list of variables available through Scopus is available at https://dev.elsevier.com/guides/ScopusSearchViews.htm

B.3.3 Data Cleaning

The main information from academic articles that we use in our analysis is the abstract, contained in the variable `description` of the SCOPUS database. We further clean the content of this variable to remove copyright disclaimers, usually present at the beginning or at the end of each abstract and unrelated to content. We do this using keyword recognition techniques. Starting from the first sentence of an abstract, we remove it if it contains at least one of the following words: "copyright", "©", "published", "publisher", "all right", or "all rights reserved". We repeat this procedure until the first sentence does not contain any of these words. We then repeat the same procedure starting from the last sentence.

B.4 Research Productivity

We use information from Microsoft Academic (MA) to measure the research productivity of all people listed as instructors in the syllabi. We download these data from Microsoft Academic Knowledge Graph (MAKG).[39] MAKG is a large resource-description framework (RDF) knowledge graph with over eight billion triples containing information about scientific publications and related entities, including authors, institutions, journals, and fields of study. The data set is based on the Microsoft Academic Graph and licensed under the Open Data Attributions license. For each researcher, Microsoft Academic lists publications, working papers, other manuscripts, and patents, together with the counts of citations to each of these documents. Due to differences in counting citations, Microsoft Academic citations do not necessarily match those from similar services such as Web of Science or Google Scholar. The correlations between all these services' citations numbers, however, are very high.

We link instructor records from the text of the syllabi to Microsoft Academic records using names, a person's history of institutions, and research fields. In the sample of syllabi used in our analysis, 44.23% (697,756 / 1,487,820) have an instructor record, covering 332,063 unique instructors. Of these instructors, 40.76% (135,364 / 332,063) are matched to a Microsoft Academic profile.

B.5 Patents

We obtain data on patents from the publicly available Patent Full-Text Database (PatFT)[40] of the US Patent and Trademark Office (USPTO). This database provides records for all patents ever issued since 1976. We use a web crawler to collect the text content of patents over this period, which

[39] We download the data based on the Microsoft Academic Graph data as of 2020-05-29 from https://zenodo.org/record/3936556#.YFndr2Qza3J

[40] http://patft.uspto.gov/netahtml/PTO/index.html

includes patents with numbers ranging from 3,850,000 to 10,279,999. We use the following variables for each patent record:

- `PatentNumber`: The unique identifier assigned to each patent record
- `Abstract`: The abstract in each patent filings
- `Year`: The year that the patent was issued
- `Class`: The International Patent Classification (IPC) assigned to each patent

B.6 National Science Foundation and National Institute of Health Grants

We collect information on grants awarded by the National Science Foundation (NSF)[41] and the National Institutes of Health (NIH)[42] to construct measures of research investment and productivity. These data are provided directly by the respective organizations; the versions used in the paper were accessed on May 25, 2021.

The NSF grant data include 480,633 grants with effective starting years ranging from 1960 to 2022. The NIH grant data include 2,566,358 grants with effective years ranging from 1978 to 2021. Both NSF and NIH grant data contain information on the host institution (institution name, country, state, and city) and the investigator (investigator name and role). In the NSF data, investigators can be listed under four figures: principal investigator (PI), co-PI, former PI, and former co-PI. In the NIH data, they can be listed under two figures: contact and non-contact.

B.6.1 Linking NSF/NIH Institutions to Syllabi Institutions

To link grants to institutions in the syllabi data and IPEDS, we use information on the institution's name and location (country, state, and city). To do so, we first perform an exact match using institution names as listed in the NSF/NIH data and in IPEDS, stripped of punctuation marks and stop words (including "and" and "the"). Then, for the remaining unmatched NSF/NIH institutions, we conduct a fuzzy matching based on name and location. We require the matching algorithm to meet the following two conditions: (1) the two institutions must be in the same city; (2) the fuzzy matching ratio must be larger than a certain threshold (specifically, we use partial ratio and token set ratio in the FuzzyWuzzy Package).[43] This method sometimes leads us to match a NSF/NIH

[41] https://www.nsf.gov/awardsearch/download.jsp

[42] https://exporter.nih.gov/ExPORTER_Catalog.aspx

[43] The package uses Levenshtein Distance to calculate the differences between sequences; its homepage is https://github.com/seatgeek/fuzzywuzzy, and we use a threshold of 80.

institution to multiple IPEDS institutions. In this case, we consider the IPEDS institution with the largest average matching ratio .

We are able to match 11.30% (2,402) of NSF institutions to IPEDS, covering 82.05% (= 394,383 / 480,633) of all NSF grants. Similarly, we are able to match 6.73% (1,573) of NIH schools to IPEDS, covering 66.53% (= 1,707,498/2,566,358) of all NIH grants. The unmatched NSF and NIH institutions are mostly non-academic, private, or not-for-profit research institutes.

B.6.2 Linking NSF/NIH Investigators to Instructors

Next, we match grant investigators to course instructors in the syllabus data. We do this via a fuzzy matching algorithm using names. The NSF and NIH data provide different investigator information to be used in the fuzzy matching, so the matching methods differ slightly between the two datasets.

NSF To match NSF investigators to instructors, we first remove duplicates within NSF based on first name, last name, email, and institutions since NSF does not provide investigator unique identifiers. We consider two investigators to be the same person if (1) they share the same email or (2) they have exactly the same first name and last name in the same school in a certain year. Next, we perform a many-to-one fuzzy matching between NSF investigators and syllabi instructors based on the names and history of institutions at which the researcher was employed. We proceed in three steps:

(i) After removing any punctuation marks from name strings, we fuzzy-match each NSF investigator name with syllabus instructor names. We calculate matching scores using the Whoswho Package[44], a Python library for determining whether two names belong to the same person.

(ii) If a match has a score of 100, we consider it successful. For matches with scores larger than 95 who have ever worked at the same school, assign an investigator to one and only one instructor as follows.

   (a) If an NSF investigator and a set of syllabi instructors have spent some common period of time at the same institution as we can observe it, we link the investigator to the instructor with the highest matching score.

   (b) If they have not spent any common period of time at the same institution, we link the investigator to the instructor with the highest matching score and lowest temporal distance between the time spent at each institution.

[44] https://github.com/rliebz/whoswho

(iii) For matches with a matching score larger than 95 but in different schools,

(a) If an instructor and an investigator are observed for the same period of time in the two datasets, we choose the match with the highest matching score.

(b) Otherwise, we choose the matching with the highest matching score and shorter time distance between observed periods between the two datasets.

This procedure leaves us with 232,206 unique investigators, 23.31% (= 54,118 / 232,206) of whom can be matched to one syllabus instructor, and corresponding to 44.28% (= 208,857 / 471,646) of all grants.

NIH Data from NIH contain investigator unique identifiers, which implies that we do not have to remove duplicates. We use these to perform a one-to-one matching between each NIH investigator and a syllabus instructor. We follow the same process as with NSF grant data. This procedure leaves us with 298,687 unique investigators, 10.07% (= 30,087 / 298,687) of whom can be matched to one syllabus instructor, corresponding to 17.69% (= 450,339 / 2,546,123) of all grants.

Our final grant data combines information from NSF and NIH grants. The syllabi sample used in our analysis covers 332,063 instructors, of whom 17.51% (= 58,136 / 332,063) have at least one NSF or NIH grant, accounting for 20.93% (= 311,350 / 1,487,820) of all syllabi.

B.7 Instructors' Job Titles and Salaries

We are able to collect the salaries of instructors employed at 490 public college and universities in 16 states. As the regulations on the disclosure of public-sector employees' salaries vary across states and over time, the temporal coverage of our data differs across states. Table BVI describes the coverage and source of the salary data.

Together with the salary data, the job title of each employee is also disclosed. We are able to identify the following titles: assistant professor, associate professor, full professor, lecturer, adjunct professor, clinical professor, professor of practice, and visiting professor. This information is available for 32,090 instructors in our syllabi sample (9.7 percent of all instructors and 13 percent of public-sector instructors), employed in 278 public institutions in 13 states. Table BVII describes how we assign job titles based on the information available in the data.

Table BVI: Coverage and Source of Salary and Job Title Data

State	Data available for	Source
CA	2011-2018	https://transparentcalifornia.com/agencies/salaries/
CT	2010-2018	http://transparency.ct.gov/html/searchPayroll.asp
GA	2010-2018	https://open.ga.gov/openga/salaryTravel/index
IA	2009-2018	https://www.legis.iowa.gov/publications/fiscal/salaryBook
IL	2010-2018	https://salary.bettergov.org/
IN	2012-2018	https://gateway.ifionline.org/default.aspx
KS	2012-2018	http://kanview.ks.gov/DataDownload.aspx
MA	2010-2018	https://cthrupayroll.mass.gov/
MD	2012-2018	https://salaries.news.baltimoresun.com/
MI	2014-2018	https://www.mackinac.org/salaries
MN	2011-2018	https://mn.gov/mmb/transparency-mn/payrolldata.jsp
NV	2009-2018	https://transparentnevada.com/
NY	2008-2018	https://www.seethroughny.net/payrolls
OK	2010-2018	https://data.ok.gov/dataset
RI	2011-2018	http://www.transparency.ri.gov/payroll/
WA	2016-2018	http://fiscal.wa.gov/salaries.aspx

Note: States for which instructor salary and job title data are available, together with available year and source.

Table BVII: Assigning Job Titles

Job Title	Definition
Adjunct Professor	Any word of the job title starts with ”adjunct”, ”adj”, ”temporary”, ”temporari”, ”temporar”, or ”part time”.
Clinical Professor	Any word of the job title starts with ”clinic” or ”clin”.
Professor of Practice	Any word of the job title starts with ”practic” or ”pract”.
Visiting Professor	Any word of the job title starts with ”visiting” or ”visit”.
Lecturer	(1) Any word of the job title starts with ””lectur”, ”lect”, ”instructor”, ”instruct”, ”instr”, ”teacher”, or ”teach”; (2) AND any word of the job title does not end with ”ship”; (3) AND job title is not identified as adjunct professor, clinical professor, professor of practice, and visiting professor.
Professor	(1) Any word of the job title starts with ””professor”, ”prof”, or ”tenur”; (2) OR any word of the job title includes ”tenr trk” or ”tenur track”; (3) AND any word of the job title does not end with ”profession”; (4) AND job title is not identified as adjunct professor, clinical professor, professor of practice, or visiting professor.
Assistant Professor	Job title is identified as professor; (2) AND any word of the job title starts with ””assist”, ”asst”, or ”assi”.
Associate Professor	Job title is identified as professor; (2) AND any word of the job title starts with ””associ”, ”assoc”, or ”asso”.
Full Professor	Job title is identified as professor; (2) AND detailed job title is not identified as assistant professor or associate professor.

Note: Procedure used to assign job titles to salary records.

Appendix C Calculating The Education-Innovation Gap: Additional Details and A Simulation Exercise

We now explain in detail the process employed to identify the knowledge terms used in our analysis, extract them from the text of syllabi and academic publications, and calculate the gap.

C.1 Extracting Knowledge Terms From Each Document

Dictionary The first step is to build a dictionary, i.e., a list of all knowledge terms. We use the list of all unique words and expressions ever used as a keywords in academic publications. We extract these keywords from the data described in Section B.3.

Term Extraction Next, we convert the text content of each document (syllabi and academic papers) into numerical data for statistical analyses. To do so, our starting point is to clean the text. First, we convert the text of each document into ASCII text using the Unidecode Python Package.[45] This allows us to handle host legacy code that does not support Unicode, non-Roman names on a US keyboard, and ASCII approximations for symbols and non-Latin alphabets. Next, we convert all capitalized characters to lowercase and use the NLTK Python Toolkit to strip out all non-word text elements, such as punctuation marks, numbers, and HTML tags. We also remove all occurrences of 280 "stop words", which include propositions, punctuation marks, pronouns, and other words that carry little semantic content.[46]

Once we have cleaned the text, we convert it into numerical data using a term-extraction algorithm called NGramMatch. This algorithm performs exact string matching of the text of each document, consisting in N-grams with N ranging from 1 to 7, with the dictionary. To do so, the algorithm extracts N-grams from text to form a basic term set. Then, it filters out all the terms which cannot be linked to any dictionary entry. In the final set, the algorithm assigns each document a frequency vector based on matched dictionary words.

C.2 A Simulation Exercise

To better understand how the education-innovation gap captures the academic novelty of a syllabus's content and to illustrate its properties, we perform a simulation exercise. In this simulation, we manually construct a set of syllabi by combining dictionary words that can be found in academic

[45] https://pypi.org/project/Unidecode/

[46] We use the stop words list using the union of all single letters and Stanford CoreNLP package: https://github.com/stanfordnlp/CoreNLP/blob/master/data/edu/stanford/nlp/patterns/surface/stopwords.txt.

publications. Each syllabus is characterized by a year (t, ranging from 1998 to 2018 to match our data), a known gap (*gap*, ranging between 0 and 1), and a parameter governing its style (*style*); we define the latter two parameters as follows. For each of these syllabi, we calculate the education-innovation gap with the procedure described in the text. We then compare it with the known gap to assess its performance.

The three parameters characterizing each syllabus govern the way the terms in it are drawn from three different buckets of words: new knowledge terms, old knowledge terms, and style words.

- New knowledge terms are (i) in the top 5% of the word frequency distribution among articles published between $t-3$ and $t-1$ or (2) words that appear in articles published between $t-3$ and $t-1$ but not those published between $t-15$ and $t-13$.
- Old knowledge terms are are (i) in the top 5% of the word frequency distribution among articles published between $t-15$ and $t-13$ or (2) words that appear in articles published between $t-15$ and $t-13$ but not those published between $t-3$ and $t-1$.
- Style words are those terms that appear in academic articles but do not belong to the previous two groups.
- gap is the share of old to new knowledge words in a syllabus.

To generate each syllabus, we use the following algorithm:

- We assign the syllabus a length of L, where $L = 10*U$ and U is drawn from a discrete uniform distribution between 1 and 50 (so that L lies between 10 and 500, with increments of 10).
- We assign the syllabus a number $L_s = L \times style$ style words, where $style$ ranges between 0.01 and 0.1 in increments of 0.01.
- The remaining $L - L_s = L_k$ words in the syllabus are drawn from the new and old knowledge terms buckets. Among these, $L_k \times (1+gap)^{-1}$ are from the new knowledge terms bucket and $L_k \times gap \times (1+gap)^{-1}$ are from the old knowledge terms bucket.

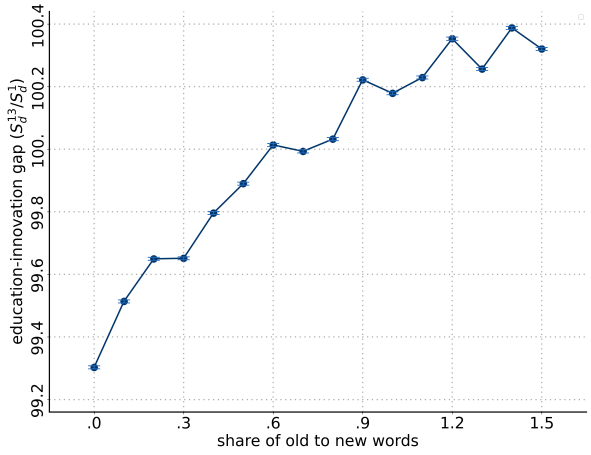
With this algorithm, we generate 10 syllabi for each set of parameters $\{t, L, style, gap\}$. The total number of generated syllabi is thus $= 10 \times 21 \times 46 \times 11 \times 16 = 1,700,160$, which is close to the sample size in our data.

Figure BXIII (panel (a)) shows the relationship between gap and our estimated education-innovation gap. The correlation between these variables is strong and equal to 0.96. By contrast, in panel (b)

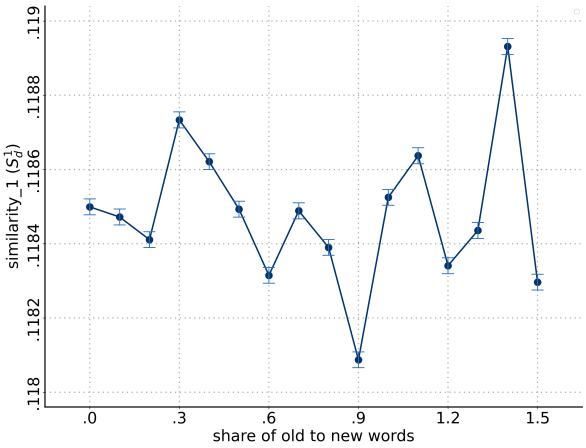
we show the relationship between gap and the cosine similarity between the syllabus and new publications (appeared in $t-3$ to $t-1$), i.e., the denominator of the education-innovation gap. This relationship is much noisier. This is likely to occur because a simple cosine similarity is likely to be affected by the overall style of the syllabus, whereas the gap is not.

Figure BXIII: Simulated Syllabi and Their "True" Gap Measure

(a) gap and The Education-Innovation Gap



(b) gap and Cosine Similarity with New Publications



Note: Panel (a) shows the relationship between gap and the education-innovation gap as defined and constructed in the paper. Panel (b) shows the relationship between gap and the cosine similarity between the syllabus and new publications (appeared in $t-3$ to $t-1$).