The Diversification of Baccalaureate Education

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Abstract

College major choices shape academic success, earnings, and broader patterns of inequality and productivity. Despite their importance, little work investigates the supply of majors and how this facet of college behavior influences student outcomes and costs in higher education. In this paper, I identify a decades-long trend in 4-year post-secondary education in the United States—the production of bachelor's degrees has diversified significantly by field of study over time. I document this pattern in multiple data sources and show that within-college expansion of program options drives this trend. Peer institution effects, or colleges' tendency to identify with and aspire to other colleges, offers the most consistent explanation for the market's collective accommodation of increased demand for a bachelor's degree since 1990. Marked changes in the demographic composition of students obtaining degrees cannot account for major diversification, nor can other factors like declines in state support for higher education, spillovers from graduate education within colleges, or changes in the business cycle and employer demand for skill. Consequently, I show major diversification led to increases in average instructional costs per student. However, major diversification also coincides with increases in 6-year graduation rates. This highlights an important trade-off for colleges: increased costs for a more diverse set of major options can attract and retain more potential graduates.

Keywords: Higher education, Major choice, Productivity, Costs, Completion
JEL Codes: I22, I23, J24, L25, L31

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1. Introduction

Bachelor's degree attainment has offered persistent individual economic gains over lower levels of education (Oreopoulos & Petronijevic, 2013) and these investments generate positive externalities in the form of increased civic engagement, reduced crime, and increased productivity across areas (Moretti, 2004). Benefits of college both to individuals and society are shaped in part by the majors or fields in which students specialize. Major choices are a function of student demand-driven factors, like socio-demographic characteristics, preferences, and information, as well as college supply-driven factors like curricular offerings and enrollment capacity constraints. Much effort has been spent unraveling the *demand side* of major choice, (see Altonji et al., 2016; Patnaik et al., 2021, for two reviews). Considerably less attention has been devoted to understanding decisions of colleges and the *supply* of majors.[1]

Colleges structure their educational offerings subject to several competing goals and constraints. These include costs and labor market demand for different types of jobs or skills, as well as historical identities or missions for serving certain types of students and academic pursuits. Yet, colleges generally seek to maximize their educational quality, broadly defined, using the revenue they can readily access or raise. Over time, the market for baccalaureate education has become increasingly stratified by institutional resources (Clotfelter, 2017) and characterized by increased competition (and collaboration) among schools within similar rungs of the resource ladder due to prospective students' diminished geographic boundaries (Hoxby, 2009) and declines in state support for public higher education.

In this paper I identify a decades-long trend in U.S. 4-year postsecondary education unifying several historical trends in college behavior, costs, and educational quality—the production of bachelor's degrees measured by their concentration across majors has diversified significantly over time. This new stylized fact covers several narrower observations about baccalaureate education including drastic enrollment declines in the humanities (Hearn & Belasco, 2015) and growing preferences for vocational majors with clearer career prospects (Clotfelter, 2017; Getz & Siegfried, 1991). These observations alone are unable to concisely summarize overall trends in bachelor's degree production across fields. In contrast, the concept of degree diversity (i.e., the inverse of concentration) captures a new and comprehensive dimension of major choice not previously stud-

[1] Some recent exceptions from Bleemer & Mehta (2021) and Thomas (2024) suggest that supply constraints from curricular decisions can affect students' major and enrollment choices in meaningful ways.

ied in the United States (US) context.[2]

The secular trend in major diversification between 1990 and 2019 was due mainly to within-college expansion of major options. Large increases in the number of students obtaining a degree and changes in the racial, ethnic, and gender profiles of recipients cannot account for the trend. Instead, over half the increase in major diversity can be attributed to supply increases in the number of majors offered by colleges. Furthermore, nearly all colleges, regardless of size, control (e.g., public or private), or highest degree, expanded their major offerings throughout the period of interest, creating less horizontal differentiation in the market for majors available to students across colleges.

The strongest explanation for major diversification relates to isomorphic tendencies found in the baccalaureate education market. Specifically, institutions responded to changes in the major diversity of their close peer institutions. Peer effect estimates using excluded peers to instrument for the average change in major diversity among an institution's chosen peers suggest an elasticity of response greater than one. That is, institutions increased their own major diversity more than in proportion to average changes of their peers. This strong effect is consistent with schools looking to attract students and improve their own quality in response to peer or aspirant institutions making similar improvements. It also aligns with other accounts of rising competition for students and resources in higher education (e.g., Marginson, 2006; Weisbrod et al., 2008). Even though colleges tend to compete in different sub-markets (e.g., by selectivity or geography), a common response to these pressures was to expand their degree production horizontally into more fields, rather than to specialize in a few majors. This is in stark contrast to increasing market concentration, firm specialization, and declining industry diversity characterizing much of the U.S. economy's private sector (Autor et al., 2020; Ekerdt & Wu, 2023).

Building from this portrait of major diversification, I next examine its implications for college costs and student success. I find that major diversification led to increased average instructional costs per student but also boosted 6-year graduation rates. This trade-off offers new insights into two prominent stylized facts about higher education from the last several decades. Rising costs can at least partly be attributed to the way institutions expanded supply into new fields. This challenges some explanations that focus on colleges' inflexible production technology and reliance on high labor costs (Archibald & Feldman, 2010), or the Cost Disease (Baumol, 2012). My re-

[2]Teixeira et al. (2013) studies this concept in Portuguese colleges highlighting prominent differences between private and publicly controlled institutions. As I will show, this is quite distinct from the U.S. case where diversification is nearly universal in the time-period of interest.

sults suggest colleges made growth- or quality-oriented curricular decisions that drove up average costs over time. I illustrate using department-level data from The Cost Study at the University of Delaware (TCS) that as colleges added majors, students substituted some enrollment toward new and related majors, leaving a hollowed-out middle group of programs with elevated average costs per credit hour.

Increasing major diversity appears also to have facilitated better matches between students and majors, as graduation rates increased about 2 percent for a 10 percent increase in major diversity. This finding refines the recent argument that increased graduation rates of the last several decades were due to grade inflation (Denning et al., 2022). Major diversity is one possible mechanism through which grades increased, not because academic standards fell, but because students gained some ability to enroll in courses that suited their academic strengths and interests better. This also provides a new connection between increased spending and student outcomes (Webber & Ehrenberg, 2010). In these ways, major diversity is more than an interesting feature, but an input in a college's production function.

With these results I contribute new context for analyses of institutional behavior and 4-year educational choices. Other studies in this vein have used differential tuition prices by major (Andrews & Stange, 2019; Stange, 2015), GPA restrictions for specific majors (e.g., Andrews et al., 2017; Bleemer & Mehta, 2021, 2022), and changes in enrollment capacity (Bianchi, 2020; Thomas, 2024) to identify changes in student behavior and outcomes. Cook (2021) explicitly modeled the number of majors a college offered arguing this had a place in colleges' objective functions through its costs. Doing so suggested students were willing to pay about $100 for an additional program. I build on this work focusing more broadly on major diversity and on the motivations for and consequences of adding programs.

I also provide new insight to the literature on costs, competition, and the market structure of higher education. Several explanations have been offered for rising costs (for a review of this literature see Cheslock et al., 2016). The Cost Disease view diminishes colleges' role in the process arguing that costly labor cannot easily be substituted or made more efficient for educational production. Other explanations place more onus on institutional responses to incentives, arguing that colleges engage in a sort of arms race for more resources and prestige, sometimes attributed to colleges lacking a concrete connection between spending and the outcomes of its students (e.g., Blair & Smetters, 2021; Bowen, 1980; Clotfelter, 1996). Consistent with these views, I frame my analysis of college behavior and preferences for major diversification around quality maximization and argue that colleges pursue this goal in relative terms, looking to peer institutions for cues on how to behave. In identifying peer effects and tying institutional preferences for major diversification to increased costs, I show that institutional supply-side responses to competitive pressures in the market for bachelor's degrees played an active role in rising costs.

This paper proceeds in distinct parts, peeling back sequential layers of the major diversification phenomenon. In sections 2 and 3, I first identify the trend in major diversity across the 4-year sector of higher education and briefly describe the data used to decipher it in detail for the rest of the paper. In section 4, I show this trend is widespread across most colleges and attributable to within-college changes to program offerings. In section 5 I argue for and show peer effects to be the strongest explanation for this behavior, ruling out other alternatives. In section 6 I analyze the consequences of major diversification highlighting increased average instructional costs in exchange for higher graduation rates. I conclude the paper with a discussion of implications and directions for future research in section 7.

2. Trends in major diversity

To measure diversity of college majors over time I turn to two large-scale public data sources, the American Community Survey (ACS) and Integrated Postsecondary Education Data System (IPEDS). Beginning in 2009, the ACS began collecting college major from students with a bachelor's degree. Pooling survey years from 2009 to 2019, I generate cohorts roughly representing the year respondents would have graduated college, assuming college exit at age 22. The large sample in the ACS allows me to track majors for graduating cohorts back to 1970.[3] Following Hemelt et al. (2023) and Conzelmann et al. (2023), I collapse the 173 ACS major codes into 71 categories for comparability across data sources and more stable groupings over time.

As a second source, I turn to IPEDS. This federally mandated survey of all colleges and universities in the US contains degree award records dating back to the late 1980s. I begin my panel in 1990 and measure bachelor's degrees awarded through 2019. The raw IPEDS data are reported at the 6-digit Classification of Instructional Programs (CIP) code level, which I collapse to the 71 categories using the crosswalk developed in Hemelt et al. (2023) in order to facilitate comparison

[3] Technically, I could measure cohorts back as far as the 1930s and 40s, but the sample sizes become very small. I choose 1970 because it is a rounded year and one for which there is adequate (weighted) sample of respondents.

to the ACS.[4][5]

Throughout the paper, I will measure major diversity using what I call the Effective Major Index (EMI). This is simply the inverse of a Herfindahl-Hirschman Index (HHI), a common measure of industry or employment concentration. I index majors, $m \in M$, where M is a the set of 71 majors. The EMI in any given year t can be written as,

$$\text{EMI}_t = \frac{1}{\text{HHI}_t} = \left[\sum_{m \in M} \left(\frac{x_{mt}}{x_t} \right)^2 \right]^{-1}, \tag{1}$$

where x_t is the total number of degrees awarded in year t and x_{mt} is the number of individuals who obtained a degree in major, m in that year. The EMI captures the diversity of bachelor's degrees awarded in a given year. An EMI of 1 would imply all students in that year majored in the same field. The more dispersed students are across different fields, the EMI increases with a ceiling of 71. This would imply equality of degrees across all possible fields within a given year where each major would have a share of 1/71.

Figure 1 plots the diversity of college majors across all graduates calculated with the ACS from 1970 to 2017 and with IPEDS from 1990 to 2019. Though the data generating processes for these sources are quite distinct,[6] they both illustrate a decisive trend: students have diversified their majors significantly over time.

The upward trajectory is particularly stark in the 1970s and 1990s from the ACS. This pattern is mirrored in the 1990s by the IPEDS data as well. The two sources diverge somewhat in the 2000s, with IPEDS flattening, until the two sources trend steeply upward together again for much of the 2010s. The numbers themselves imply that for the last three decades, the effective number of majors for bachelor's degrees have risen between 20 and 30 percent or about 5 to 7 effective majors. This implies the dispersion of students across majors has become significantly more even over time, instead of heavily favoring a few larger majors as was the case in earlier years of the panel.

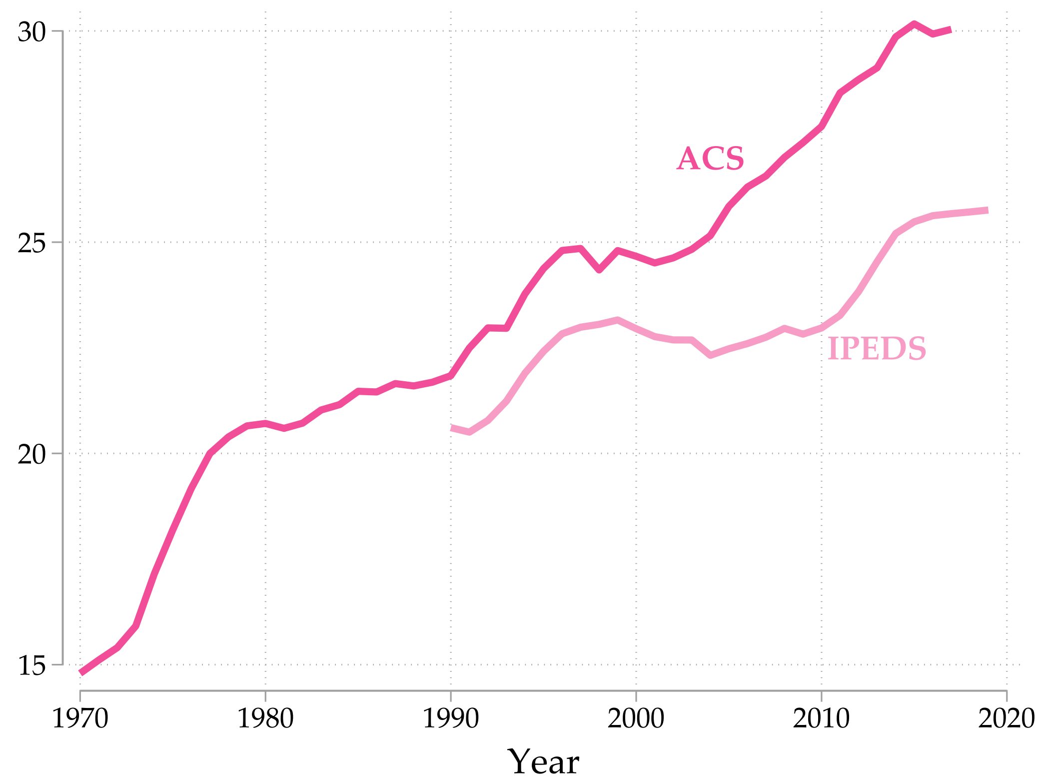
To contextualize this pattern I identify some of the most popular majors in the beginning of the period and see how their appeal has changed throughout the decades of observation. In 1970,

[4]Three different vintages of 6-digit CIP codes were used to track degree awards in this time period (versions 1990, 2000, and 2010), which I harmonized at the 4-digit level prior to collapsing in the final 71-category major classifications used in the paper. More information about this process can be found in the Data Appendix B

[5]The trends in major diversification described here are robust to using 2-digit CIP aggregations as well.

[6]ACS contains self-reported education levels and majors while IPEDS degree counts are reported by colleges and universities.

Figure 1: Effective Major Index from the ACS (1970-2017) and IPEDS (1990-2019)



Notes: The EMI is calculated as the inverse of the sum of squared shares of 71 possible bachelor's degree majors in each year. See Equation 1.

the top 4 fields were Education, Business, the Humanities, and Psychology together encompassing nearly half of all bachelor's degrees (47%). By 2017, these fields plus Biology made up the top 5 most popular, but account for just 30 percent of all degrees.

The ten fields with the largest absolute change in share of degrees from IPEDS between 1990 and 2019 provide mixed support for previous attempts to categorize broad trends in 4-year degrees. Depicted in Appendix Figure A1, Nursing gained more ground than any major, increasing its share by 4.4 percentage points. Yet, Education dropped 5.5 percentage points. These two alone cloud the suggestion that students and colleges have come to favor "vocational" majors to more general degrees over time. Teaching is among the most specific majors for its direct path to a particular occupation, and yet its share has fallen dramatically. Similar juxtapositions can be made in other common gaining or declining majors like Accounting, which lost almost 2 percentage points, versus Computer Science, which gained about 1.7 percentage points.

Looking only at specific types of majors mischaracterizes the evolution of major choice. The EMI more thoroughly captures the changes over time, is agnostic to major type (e.g., vocational vs. general), and is not defined by a single or small group of majors (e.g., Humanities).

Despite the EMI's ability to summarize a trend in major production, the origins of major diversification are not immediately apparent. It could derive from shifts in students' demand for majors across a fixed set of fields, adjustments to institutions' supply of educational offerings, or some combination of these two factors. While I will not precisely parse the contributions of student demand from institutional supply in this paper, I provide several pieces of empirical evidence in favor of supply-side mechanisms. That is, the upward trend in major diversity would not have been possible without widespread institutional expansion of major offerings, which I document herein.

3. Data sources

To explore the origins of major diversification and its ramifications for higher education, I recruit the use of several data sources. In general, the years of interest for this study run from 1990 through 2019, covering three full decades of information. I briefly document these data in the subsections that follow, though more robust descriptions of sample selection, harmonization, and validity checks can be found in Appendix B.

3.1. IPEDS

The majority of the data for this paper come from IPEDS. What can be described as a mandatory census of all colleges and universities that receive federal funds for higher education, IPEDS is both comprehensive and relatively complete, at least with respect to basic measures of institutions in the US. I limit my sample to schools and years between 1990 and 2019 in which at least one bachelor's degree was awarded. This includes public, private non-profit, and for-profit colleges in all 50 states and Washington, D.C., but I exclude schools in Puerto Rico and other outlying islands and territories. The sample includes some schools traditionally viewed as 2-year institutions (e.g., community colleges), but only in years when they may have awarded a bachelor's degree. The sample contains 3,236 total institutions between 1990 and 2019. This number grows significantly over time, from 1,724 institutions in 1990 to 2,333 in 2019. 1,423 institutions awarded degrees during all 30 years of the panel and the mean number of years degrees were awarded overall was about 20.

Outside of degree completions, I harmonize and include institution characteristics, like control, highest degree offering, a school's location, and enrollment and degree completions by race/ethnicity and gender. I also obtain yearly full-time equivalent (FTE) enrollment of undergraduate and graduate students,[7] six-year bachelor's degree graduation rates, and the state of residence for incoming first-year students.

I also harmonized institution-level expenditures and revenues to explore how major diversification affects costs per student. I focus on instructional, academic support, and student services spending, and calculate total revenue net hospital contributions, and the total financial support generated from state governments. I adjust all expenditure and revenue variables using the Consumer Price Index (CPI) to 2019 dollars and divide all dollar values by FTE for analysis, unless otherwise noted.[8]

The final data elements I use from IPEDS are school-identified lists of peer institutions. These lists became available as an optional submission starting in the year 2010, providing 10 potential years of lists for each school. The selection of peers provides institutions a way to compare themselves to others along core metrics reported to IPEDS, like enrollment, completion, financial aid, tuition, etc. The comparisons are made in a public *Data Feedback Report*, which is an annual report

[7] For details on estimating this for earlier years see Appendix B

[8] I also use the Higher Education Price Index (HEPI), which is another measure of inflation arguably more specific to the types of costs typically incurred by higher education institutions. My results using this method of adjustment do not substantively change the results.

of the institution's own data along with the mean of the peer institutions it identified in the reporting process.[9] I provide more description of peer lists and discuss selection and their analytic use in Section 5.

3.2. The Cost Study at the University of Delaware

In some analyses of costs, I use department-level data collected as part of the TCS. Conducted yearly with data available between 1998 and the present, TCS is a voluntary data collection of department-level direct instructional costs, credit hours taught, and faculty teaching loads. Schools opt to participate in the study yearly and need not participate every year. I subset the full sample to schools that reported instructional expenditures and student credit hours that were also in my IPEDS analytic sample for an unbalanced panel of 622 institutions.

These data are typically used by reporting institutions to benchmark their own instructional spending against others in the sample. Recently, the data have been used to explain differences in instructional costs per student credit hour across different fields (Hemelt et al., 2021) and to estimate the responsiveness of credits and faculty distributions to shocks for major-specific employer demand for skills (Conzelmann et al., 2023).

While the TCS sample is not necessarily representative of all 4-year colleges in the US, I show in appendix Figure A2 the EMI in terms of credits earned across participating institutions maps very closely to the bachelor's degree EMI from IPEDS between 1998 and 2019.

3.3. UNC System Microdata

To help explore bachelor's degree program expansion and its spillover effects on direct instructional costs I use administrative data from the 16 public 4-year institutions part of the University of North Carolina System. Specifically, I use data on course-taking of all students in the UNC system between the 2012 and 2020 academic years to generate similarity measures between each pair of majors. I also use administrative records cataloging the dates on which new bachelor's degree programs were approved by the UNC System between 1990 and 2019 to validate new program entry patterns and assignment rules in IPEDS.

4. The Origins of Major Diversification

To distinguish different factors that may have led to major diversification I begin by generating college-level EMI values over time. The college-year EMI can be expressed,

[9] See here for an example: https://nces.ed.gov/ipeds/DFR/2019/ReportHTML.aspx?unitid=199120

$$\text{EMI}_{it} = \left[\sum_{m \in M_i} \left(\frac{x_{imt}}{x_{it}} \right)^2 \right]^{-1}, \tag{2}$$

where I sum the squared shares of each major m within the set of majors, M_i offered at a given school, i. This yields a value on the same scale as in equation 1 with a ceiling unique to the number of programs offered at each school in year t. Throughout the rest of the paper, my interest will be in the degrees-weighted value of EMI_{it}. This does not equate to the overall population EMI_t because schools with varying sizes may specialize (or not) in different fields to varying degrees.[10]

I plot the weighted EMI in Figure 2 on the left-hand side. And on the right, for comparison, I plot the raw weighted average number of majors in which degrees were awarded. The average number of programs is also a measure of degree diversity but disregards the distribution of awards across fields. By visual inspection, the trends in the EMI map closely with an increase in the average number of majors within schools. This relationship need not be mechanical and is entirely possible for major diversity to increase holding the number of majors in each school fixed.[11] If this were the case, the average number of majors over time would remain relatively flat, suggesting students shifted their choices across a relatively fixed set of major offerings. However, the trend in major offerings is positive and highly correlated with the EMI.

4.1. Diversification occurred primarily within colleges

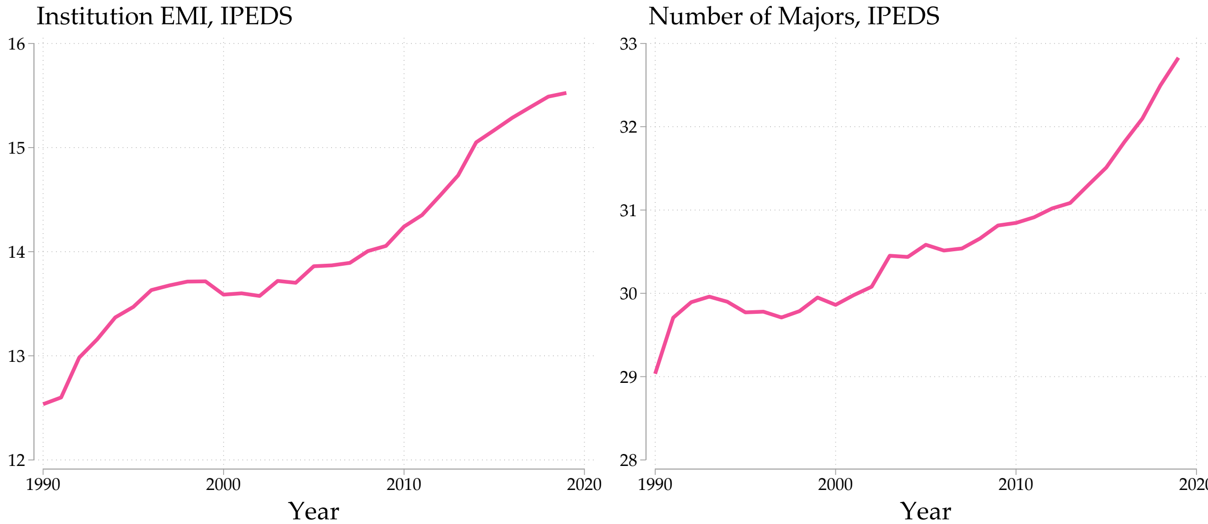
Next, I characterize the increase in the EMI as a common trend across most colleges and universities, rather than a sector- or type-specific one. As a result, colleges became significantly more homogeneous in their degree diversity over time. For example, liberal arts colleges diversified their degree production more significantly than comprehensive research universities throughout this period, growing more alike on this dimension. Finally, I rule out a significant role for college entry or exit in explaining the trend. To clarify these points I decompose the yearly changes in the institution EMI from 1990 to 2019, following the work of Melitz & Polanec (2015) and Olley & Pakes (1996).

First, I define the $\log(\text{EMI}_{it}) = Y_{it}$. The degrees-weighted average log EMI across all colleges in year t can be written,

[10] Consider an extreme scenario where all schools award degrees in a single field. If we allow school size to vary, the population EMI will vary over time based on the allocation of students across schools, while the within-school EMI would remain 1 for all years, by construction.

[11] For instance, a hypothetical school with just two majors has students who prefer major one 3:1 in time period 1, yielding an EMI of 1.6. In period 2, students shift to parity, 2:2, yielding an EMI of 2.

Figure 2: Institution EMI and number of majors, 1990-2019.



Notes: Both sets of estimates are weighted by degrees granted. EMI=effective major index. The total number of programs come from the full list of 71, as referenced in the main text.

$$Y_t = \sum_{i \in I} \left(\frac{x_{it}}{x_t} \right) Y_{it}, \tag{3}$$

where the term in parentheses is the share of all bachelor's degrees awarded in year t at a given institution i. I decompose the year-over-year changes to Y_t where institutions can fall in and out of the sample in each period. For any two years of the panel, $t = 1, 2$, institutions are classified into one of three groups of *continuers*, new *entrants*, and *exiters*. These groups are indexed by $g \in \{C, E, X\}$ respectively. Continuing institutions are those that award degrees in both periods. Entering schools awarded degrees in the second period, but not the first. And schools categorized as exiters awarded degrees in the first period, but did not award any in the second. I decompose the change in Y_t from $t = 1$ to $t = 2$ into:

$$\Delta_1^2 Y = \underbrace{\left(\frac{x_2^E}{x_2} \right) \left(Y_2^E - Y_2^C \right) - \left(\frac{x_1^X}{x_1} \right) \left(Y_1^X - Y_1^C \right)}_{\text{net entry}} + \underbrace{\Delta \overline{Y}^C}_{\text{within } C} + \underbrace{\Delta \text{cov}_C \left(\frac{x_i}{\overline{x}^C}, Y_i \right)}_{\text{between } C} \tag{4}$$

Here, x_t^g refers to the number of degrees awarded in group g and Y_t^g is the weighted average log EMI for each group in the respective time periods 1 or 2. The first bracketed expression quantifies the contribution of entering and exiting colleges on the change in log EMI based on their share of the total degrees and major diversity relative to continuing institutions. A positive value for net entry implies that the degrees awarded by schools who entered during the period were more diverse relative to continuing and exiting colleges, where a negative value would imply the opposite.

The second bracketed term captures the change in log EMI attributable to changes within continuing colleges. Here, $\overline{Y}^C$ is the average unweighted change in the log EMI among continuing colleges. Positive values imply the average continuing college diversified their degrees awarded, where negative values imply declining diversity. Large values in the positive (or negative) direction suggests a more ubiquitous trend across institutions becoming more (less) diversified in their degrees awarded.

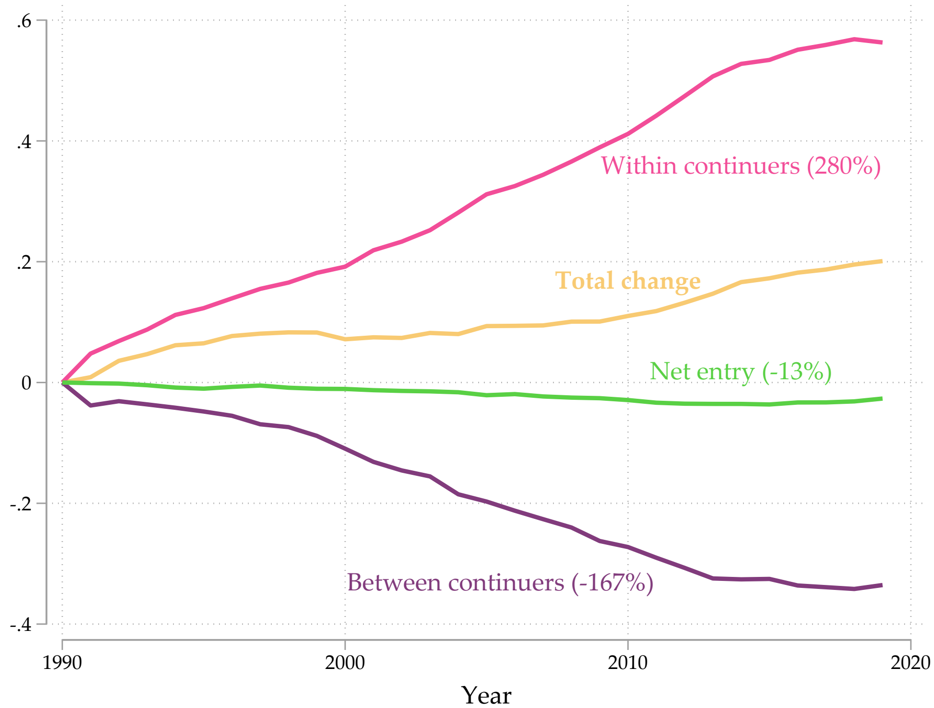
The third and final bracketed term measures the contribution of between-college variation in the EMI among continuing schools. This term helps quantify the relationship between diversification and institutional size. It is defined as the change in the covariance between the relative size of each continuing institution, where $\overline{x}^C$ is the average size of continuing colleges, and the college-specific EMI, Y_i. Interpreting its value depends on the sign of the covariance. A declining covariance could indicate a strengthening negative relationship between college size and degree diversity ($\text{cov}_2 < \text{cov}_1 < 0$).[12] A declining between-college term could also indicate a declining positive relationship between size and diversity ($0 < \text{cov}_2 < \text{cov}_1$). This implies a pre-existing relationship between college size and major diversity that has decreased or become less prominent over time. Degree production would no longer be as predictive of major diversity in this case.

The results of this exercise depicted in Figure 3 reveal several interesting facts about the evolution of bachelor's degree diversity. The total change in the EMI from 1990 to 2019 of 0.2 log points was driven by two strong bifurcating forces. The first was a large, positive diversification of majors within continuing colleges. This within-school diversification was almost 3 times the aggregate change at 0.55 log points. The second was a steep decline in between-college variation. The relationship between college size and major diversity declined by about 0.33 log points throughout the period.

The large within-college value suggests the typical behavior of a college throughout this period was to diversify. The decline in between-college variation refines this story suggesting that smaller institutions like liberal arts and master's institutions were diversifying at a faster rate than larger comprehensive institutions who began the period with higher levels of major diversity. In effect,

[12] This case is the focus of Ekerdt & Wu (2023) and their analysis of the decline in industry diversity of manufacturing firms in the US, where its large negative values over time suggests heterogeneity in the type of firm driving the decline in diversity. Namely, large firms moved toward specialization, arguably driven by demand for higher quality goods in the US over time.

Figure 3: Decomposition of the change in log EMI 1990-2019.



Notes: This figure decomposes the total change in the log EMI into three main components described in Equation 2. The percentages sum to 100, representing the share of the total change.

these colleges caught up to comprehensive research universities and looked much more like them in terms of their bachelor's degree production in 2019 than in 1990.

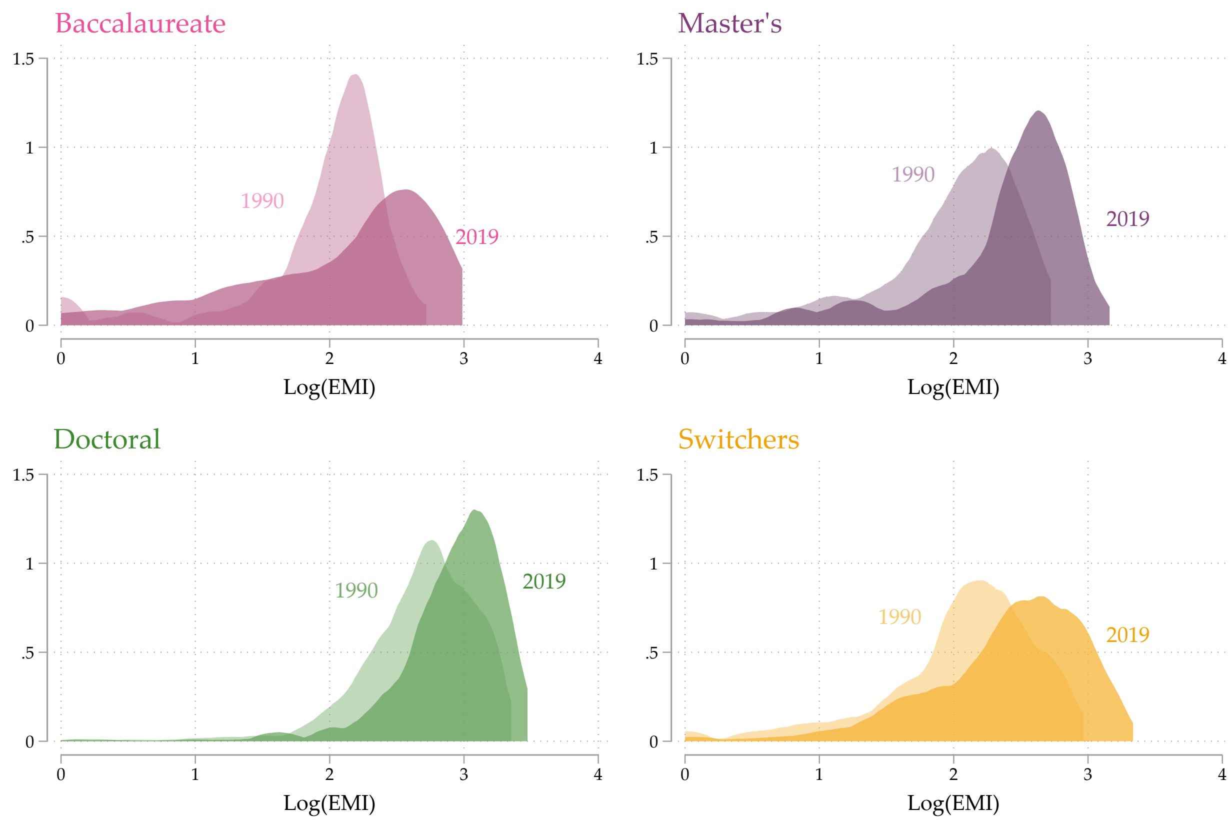
The role of net entry in the market for bachelor's degrees plays a minimal role in explaining the total change in major diversity (about -0.03 log points). Starting a new college is costly as is offering bachelor's degrees for the first time on top of other programs. Schools who enter are not likely to compete in the share of degrees with well established institutions.[13]

To further illustrate the main takeaways from this exercise, I plot the distributions of the log EMI for four different types of institutions based on their highest educational offerings in 1990 and 2019. Figure 4 shows that majors for bachelor's degrees diversified, regardless of highest degree offering. This is visually apparent from the shift in each distribution rightward from 1990 to 2019. "Switchers" in the bottom right panel of Figure 4 in orange are schools that added or eliminated degree capacity in the panel.[14]

[13]This decomposition partially masks the role entering institutions play in the long-run. Over a quarter of institutions in the full panel "entered" the market at some point after 1990. The persistence of once-entrants contributes a large portion to the overall trend, as they became continuing colleges after initial entry. This decomposition is shown in appendix Figure A3.

[14]Switching anytime between 1990 and 2019 is quite prevalent, encompassing nearly 40 percent of institutions and 34 percent of all degrees by the end of the panel in 2019. The vast majority of schools in this group gained capacity (94%)

Figure 4: Density of the log EMI in 1990 and 2019, by highest degree offering



Notes: Each panel is a group of institutions based on the highest degree offered in 1990 and 2019. "Switchers" are those whose highest degree offering was different in 1990 than in 2019, dominated by schools adding higher degrees (94%).

The distribution for doctoral institutions in green shifted right less sharply, where it was more pronounced for the other groups. Doctoral institutions in 1990 tended to house more colleges and departments than smaller master's and baccalaureate institutions. Yet, since 1990 their share of bachelor's degrees awarded declined 5 percentage points (from 55 to 50 percent) as many other institution types expanded their degree-granting capacity and added major options along the way.

I formalize the contribution each type of college made to overall major diversification by rewriting the continuing college portion of the decomposition in Equation 2 as the change in the weighted average EMI among mutually exclusive groups of continuers. Grouped by their respective degree offerings, $h \in \{MB, D, S\}$, and combining baccalaureate and master's institutions (MB), the decomposition becomes,

$$\Delta_1^2 Y = \text{net entry} + \underbrace{\sum_h \left(\frac{x_2^h}{x_2^C} \cdot Y_2^h\right) - \left(\frac{x_1^h}{x_1^C} \cdot Y_1^h\right)}_{C \text{ group-specific contributions}}, \tag{5}$$

where Y_t^h is the (degree weighted) average log EMI for each continuing group h and the changes are weighted by the group's overall share of continuing institution degrees in the respective time period. I plot each group's cumulative contribution to the overall change in log EMI over time in Figure 5.

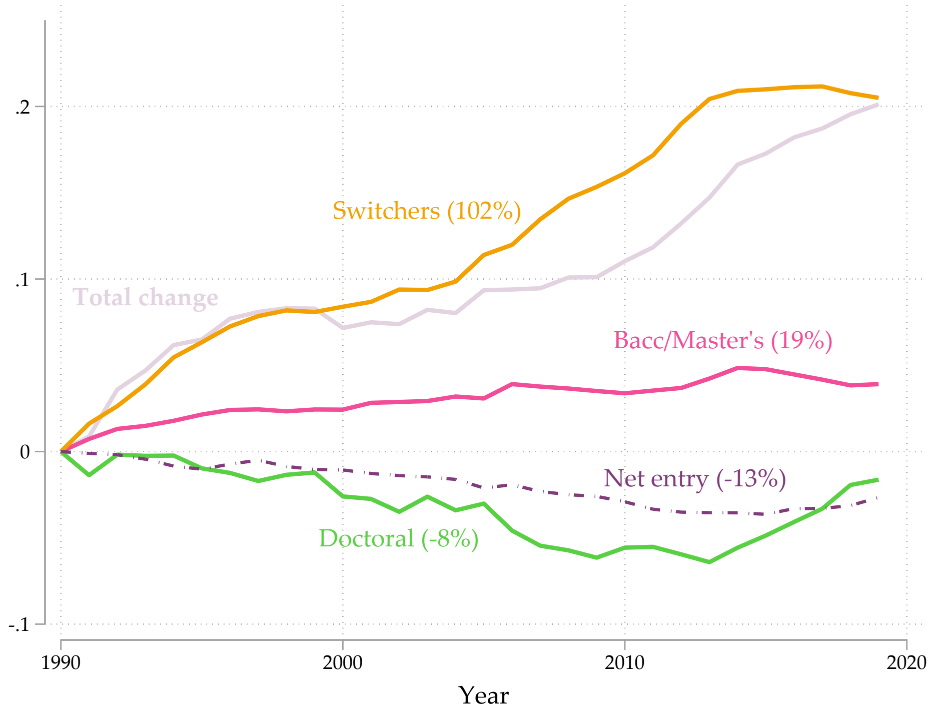
This exercise reveals that switchers were most responsible for the increase in major diversity. Somewhat paradoxically, the doctoral institutions contribute negatively to major diversification during this time (about -.02 log points). This does *not* suggest a decrease in major diversity among these institutions but instead reflects a relative decline in their share of all bachelor's degrees they awarded paired with a relatively small increase in degree diversity from 1990 to 2019. Both switchers and baccalaureate and master's institutions increased their overall share of degrees awarded between 1990 and 2019 from 30 to 34 percent and from 15 to 16 percent respectively. This and relatively large increases in major diversity among these institution groups yields net positive contributions to the overall change in log EMI.

4.2. Oaxaca-Blinder Decomposition

In this section I decompose the change in the log EMI from 1990 to 2019 into observable student characteristics, institutional attributes, and a residual term using an Oaxaca-Blinder decomposition. This exercise helps parse the importance of different demand- and supply-side factors that

adding higher degree offerings over time, rather than eliminating them.

Figure 5: Decomposition of the change in log EMI 1990-2019, by institution type.



Notes: Baccalaureate and Master's colleges are grouped together. "Switchers" are those whose highest degree offering changed at some point between 1990 and 2019. Yearly estimates are generated by taking the cumulative sum of changes calculated for each group h from Equation 5.

could contribute to degree diversification.

First, Table 1 presents the means and standard deviations for these key variables across institutions in 1990 and in 2019 along with their differences. As discussed in the previous section, the EMI increased overall by 0.2 log points in three decades. During this time, undergraduate enrollment changed dramatically both in scale and in the composition of students attending. FTE enrollment increased by over 0.35 log points and was particularly strong among URM, like Hispanic students, whose share of all degrees increased by about 10 percentage points, and Black students and women, whose share increased by about 4 and 5 percentage points respectively.[15]

Table 1: Changes among Bachelor's degree granting colleges between 1990 to 2019

	Mean (1990)	SD (1990)	Mean (2019)	SD (2019)	Difference
Log(EMI)	2.377	0.618	2.578	0.668	0.201
Log(Number of BA programs)	3.235	0.628	3.362	0.637	0.126
Log(Undergraduate FTE)	8.851	1.076	9.202	1.154	0.351
Student characteristics					
Share BAs awarded Black	0.056	0.115	0.092	0.118	0.036
Share BAs awarded Hispanic	0.031	0.057	0.136	0.134	0.105
Share BAs awarded Foreign/Intl	0.025	0.033	0.052	0.056	0.027
Share BAs awarded Other non-white	0.041	0.064	0.114	0.090	0.073
Share BAs awarded Race unknown	0.030	0.114	0.034	0.051	0.004
Share BAs awarded Women	0.530	0.107	0.574	0.101	0.045
Institution attributes					
Public Highly Selective	0.057	0.232	0.099	0.299	0.042
Public Less Selective	0.601	0.490	0.560	0.497	-0.041
Private Highly Selective	0.068	0.252	0.085	0.278	0.016
Private Less Selective	0.268	0.443	0.210	0.408	-0.058
For-profit	0.006	0.075	0.046	0.210	0.040
Highest degree offering: Bachelor's	0.099	0.299	0.048	0.214	-0.051
Highest degree offering: Master's	0.343	0.475	0.170	0.375	-0.173
Highest degree offering: Doctorate	0.558	0.497	0.782	0.413	0.224
Share of degrees BA level	0.733	0.153	0.703	0.162	-0.030
State funding					
Share of revenue from state	0.304	0.229	0.167	0.156	-0.137

Notes: EMI=Effective Major Index is the inverse of the sum of squared shares of each major for which bachelor's degrees were awarded by a college or university in a given year. Intl=International. All estimates are weighted by the number of bachelor's degrees awarded by a given institution in 1990 or 2019 respectively. Selectivity is determined based on Barron's Competitiveness Index where highly selective includes the top two categories and less selective includes all others. Reliance on state funding is calculated as the share of total non-hospital revenue derived from state appropriations and financial aid to students.

Colleges also expanded their curricular offerings both for baccalaureate and graduate education significantly over this period. For instance, the share of BAs being awarded by schools offering

[15] Unfortunately, measures of student socioeconomic status or academic preparedness upon college entry are not available in IPEDS until much later in the panel, or are only available for a subset of schools (e.g., test scores).

a doctoral degree grew from 56 to over 78 percent in 2019. Another interesting descriptive fact is that institutions grew their number of BA program offerings by about 0.13 log points between 1990 and 2019. As I will show, this growth in the number of majors is a key driver of overall major diversification nationally.

I also include the total share of non-hospital revenue for each institution generated from state appropriations and state financial aid (e.g., need or merit-based grants to students). Reliance on state funding fell from 30 percent to less than 17 percent during this time.

Following other similar work to decompose changes in graduation rates over time by Bound et al. (2010) and Denning et al. (2022), I perform my EMI decomposition on the full sample and different institution types separately. These sets of results can be found in Table 2. In the first column with the full sample, the chosen covariates explain about two-thirds or 67 percent of the observed increase in the log EMI.

Table 2: Oaxaca-Blinder Decomposition of Change in Log(EMI) from 1990 to 2019

	Full Sample	Public highly selective	Private highly selective	Public less selective	Private less selective	For-profit
Log EMI 2019	2.578	3.042	2.606	2.761	2.164	1.208
Log EMI 1990	2.377	2.591	2.356	2.528	2.033	0.722
Total Change	0.201	0.451	0.250	0.232	0.131	0.486
Explained changes	0.134	-0.166	0.082	0.154	0.071	0.839
	(67%)	(-37%)	(33%)	(66%)	(54%)	(173%)
Student characteristics	-0.066	-0.381	-0.084	-0.058	-0.071	0.078
	(-33%)	(-84%)	(-34%)	(-25%)	(-54%)	(16%)
Institution characteristics	0.045	0.0002	-0.003	0.042	0.007	-0.067
	(22%)	(0%)	(-1%)	(18%)	(5%)	(-14%)
State financial support	0.046	-0.022	0.004	0.071	-0.004	-0.027
	(23%)	(-5%)	(2%)	(31%)	(-3%)	(-6%)
Log(Undergraduate FTE)	0.008	0.014	-0.003	0.013	0.001	0.033
	(4%)	(3%)	(-1%)	(6%)	(1%)	(7%)
Log(Number of BA Programs)	0.101	0.223	0.168	0.086	0.138	0.822
	(50%)	(49%)	(67%)	(37%)	(105%)	(169%)
Unexplained (residual)	0.067	0.616	0.168	0.078	0.060	-0.353
	(33%)	(137%)	(67%)	(34%)	(46%)	(-73%)

Notes: EMI=Effective Major Index is the inverse of the sum of squared shares of each major for which bachelor's degrees were awarded by a college or university in a given year. Student characteristics include the share of BA recipients that are Black, Hispanic, Foreign/International, of unknown race/ethnicity, all other non-white, and the share that were awarded to women. Institution characteristics include the highest degree offering (bachelor's, master's, or doctorate), the share of all degrees awarded that were BAs, and institution category combining selectivity (top-two Barron's categories and all others) with control (public or private non-profit), and a separate group for for-profit institutions. State financial support is the share of total non-hospital revenue derived from state appropriations and financial aid to students. Both undergraduate enrollment measured in full-time equivalent (FTE), and the number of BA programs were log transformed for this exercise.

Compositional changes in students obtaining bachelor's degrees negatively contributed to overall diversification, conditional on institution supply-side factors and state funding. In the absence of increases to female and non-white college graduates between 1990 to 2019, I estimate that major diversity would have increased by another 7 percent than what was observed. This finding is consistent with long-standing gaps between women and men in attainment and persistence in STEM fields (e.g., Sloane et al., 2021) and similar gaps between URM and white students (e.g., Gelbgiser & Alon, 2016). It could also be indicative of supply restrictions on some types of majors, like business. These institutional policies, highlighted by Bleemer & Mehta (2021), tend to decrease URM and low-income student enrollment in fields with GPA restrictions. In general, the patterns found here suggest demographic shifts in 4-year college degree attainment tended to suppress major diversification. This may be due to differential student preferences, preparedness, or institutional policies restricting enrollment in certain fields.

Changes to overall undergraduate enrollment explains less than 5 percent of the positive change in the EMI, conditional on the other factors in the decomposition. This is consistent with the declining positive relationship between institution size and degree diversity shown in the previous section. About 22 percent of the change in EMI was related to other institutional attributes, particularly increases in the share of institutions offering master's and doctoral degrees.

Institutional reliance on state funding was associated with about a 5 percent increase in the EMI (23 percent of the total change). Lower levels of state funding seen in 2019 compared to 1990 were predictive of higher major diversity. This pattern was driven mainly by non-selective public institutions who make up a large share of degree awards and rely more heavily on state funding to operate and attract students. Among the most selective public institutions, state funding declines do not appear to have had an impact on their increases in major diversification. Across institution groups, declining revenue share from the state was accompanied by colleges diversifying their degree offerings.

The most prominent factor explaining major diversification was the (log) number of BA programs offered within an institution. About 50 percent of the aggregate increase in the EMI can be attributed to secular increases in the number of degree programs. While there is some variation across institution type, this relationship remains strong and positive throughout the different subsamples and is particularly prominent among non-public institutions. This could perhaps be due to fewer administrative barriers to adding programs for private institutions, where public institutions are often subject to larger system-wide governing bodies with rules against duplication of programs within a system. Still, public institutions also expanded BA program offerings significantly and this increase remains the most predictive of the EMI changes over other factors.

To summarize the descriptive results thus far, I have identified significant increases in diversity of majors for bachelor's degrees in the US over three decades. The empirical evidence points to a prominent role for within-institution diversification of BA programs in explaining this trend. In contrast, compositional changes in students obtaining a bachelor's degree drove down major diversification. As the market for bachelor's degrees in the US swelled, colleges and universities grew to look more like one another, choosing to expand into new undergraduate programs and less so vertically within their established programs.

5. Peer institutions and Major Diversification

In this section I show that major diversification, driven heavily by changes to the supply of program offerings, can be attributed to isomorphism in the market for bachelor's degrees. Specifically, colleges behaved in ways consistent with improving their own relative quality or prestige among a group of close peer institutions. This explanation outperforms others including spillovers from graduate education and responses to external factors like changes to state funding or the business cycle.

5.1. Defining Peer Institutions

To define peer institutions, $p(i)$, I use peer lists from IPEDS reported from 2010 through 2019. Since these lists are optional and not all institutions report them, I present in Table 3 basic descriptive statistics for institutions who did and did not submit lists. About 53 percent of the institutions in my analytic sample submitted peer lists at least two times out of 10 possible submissions. However, the schools who submit lists awarded over 85 percent of all bachelor's degrees between 1990 and 2019. Schools who did not submit peer lists awarded bachelor's degrees for fewer years throughout the panel (15 vs 25 years) and were also disproportionately for-profit colleges or non-selective in admissions (31 vs. 16 percent and 87 vs 44 percent) suggesting schools that submit peer lists are more established, more likely to be engaging in some selective admissions process, and much larger producers of the country's bachelor's degrees overall.

I subset each school's cumulative set of peers from all possible lists to the top-10 most submitted institutions, including ties, and require that a school be listed at least two times to be considered a close peer. This improves the overall stability of the lists across time.[16] I assign one stagnate list

[16] As shown in appendix Table A1, the average year-over-year overlap of peer lists within institution is between 0.95 to

Table 3: Descriptive statistics of institutions that select peers versus those that do not

	Did not Select Peers		Selected Peers	
	Mean	SD	Mean	SD
Number of Institutions	1,517		1,719	
Share of institutions	0.47		0.53	
Share of all BA's awarded (1990-2019)	0.15		0.85	
Control: Public	0.14	0.34	0.31	0.46
Control: Private non-profit	0.56	0.50	0.53	0.50
Control: For-profit	0.31	0.46	0.16	0.36
Selectivity: High	0.01	0.12	0.10	0.30
Selectivity: Moderate	0.11	0.31	0.46	0.50
Selectivity: Low	0.87	0.33	0.44	0.50
Degree-weighted Avg Log(EMI)	2.14	0.75	2.55	0.62
Avg yearly BA's awarded	183.94	576.95	776.39	1247.97
Avg years BA's awarded (max 30)	13.53	10.81	25.22	8.41
Avg share degrees: Associate's	0.29	0.35	0.16	0.29
Avg share degrees: Bachelor's	0.55	0.33	0.64	0.28
Avg share degrees: Graduate	0.16	0.25	0.20	0.21
Highest degree offering: Bachelor's	0.53	0.50	0.24	0.42
Highest degree offering: Master's	0.26	0.44	0.33	0.47
Highest degree offering: Doctorate	0.21	0.41	0.44	0.50

Notes: Statistics are unweighted unless noted otherwise. EMI=Effective Major Index is the inverse of the sum of squared shares of each major for which bachelor's degrees were awarded by a college or university in a given year. Institutions that selected peers are those who submitted lists of peer institutions as part of IPEDS reporting and Data Feedback Reports. I include only schools who submitted these lists 2 or more times between 2010 and 2019. Selectivity is derived from Barrons Competetiveness Index where highly selective groups the first two categories (Most and Highly competetive), moderately groups the next two (Very Competetive and Competetive) and the third category includes all others. Averages within school are taken over all possible years during which BAs were awarded according to IPEDS.

of peers for each institution throughout the panel, varying only if peers drop in or out of being a bachelor's degree producer (i.e., not in the analytic sample in a given year). This implicitly assumes peer groups identified in the last decade of the panel were also peers in the earlier two decades as well.

I further provide some descriptive information on how institutions list peers, with full details available in Appendix Table A2. On average, colleges tend to choose "aspirant" peers. A school's own 6-year graduation rate and instructional expenditures per FTE are about 90 and 96 percent that of the peer group across all years of data. Schools also tend to list peers with higher enrollment than they themselves posses. Average undergraduate FTE enrollment of focal institutions is just 78 percent that of its peers. Finally, the geographic variation of peer groups is quite vast. The average distance from focal institutions to its peers is 587 miles. But 10 percent of colleges choose average peers that are within 100 miles, while some 10 percent of colleges list peers over 1000 miles away, on average.

5.2. Peer Effects Empirical Strategy

To estimate how colleges change their major diversity in response to their peers, I begin with a canonical linear in means specification from the peer effects literature (e.g., Manski, 1993; Moffit, 2001).

$$Y_{i,t} = \beta_1 \overline{Y}_{p(i),t} + \mathbf{\Gamma} \boldsymbol{X_{i,t}} + \mathbf{\Pi} \boldsymbol{\overline{X}_{p(i),t}} + \eta_i + \eta_t + \epsilon_{i,t}, \tag{6}$$

where Y is the the log EMI regressed onto the degrees-weighted average log EMI of an institution's peers, a vector of time-varying institution characteristics, $\boldsymbol{X_{i,t}}$, analogous time-varying average peer characteristics $\boldsymbol{X_{p(i),t}}$, and school and year fixed effects. The vector of time-varying controls captures changes to student composition that is potentially correlated to peer shocks and to changes in the focal institution's EMI. This vector includes the share of BAs awarded to Black and Hispanic students, women, and foreign students. It also includes the share of the student body enrolled part-time and the share of graduate students. To account for differential trends in the evolution of the EMI that may occur for institutions newer to the market for bachelor's degrees (e.g., former 2-year college), I also include in $\boldsymbol{\overline{X}_{i,t}}$, a school's "age" and its quadratic for the number of years it awarded BAs within the panel at each time, t. Finally, I include (log) under-

0.99, with the overlap between lists submitted in 2010 and 2019 is about 0.77 (i.e., lists compared 10 years apart). This high level of stability suggests that schools only marginally change who they consider to be their peer institutions over time.

graduate enrollment of the focal institution and peers' average. Even though capacity is one way institutions could respond to changes in peer quality, my interest is in isolating the effects of major diversification net of enrollment increases.[17]

Given the length of the panel, institution fixed effects may not capture meaningful "fixed" differences over time.[18] As a second approach, I estimate a similar equation in stacked 6-year long differences. Differencing equation 6 in 6-year increments effectively removes fixed characteristics of the institution over each 6-year interval. Keeping base-year fixed effects, the new estimating equation becomes,

$$\Delta_{t_0}^{t_6} Y_i = \gamma + \beta_2 \Delta_{t_0}^{t_6} \overline{Y}_{p(i)} + \boldsymbol{\Gamma} \left(\boldsymbol{\Delta_{t_0}^{t_6} X_i} \right) + \boldsymbol{\Pi} \left(\boldsymbol{\Delta_{t_0}^{t_6} \overline{X}_{p(i)}} \right) + \eta_{t_0} + \Delta_{t_0}^{t_6} \epsilon_i \tag{7}$$

Identifying peer effects is difficult for two main reasons. First, the reflection problem, highlighted by Manski (1993), arises in trying to separate a group effect on an individual from the individual's effect on the group, particularly when the outcomes are determined simultaneously. The existence of institution-specific peer groups in my setting helps to alleviate this concern. For example, there are excluded peers that are peers of peer institutions that are absent an institution's own list. On the issue of simultaneity, my estimated effects are robust to lagging the peer measures by one or two years.

The second problem in identifying peer effects is the potential existence of correlated effects: unobserved factors affecting a group of institutions that are also correlated with major diversification. In my setting, this could be labor market shocks affecting students' college decisions (like where and what major to pursue), which might also relate to an institution's decision to diversify its major offerings. To overcome this issue, the non-overlapping peers can be used to instrument for peer behavior. This point is illustrated by Bramoullé et al. (2009) using a hypothetical triad between a focal institution i, its peer p, and its peer k, where p affects i, and k affects p, but k only affects i through its effect on p and not directly.

Following this logic, I instrument for first degree peers' EMI ($\overline{Y}_{p(i)}$) using measures from excluded peers of peers, defined by the function $k(\cdot)$, collecting institutions that are peers of the focal institution's peers, $p(i)$, but not part of the institution's own set. One intuitive approach is to instrument for first peers' EMI using the log average EMI of excluded peers, $\overline{Y}_{k(i)}$. Another ap-

[17] It is worth noting that enrollment was not a significant predictor of the change in the EMI from Section 4.2. The results presented here are also robust to excluding controls for enrollment.

[18] Recent work by Millimet & Marc (2023) formalizes the bias this might create in unit fixed effects models and suggests several variations of first-difference regressions to alleviate the concern.

proach, illustrated by De Giorgi et al. (2010), is to use average covariate values of excluded peers as instruments instead of their outcome values. In this case, a vector of average student-body characteristics for excluded peers, $\bar{X}_{k(i)}$, is likely to be highly correlated with the outcomes, but perhaps less susceptible to correlated effects. These overidentified models have a precedent in the peer effects literature and require a generalized two-stage least squares (2SLS) estimation procedure as in Lee (2003), abbreviated GMM2S.

Either of these IV strategies may yet be biased from strategic listing of peer institutions. Peer lists themselves could be endogenous to the choices schools make to undergraduate curriculum and offerings, which would be problematic if schools select institutions strategically based on their expectations for how it would look for comparisons. Fortunately, schools do *not* appear to be selecting peers to improve their relative appearance, at least generally speaking. As described in the previous section and in Appendix Table **??**, schools tend to choose "aspirant" peers with 6-year graduation rates and instructional expenditures per FTE higher than that of the focal institution. This behavior is preferable for identification since institutions should be more likely to follow the major diversity behavior of institutions at or above their own output than those below them. That aspirant institutions are well-represented in the peer lists also diminishes the concern that true peers would show up as excluded peers having been omitted from the observed list.

The IV strategy could also fall short of addressing correlated effects among peer groups without "network" fixed effects (Bramoullé et al., 2009). Schools might self-select into peer groups based on shared characteristics, like admissions selectivity, geography, or prestige, that are omitted or unobserved in the model yet also correlated with the evolution of major diversity. In my setting, I do not have clear network delineations barring institutions of some type from being peers of another.[19] In lieu of clear network fixed effects, I test the inclusion of several pseudo-network indicators interacted with year, none of which substantively change the main results. These include admissions competitiveness groupings, state geography, and deciles of both instructional expenditures and graduation rates.

Table 4 presents estimates from both the fixed effects and long difference models and various strategies for dealing with endogeneity concerns. Across specifications, the evidence for peer effects in this market is strong. Notice first, the two separate estimating equations provide qualitatively similar results, with the fixed effects approach providing more stable point estimates across columns. Both the ordinary least-squares (OLS) and Instrumental variables (IV) approaches show

[19] In individual peer-effect literature, networks are often bounded by things like schools or classrooms.

a large and positive elasticity of response to peers in the focal institution's major diversity. In columns 1 and 4, OLS estimates imply that focal institutions increase their major diversity by 2-3 percent for each 10 percent increase in the peers' average EMI.

These OLS estimates are significantly smaller than those from the IV specifications whose elasticities center around 1.5. Columns 2 and 5 using the average major diversity among peers of peers, $\overline{Y}_{k(i)}$, show slightly larger elasticities between 1.7 and 2.3. The first stage is strong with F-statistics greater than 40.[20] Columns 2 and 5 instrument for peers' average EMI using the average covariates of excluded peers. Here, the first-stage F-statistic is smaller in magnitude, yet still about 25 on average. The elasticity estimates from instrumenting with $\bar{\boldsymbol{X}}_{\boldsymbol{k}}$ are comparable, though slightly more modest suggesting an 11-14 percent positive response in major diversity as a result of a 10 percent increase in peers' major diversity. To address potential common geographic or political shocks occurring across time, I also show estimates including year-by-state fixed effects. Their inclusion does not meaningfully change the estimates.

The increase in point estimates between the OLS and IV models could be due to heterogeneity in peer networks and in the shocks these groups experience. For example, some schools may cluster in peer networks that are more homogeneous in performance, prestige, or geographic location than others. In these networks, correlated shocks from shared factors like the labor market, student demand, or state-level policy may change the salience of peer behavior or make responses to them more or less beneficial. More diffuse networks, perhaps those characterized by more selective institutions, face common shocks broader in scope (e.g., national vs. local trends). It is unclear theoretically whether this heterogeneity would work for or against peer interactions, though the OLS estimates suggest a downward bias in this particular case. The IV estimates using excluded peer measures that are arguably uncorrelated with these common network shocks yield a more robust positive response in major diversification.

5.3. Contextualizing Peer Effects

In this section, I offer some robustness checks of these results and a brief exploration of one mechanism driving institutional peer effects.[21] One concern with my analysis may be that peer lists fail to provide information beyond that of a group of randomly drawn institutions. The near universal within-school diversification of majors could mean that any group of institutions would

[20]Detailed estimates from the first-stage can be found in Appendix Table A3.

[21]An in-depth treatment of this behavior is outside the scope of this paper, though would be an interesting extension of this work.

Table 4: Peer Institution Effects on Major Diversification

	1 OLS	2 2SLS	3 GMM 2S	4 OLS	5 2SLS	6 GMM 2S
Panel A. Fixed Effects, Outcome=Log(EMI)						
Peers' Log(Average EMI)	0.313**	1.718**	1.138**	0.223**	1.734**	1.168**
	(0.0756)	(0.319)	(0.259)	(0.0770)	(0.316)	(0.265)
Instrument(s)	-	$\overline{Y}_k$	$\overline{\boldsymbol{X}}_{\boldsymbol{k}}$	-	$\overline{Y}_k$	$\overline{\boldsymbol{X}}_{\boldsymbol{k}}$
First-stage F	-	48.16	24.31	-	63.17	27.06
School FEs	✓	✓	✓	✓	✓	✓
Year FEs	✓	✓	✓	✗	✗	✗
State-by-Year FEs	✗	✗	✗	✓	✓	✓
N Observations	43,057	42,903	42,903	43,031	42,877	42,877
N Clusters	1702	1690	1690	1702	1690	1690
Panel B. Stacked Long Differences, Outcome= Δ_{t0}^{t6}**Log(EMI)**						
Peers' Δ_{t0}^{t6}Log(Average EMI)	0.280**	2.285**	1.416**	0.204**	2.346**	1.431**
	(0.0472)	(0.437)	(0.293)	(0.0506)	(0.462)	(0.299)
Instrument(s)	-	$\overline{Y}_k$	$\overline{\boldsymbol{X}}_{\boldsymbol{k}}$	-	$\overline{Y}_k$	$\overline{\boldsymbol{X}}_{\boldsymbol{k}}$
First-stage F	-	43.61	23.10	-	45.44	25.28
Base Year FEs	✓	✓	✓	✗	✗	✗
State-by-Base Year FEs	✗	✗	✗	✓	✓	✓
N Observations	32,978	32,880	32,880	32,954	32,856	32,856
N Clusters	1609	1602	1602	1608	1601	1601

Notes: * $p < 0.05$, ** $p < 0.01$. Standard errors clustered at the institution-level are in parentheses. All models are weighted by the base-year total number of BA degrees. Panel A presents estimates from a school fixed effects approach estimating the effect of the weighted average log(EMI) of an institution's peers on the institution's own log(EMI). Columns 1 and 4 present traditional linear-in-means estimates including institution covariates and corresponding peer group averages. These controls include the log undergraduate enrollment, share of a school's total enrollment that is part-time, share graduate students, the share of bachelor's degrees awarded to women, to students that were either Black or Hispanic, to foreign or international students, and the number of years in the panel the school had awarded BA degrees and its quadratic. Column 2 and 5 instrument for peers' log(EMI) using the average peers of peers' log(EMI), Y. Panel B presents analogous estimates from a stacked-long differences specification regressing the 6-year changes in the outcome on the 6-year changes in the instruments and control variables. Columns 3 and 6 are estimated using a 2-stage generalized method of moments weighting procedure where excluded instruments are the control variable averages (X's) of all peers of peers, identified by $k(i)$.

be predictive of changes in a school's EMI. To alleviate this concern, I randomly select new peer groups for each institution 100 times and create placebo peer and 2nd degree peer EMI measures and re-run the main estimates from Table 4. Appendix Figure A4 shows that the actual peer lists carry useful information with estimates from random peer lists all centering around zero and the original estimate reaching 3 to 5 times larger than even the most extreme positive placebo estimates.

If the specific set of chosen peers is indeed important, then my results should also be robust to removing a small set of "influential peers." Colleges might aspire to behave like the most prestigious institutions within their metaphorical reach, akin to following industry leaders in other sectors of the economy. In this case, the behavior of other less prominent peers may not be as important, and the list as a collective network only a noisy signal. I test this by removing the most influential peer from every school's list and separately, by removing the top five percent universally influential peers from the full sample. I estimate influence by calculating the frequency that each college is listed as the peer of another, then break ties using Barron's competitiveness index (i.e., more competitive indicates more influential) and undergraduate FTE enrollment (i.e., larger enrollment equates to more influence).

Neither of these exercises change the main point estimates in a significant way. The detailed results are in Appendix Table A4. In general, the IV estimates are slightly larger when influential peers are removed. For instance, in 2SLS models the elasticity of response to peer diversity is nearly 2 versus 1.7 in the main models. Furthermore, the statistical power of the first stage is somewhat larger when influential peers have been removed (e.g., F-statistic of 96 vs. 48). These results suggest that "industry leaders" in higher education do not drive the majority of the peer effects I observe on the dimension of degree diversity. Instead, an institution's network of peers drives behavior, and this is more nuanced than what a single school or even a few schools might capture.

Still, the channels through which peer behavior drives major diversity remain speculative. I attempt to elucidate one prominent mechanism, new program adoption, and test whether colleges are more likely to introduce new programs when their peer groups have introduced it first, or experience more growth in that major in preceding years. I run a series of survival models, where programs a school does not yet offer (but theoretically could) are "at risk" of being adopted. The dependent variable thus takes a value of zero in all years where the program is not (yet) offered, and one if a school does begin awarding degrees in that major, at which point the program exits the dataset.

Colleges are indeed more likely to offer a new major when more of their peers offer it. These results can be found in Appendix Table A5. One additional peer who offers the major in the preceding year increases the likelihood an institution begins awarding bachelor's degrees in that field by 0.01 percentage points. Though small in magnitude, this is highly statistically significant and represents a 12 percent increase from the baseline probability of adopting a new program (0.009). In similar spirit, an 100 degree increase in awards among peers in a given major increases the probability a school introduces that program for their own students by 0.006 percentage points, a 7 percent increase from the baseline probability. New programs are the largest driver of major diversity and this analysis suggests that colleges take the offerings of their peers into consideration when expanding into new fields.

5.4. Ruling out alternative explanations

While the evidence for peer effects and major diversification is strong, there are other candidate explanations that could feasibly coincide with, precede, or even generate the estimated peer relationships. I describe three such possibilities and the evidence for and against them briefly below. For a more thorough description of the analyses, see Appendix Section C.

Graduate Education Spillovers. Adding new graduate programs or expanding existing ones could make undergraduate course offerings in the same or closely related fields easier to expand due to increases in the labor needed to teach and support them, like new faculty, administrative staff, and graduate students. To test this possibility, I use IPEDS data on graduate degree awards by field. I also track the highest degree offerings of each school over time for a dynamic difference-in-differences comparison of the EMI for switching institutions that expanded into graduate education to baccalaureate colleges that did not.

The results among schools already offering graduate degrees (intensive margin) suggest that the lagged value of the institution's graduate-degree EMI is positively related to the undergraduate EMI, with an elasticity estimate around 0.1. However, this could reflect overall institutional priorities for diversification of programs, and not necessarily that graduate education caused changes in the undergraduate EMI. The event study estimates testing the extensive graduate education margin are in effect null and imprecise, suggesting schools that expanded into graduate education did not diversify their bachelor's degrees any more than colleges that remained focused on awarding bachelor's degrees. This piece of evidence is more concrete against graduate spillovers, and together these results suggest a minimal role for its explaining major diversification.

Declining state support. I also tested whether the share of total revenue generated from state funding or the level of state support per FTE had an effect on changes in the EMI.[22] In the aggregate, the results show a very small positive relationship between state support and major diversification, with elasticities of about 0.01. However, less selective public institutions appear to diversify their major offerings more significantly when state support remains high. Since state support declined over this time period, this result paints lack of state support as a barrier to increasing major diversity, at least among the institutions that historically relied on that support most. Still, even for these schools, the effect is small relative to peer effects – a 10 percent decline in state dollars per FTE was associated with between 1 and 2 percent decline in major diversity.

Changes in the business cycle and employer demand. Broader changes in the labor market may also influence colleges' decisions to diversify their major offerings. Specifically, I tested whether an institution's effective unemployment rate or the ratio of occupational demand for majors they were not (yet) offering to those they were offering was related to the EMI. Unemployment captures a feasible shock to student demand for 4-year higher education that colleges may accommodate by expanding majors and enrollment. The occupational ratio captures shocks on the employer demand side of the market, where higher values indicate relative strength in demand for majors the school does *not* currently offer, issuing a potential incentive for adoption of new majors aligned to the labor market. In both employment metrics, I use the share of an institution's incoming first-year degree seeking students from each state as weights to give each college its own unique "market" from which the employment shocks might feasibly flow to institutional decision-making.[23]

I find the unemployment rate does not meaningfully predict major diversification. Though the elasticities are positive and on the order of about 0.1, they are imprecise.[24] This does not contradict the findings in Blom et al. (2021), but instead suggests shifts taking place in major choice due to the business cycle do not produce more (or less) major diversity in the aggregate. The ratio of demand for potential new majors to existing majors has a precisely estimated elasticity of about 0.1. This is still small relative to peer effects, but suggests that colleges do respond modestly to employer demand in determining new programs to introduce.

[22] This excludes hospital revenue.

[23] This market weighting approach is similar to that in Conzelmann et al. (2023), where the interest was in post-graduate labor markets. Here, I focus on the areas where colleges draw incoming students, which has clearer theoretical ties to major supply decisions.

[24] This holds even when instrumenting for unemployment using the lagged value to address concerns of measurement error.

6. Consequences of major diversification

The most consistent explanation for major diversification in baccalaureate education is colleges' tendencies to follow and compete with peer institutions in similar markets for students and resources. As the final contribution of this paper, I explore the consequences of this peer-driven major diversification with two main inquiries relating to costs and completion.

6.1. Major diversification and college costs

Four-year college expenditures per FTE across spending categories have increased significantly in the three decades of interest in this paper, even after adjusting for inflation. Total educational and general (E&G) expenditures increased by almost 50 percent (0.4 log points), driven mainly by increases in instructional expenditures, which account for almost half of all E&G. Though smaller in the overall share of expenditures, academic and student services per FTE doubled in 30 years increasing by 0.7 log points.[25] Over 30 years ago Getz & Siegfried (1991) suggested that students were shifting what they studied away from cheaper majors in the 1970s and 80s, like English and Education, to more expensive ones like Engineering and Business. It is not clear whether the fields that gained (lost) ground in the share of overall enrollment or degrees were those that were more (less) expensive in the aggregate.[26]

The literature offers several broader explanations for rising costs of college, including that colleges operate similarly to other labor-intensive fields like healthcare and law. Costs in these fields have risen due to an inability to increase productivity through changes to production technology, also known as the Cost Disease (Archibald & Feldman, 2010; Baumol, 2012). Others have focused on the goal of higher education institutions and their constant pursuit of quality and prestige (Blair & Smetters, 2021; Bowen, 1980; Clotfelter, 1996). These common goals create incentives to spend more on long-term, yet expensive investments in facilities, new services, and programs for their students.

I demonstrate that increases in major diversity, driven by colleges' responses to their peers, increased instructional costs per FTE and costs per student credit hour. These pieces of evidence suggest that added administrative and instructional complexity drove up the average costs of delivery by spreading students' course-taking more thinly across departments within a college.

[25] Appendix figure A5 graphs these cumulative changes across spending types for my analytic sample using IPEDS expenditure data.

[26] Hemelt et al. (2021) show costs per student credit hour in Education were about 38 percent more expensive than those in Biology for the academic years 2015 through 2017. The relatively cheaper Biology has gained significantly in terms of the share of degrees awarded, while education has fallen out of favor with students for several decades.

Using expenditure data from IPEDS, I first show that changes to the EMI were accompanied by higher per-student costs. Because the EMI could relate to unobserved factors in institution decision-making that are correlated with overall costs, I also present 2SLS estimates instrumenting for the EMI using the 2nd degree peers' EMI described in previous sections. I continue to condition on student body characteristics of the focal institution and the averages among the institution's first-degree peers. In some specifications, I also include a control for the average peers' outcome, in this case expenditures.

The resulting 2SLS estimates have a local average treatment effect (LATE) interpretation, or a peer-driven effect of the EMI on costs per FTE. The LATE is intrinsically interesting because it isolates effects of diversification arising from peer responses in the market, a behavior shown to be prevalent in Section 5. Major diversification might also occur for more idiosyncratic reasons, not captured in the 2SLS estimates necessarily. For example, some colleges may add programs due to a private donation or some strategic initiative in absence of shocks from peer institutions. The effect estimates here capture something different, namely, degree production responses to average peer network behavior and the resultant change in expenditures within the college.

In Table 5 I present results from both OLS and 2SLS estimates of the relationship between major diversity on instructional expenditures per FTE and separately on academic and student services expenditures per FTE. I report only the fixed effects specifications, though the results are robust to using the stacked-long differences approach as well. The OLS estimates suggest a 10 percent increase in major diversity increases instructional costs per FTE by about one-half of one percent (0.6 percent). This effect is consistent across the specifications and statistically significant ($p<0.01$). Student and academic services spending is imprecise, though is positive and of slightly smaller magnitude to the OLS estimate for instructional expenditures.

The 2SLS estimates suggest a more prominent link between major diversification and expenditures. Peer-driven increases in the EMI yield elasiticites between 0.25 and 0.35 for instructional expenditures, even after controlling for average peer expenditures. The elasticity for academic and student support range from 0.25 to 0.4, and are somewhat more sensitive to controlling for corresponding peer measures. Increases in major diversity arising from responses to peer networks raised instructional and supplementary costs per student.

Table 5: Effects of Major Diversification on Expenditures per FTE

	1 OLS	2 2SLS	3 OLS	4 2SLS	5 OLS	6 2SLS
Panel A. Outcome = Log(Instruction per FTE)						
Log(EMI)	0.057**	0.374**	0.059**	0.241**	0.062**	0.314**
	(0.015)	(0.096)	(0.015)	(0.090)	(0.014)	(0.088)
First stage F-statistic	-	63.71	-	66.07	-	63.37
School FEs	✓	✓	✓	✓	✓	✓
Year FEs	✓	✓	✓	✓	✗	✗
State-by-Year FEs	✗	✗	✗	✗	✓	✓
Control for peers' outcome	✗	✗	✓	✓	✓	✓
N Observations	42,601	42,447	42,599	42,446	42,573	42,420
N Clusters	1695	1683	1695	1683	1695	1683
Panel B. Outcome = Log(Acad & Student Support per FTE)						
Log(EMI)	0.042	0.421**	0.035	0.238	0.041	0.383**
	(0.028)	(0.14)	(0.029)	(0.135)	(0.025)	(0.134)
First stage F-statistic	-	64.57	-	62.96	-	58.16
School FEs	✓	✓	✓	✓	✓	✓
Year FEs	✓	✓	✓	✓	✗	✗
State-by-Year FEs	✗	✗	✗	✗	✓	✓
Control for peers' outcome	✗	✗	✓	✓	✓	✓
N Observations	42,533	42,381	42,531	42,380	42,628	42,477
N Clusters	1693	1681	1693	1681	1695	1683

Notes: * $p < 0.05$, ** $p < 0.01$. FTE=Full-time equivalent. All models are weighted by the base-year total number of BA graduates. Standard errors clustered at the institution-level are in parentheses. Columns 1, 3, and 5 are OLS estimates of the log(EMI) on expenditures per FTE including institution covariates and analogous peer group averages. These controls include the log undergraduate enrollment, share of a school's total enrollment that is part-time, share graduate students, the share of bachelor's degrees awarded to women, to students that were either Black or Hispanic, to foreign or international students, and the number of years in the panel the school had awarded BA degrees and its quadratic. Columns 2,4, and 6 present 2SLS estimates instrumenting for the institution's own log(EMI) using the average log(EMI) of excluded peers (or peers of peers). Columns 3-6 include an additional control for the average expenditure outcome for the institution's peers.

6.2. Department level cost analysis

I further elucidate these aggregate increases in instructional spending using department level data from TCS to show that the introduction of new majors within a college caused sustained increases in costs per credit hour for some pre-existing majors. Recall, increases in the number of BA program offerings was the largest contributor to the aggregate change in the EMI from 1990 to 2019. The addition of new programs generates spillovers within colleges, as students substitute away from courses in some departments toward course offerings in the new discipline.

To demonstrate this, I use a subset of perennial participants in TCS and a dynamic Two-Way Fixed Effects (TWFE) event study regression design. I estimate the effects of new program adoption on costs per student credit hour in each department where treatment of any one program is determined by its similarity to new programs that are adopted at the institution. Similarity is measured using aggregate course-taking patterns using administrative data from the UNC System of public institutions and the overlap in credits earned across students receiving degrees in different majors.[27]

My results suggest a U-shaped relationship between new field introduction, course similarity, and costs. Pre-existing majors either very distantly or very closely related to new majors do not experience meaningful average changes in instructional costs per credit hour after new programs are introduced. However, majors in the middle of the similarity distribution experience significant increases in costs due to a decline in credit hours taken in these fields and slow adjustments to course offerings and instructor labor.

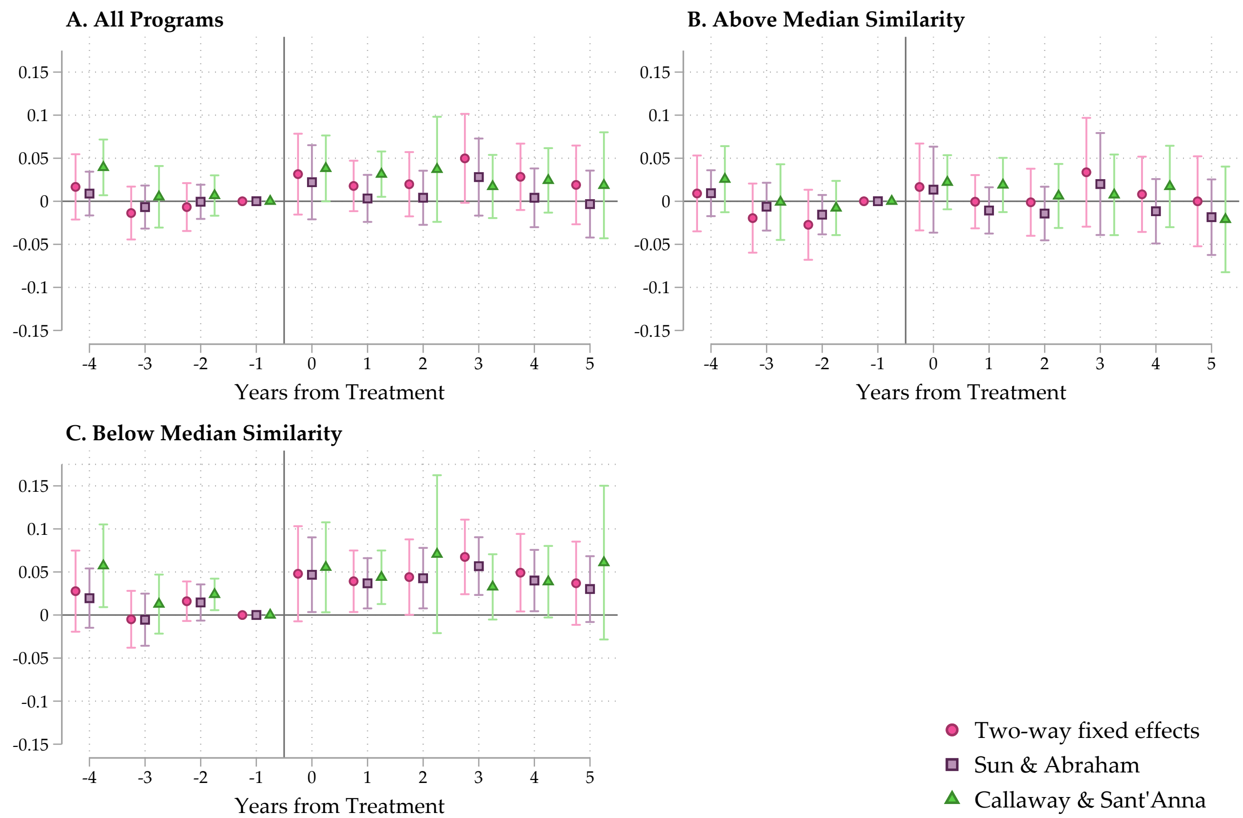
Figure 6 contains three panels of estimates to this effect. Panel A contains the event study estimates for all treated programs, Panel B contains estimates using only those treated programs with course similarity above the median for the treated sample, keeping the comparison (untreated) units constant. And Panel C uses above median similarity programs, removing below median similarity programs. The results across all programs suggest modest average cost per credit hour increases between 3 and 5 percent due to new program additions. These are more prominent between years 3 and 5 after new programs were introduced, followed by some decay toward parity.

Department-level cost increases originate in below-median similarity programs, that is, programs that are somewhat but not closely related to new programs. Shown in Panel C, below-median similarity fields experience significant increases in average costs between 5 and 7 percent

[27] For details on the sample and treatment construction as well as further details on the econometric approach used here, see Appendix B.

in some years after treatment, with an overall average between 4 and 5 percent. This is in contrast to closely related majors in Panel B, who experience small and imprecise cost increases after a new program originates. This suggests an agglomeration story, where closely related programs capture spillover enrollment from a new major in close proximity to its own curriculum. Moderately related fields, identified here as those in the upper-middle distribution of course similarity (below median among treated units), experience significant increases in average instructional costs per credit hour due to both declining enrollment and elevated costs. Indeed, similar regression estimates of credit hours taken (the denominator of the previous outcome) show a decline among below-median fields and modest increases among the more similar majors.

Figure 6: Event Study Estimates of Effect of New BA Program Introduction on Log Instructional Expenditures Per Credit Hour from TCS



Notes: Timing is relative to the first year in which a new related BA program was introduced at that institution. Comparison programs are those whose institution did not yet introduce a new BA program related to that field. “Related” fields were calculated using course-taking data from the UNC system and cosine similarity measures between major pairs. I use a threshold of 0.25 and higher similarities to define “treated” when a new program is introduced. Estimates are weighted by total credit hours awarded by program each year.

6.3. Major diversification and graduation rates

Over the last two decades 6-year bachelor's degree completion rates have increased significantly, reversing a secular decline during the decades prior attributed mainly to declines in student preparedness (Bound et al., 2010). Denning et al. (2022) explore the reversal and attribute the increase to grade inflation, ruling out changes to preparedness and institutional characteristics. Another possibility is that changes to course and major availability, which I have shown increased significantly within the average college over time, could also have played a part in increased grades and completion. There are two plausible ways major diversity could give rise to increased grades. With more programs to choose from, students may sort themselves more efficiently into courses and majors where they have interest and ability. The second is interdepartmental competition for students—as program diversity rises within a college, competition for student enrollment might also rise across departments. One way a department might try to lure students into their courses is to lower grading standards. Despite my inability to parse these two channels in this paper, the existence of one or both phenomena provides a theoretical link between major diversification, grade inflation, and increased graduation rates.

I test one of these links by regressing 6-year graduation rates in a given year from 1997 through 2019 onto 5-year changes in the log EMI with t_5 corresponding to the year prior to that which graduation rates were measured (e.g., 1991 through 1996 changes for graduation rate observed in 1997).[28] This is slightly different from the estimating equations used in past sections with clear delineations between fixed effects and long-differences. Here, it is a combination of the two, with emphasis on each cohort's exposure to changes in major diversity where a single year does not capture this.

As with expenditures, I estimate this relationship both with OLS and with 2SLS, again instrumenting for the EMI using peers of peers' average EMI. If increases in major diversity allow students to sort more efficiently into fields in which they have an academic advantage or more interest, then it may give way to higher graduation rates. Likewise, if major diversity leads to more interdepartmental competition for enrollment and grade inflation, then graduation rates should also rise. The results in Table 6 show some evidence of this. While the OLS estimates are essentially null, peer-driven increases to the EMI on the order of 10 percent give rise to about a 3.3 percent increase in graduation rates. Controlling for peers' average graduation rates attenuates the effect

[28] I exclude the 6th year to remove some of the cohort's contribution to the metric. This is not a perfect proxy since students who complete faster than 6 years will technically contribute to the 5-year change in the EMI, though, the results are robust to using the full 6 year change or shorter, 4-year changes as well.

size, closer to a 2 percent increase for every 10 percent increase in the EMI. With an overall mean of about 59 percent, this is between a 1 and 3 percentage point increase in the average graduation rate attributable to major diversification.

Table 6: Effects of Major Diversification on 6-year Graduation Rates

	1 OLS	2 2SLS	3 OLS	4 2SLS	5 OLS	6 2SLS
Panel A. Outcome = Log(6-year graduation rate of t0 entry cohort)						
Δ_{t0}^{t5}Log(EMI)	0.003 (0.010)	0.336** (0.101)	-0.001 (0.010)	0.196* (0.0875)	-0.002 (0.009)	0.214* (0.097)
First stage F-statistic	-	40.08	-	32.43	-	27.22
School FEs	✓	✓	✓	✓	✓	✓
Year FEs	✓	✓	✓	✓	✗	✗
State-by-Year FEs	✗	✗	✗	✗	✓	✓
Control for peers' outcome	✗	✗	✓	✓	✓	✓
N Observations	29,497	29,422	28,392	28,328	28,374	28,310
N Clusters	1505	1499	1504	1498	1503	1497

Notes: * $p < 0.05$, ** $p < 0.01$. All models are weighted by the number of students in each graduation rate cohort. Standard errors clustered at the institution-level are in parentheses. Column 1 presents OLS estimates controlling also for the 6-year change in the share of students enrolled part-time, graduate enrollment, the share of bachelor's degrees awarded to women, Black and Hispanic students, foreign students, and the number of years the school had awarded BAs within the panel and its quadratic. Column 2 presents estimates from a 2SLS where the first stage regresses the 6-year change in the log EMI onto the same 6-year average change for peers of peers and controlling for the same additional covariates listed above.

7. Conclusion

Colleges and the market for baccalaureate education have evolved significantly over time. Surrounded by changing student demand, government funding priorities, and labor markets, colleges diversified their degree production to accommodate such shifts with long-term implications on the aggregate supply of skill. The literature has focused on how colleges have become more stratified in their endeavor to educate students due to competitive pressures and quests for quality and prestige (Blair & Smetters, 2021; Clotfelter, 2017; Hoxby, 2009). In this paper, I characterize a trend common to most all baccalaureate-granting institutions and offer a way colleges have grown significantly more alike than different. Over the last several decades, the average college consistently expanded their major offerings and prioritized diversifying degree awards across majors, rather than specializing in a smaller number of core fields.

I illustrated the secular trend in major diversification across several data sources and showed it was predominantly driven by within-college changes to curricular offerings and prioritization of new programs. In tandem, the between-college variation in major diversity declined significantly, suggesting that smaller, less diverse colleges at the beginning of the panel (e.g., liberal arts) diversified at a faster rate, gaining significant ground on comprehensive research universities that traditionally offered the most diverse major options.

College behavior within this dimension was driven by peer effects. Consistent with other analyses of college decision-making (e.g., Acton et al., 2022; Blair & Smetters, 2021), they tended to care about their own relative positions and standing within groups of institutions with similar missions, resources, and students and responded to the average actions taken by those networks. This finding establishes a new way in which these peer effects manifest through the curricular offerings and priorities of colleges. This relates to other expositions of college mission drift and isomorphism (Jaquette, 2013; Morphew & Huisman, 2002). Typically construed as negative, I offer nuance to this notion. The diversification of degrees in accordance with peer institutions was perhaps necessary for smaller colleges to attract students and likely enhanced the quality of education provided through increased instructional value and completion.

On college instructional costs, I showed major diversification increased them through enrollment substitution patterns toward new and closely related programs. This result adds something new to a persistent debate on the reasons for rising costs in higher education. The way institutions tended to grow, horizontally rather than vertically, added organizational complexity and spread enrollment across more fields, driving up average costs per student. This contextualizes the prestige and resource dependency arguments for upward trends in costs, and to some degree challenges the passive role of institutions in the productivity-locked, labor-driven theory of the Cost Disease. Yet, enrollment substitution may not be the only mechanism driving this result. Future research could look more specifically at the characteristics of new program offerings and decipher the contribution of different types of faculty labor (i.e., tenure vs. non-tenure track) and the degree to which institutions alter these choices when the college overall is diversifying.

While I document that major diversification increased graduation rates, much is still left for future research on this topic as well. Existing micro-evidence on college course scarcity and its effects (or lack thereof) on student behavior offers some guidance on how one might think about diversity of options as a mediating factor in this process (Kurlaender et al., 2014; Robles et al., 2021). Availability of close course or major substitutes could insulate students from negative outcomes in credit accumulation or time to degree. Future research could also explore cross-disciplinary skill accumulation and its effects on long-run career outcomes, building on work like that of Han et al. (2023). This is particularly relevant as recent research points to the deterioration of skill relevance and flatter lifetime earnings curves in STEM fields (Deming & Noray, 2020). My results confirm colleges shape student access to different fields, which creates variation in the extent to which they might benefit from diversification while enrolled.

Finally, this paper speaks to ongoing policy discussions and challenges within and across colleges in the United States. Many college leaders propose program elimination and downsizing when faced with financial difficulties (e.g., Quinn, 2020). While my analyses focus on the historical precedent of expanding programs, they still offer some insight into how the opposite might affect students and stakeholders in the aftermath of cost-cutting measures. As intended, these measures will likely reduce average costs per student but at the expense of educational quality and student outcomes. College majors do not exist in silos and their relationships with other majors generate spillover effects, both on costs and on students' skill accumulation. This paper provides several pieces of concrete evidence to this effect, with room for further exploration on the precise mechanisms and magnitudes. As higher education plods through the post-pandemic era with different challenges than prior decades, the degree to which colleges continue to diversify or reverse these trends in the supply of college majors is one way to assess the state of the field, more broadly.

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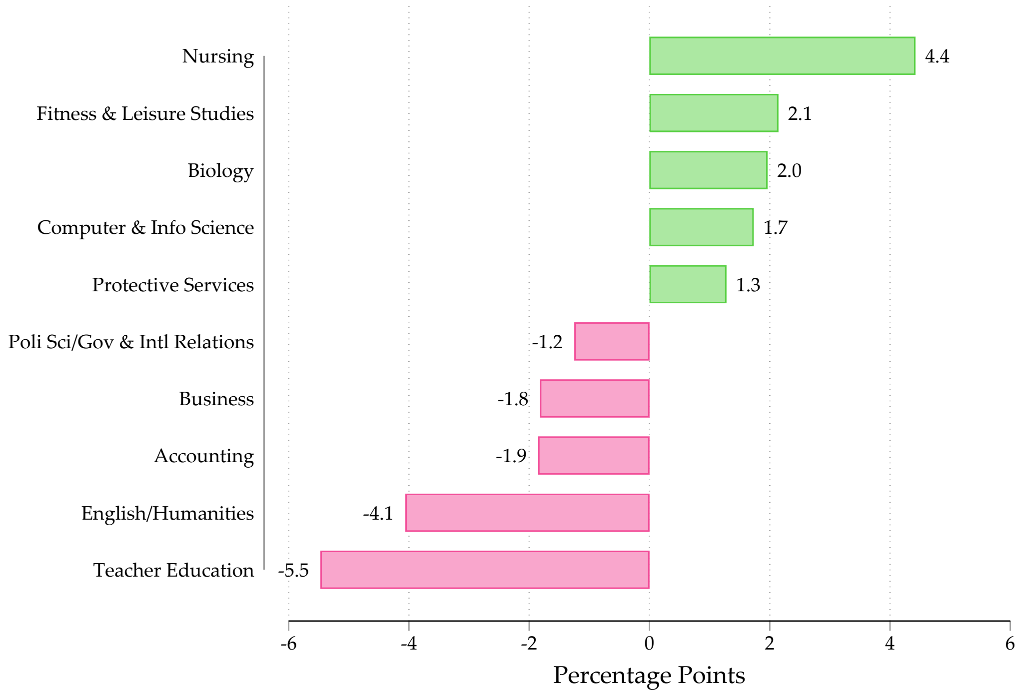
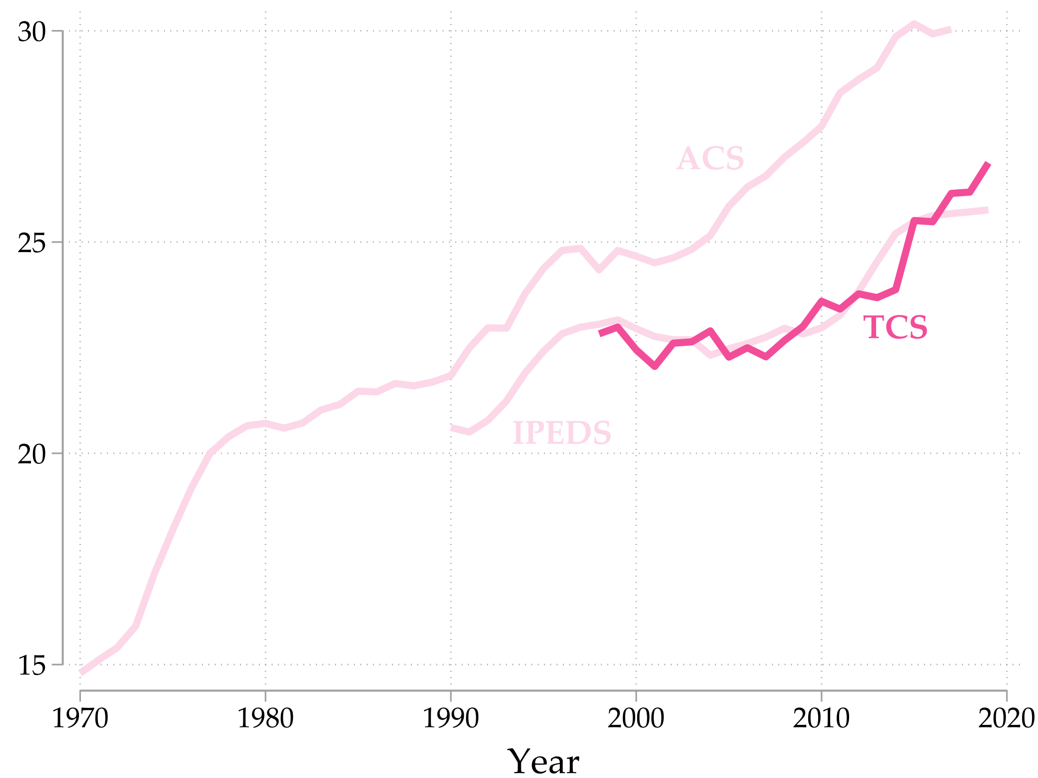
A. Additional Tables and Figures

Figure A1: Top and bottom 5 major share changes, 1990 to 2019.



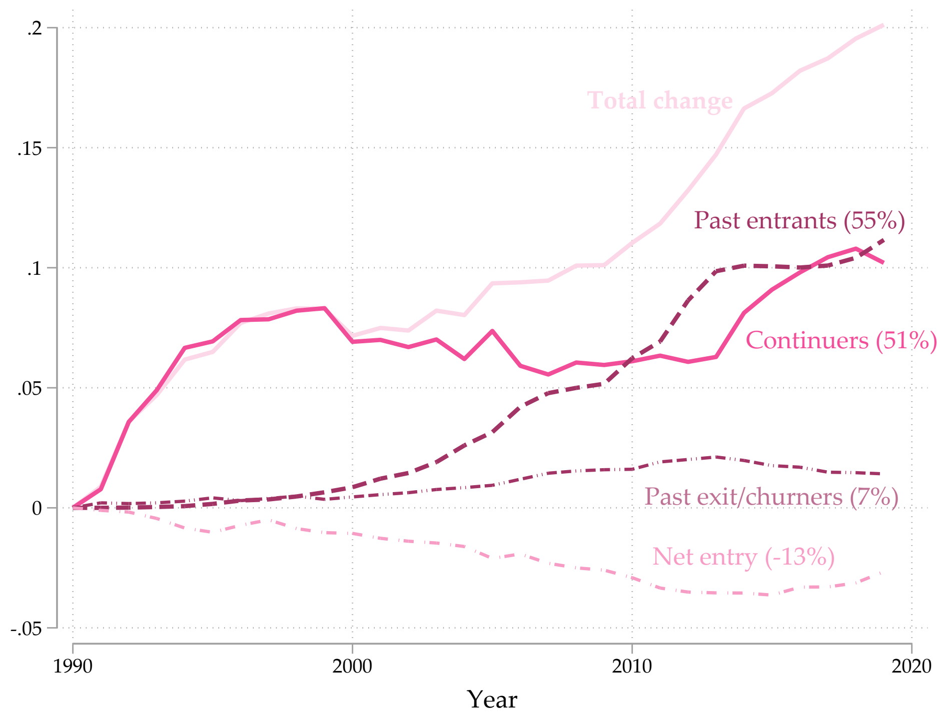
Notes: Bars represent the total change from 1990 to 2019 in the share of all bachelor's degrees awarded by colleges in the analytic sample.

Figure A2: The Cost Study EMI using student credit hours, 1998-2019.



Notes: The EMI for the TCS sample is calculated using the squared shares of student credit hours taught in the 71 possible fields and summed across fields as opposed to bachelor's degrees as in IPEDS and the ACS. The original IPEDS and ACS EMI time-series are shown in lighter color for reference.

Figure A3: Decomposition of the change in log EMI, by fixed entry or exit status 1990-2019.



Notes: This figure decomposes the total change in the log EMI similar to that depicted in Figure 3, only breaks continuing institutions into groups based on when they entered or exited the market for bachelor's degree awards.

Table A1: Yearly Peer List Overlap

	Mean	SD	Institutions	min	max
Number of years peers submitted	8.735	2.140	1,719	2	10
Overlap Statistics					
2010 to 2011	0.960	0.155	1,384	0	1
2011 to 2012	0.970	0.138	1,515	0	1
2012 to 2013	0.983	0.101	1,523	0	1
2013 to 2014	0.950	0.182	1,506	0	1
2014 to 2015	0.961	0.171	1,541	0	1
2015 to 2016	0.949	0.179	1,457	0	1
2016 to 2017	0.976	0.124	1,480	0	1
2017 to 2018	0.975	0.118	1,445	0.0714	1
2018 to 2019	0.992	0.0638	1,438	0.0833	1
2011 to 2019	0.796	0.321	1,247	0	1
2010 to 2019	0.771	0.330	1,137	0	1

Notes: These estimates reflect the sample mean across institutions of a within-institution similarity of peer lists in year t and $t-1$. Called a Jaccard Index (J), this ranges from 0 to 1, and can be thought of in percentage terms. A J of 0.9, for example, would indicate a 90 percent overlap between lists in year t and $t-1$. Institutions that selected peers are those who submitted lists of peer institutions as part of IPEDS reporting and Data Feedback Reports. I include only schools who submitted these lists 2 or more times between 2010 and 2019.

Table A2: Focal Institution to Peer Group Average Comparisons

Variable	Mean	p10	p25	p50	p75	p90	School-Years (N)
Instructional expeditures per FTE	0.96	0.54	0.70	0.87	1.06	1.35	45,802
Six-year Graduation Rate	0.90	0.61	0.78	0.91	1.01	1.12	30,166
Admission Rate	1.11	0.74	0.92	1.09	1.27	1.47	23,816
Undergraduate FTE	0.78	0.15	0.45	0.74	1.00	1.26	46,716
Distance (miles)	587.57	105.90	231.50	513.97	828.97	1145.69	50,112

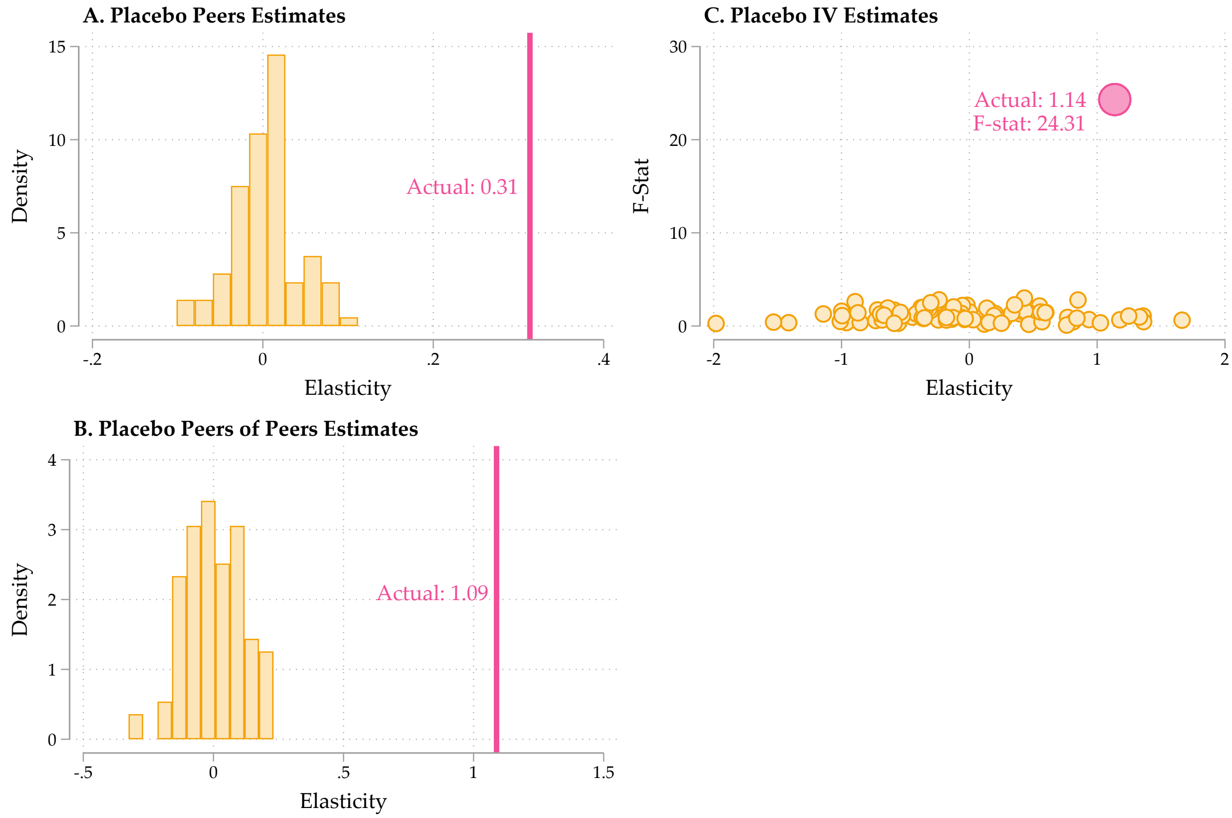
Notes: The first group of variables are calculated as a ratio of the focal institution to its peer group average within a given year. Instructional expenditures per FTE are adjusted for inflation using the Consumer Price Index. Distance is the average crow-flies or shortest path along the earth's surface between the focal institution and its set of peers. Columns beginning with "p" refer to percentiles.

Table A3: First Stage Results from IV Peer Estimates

	1	2	3	4
	$\overline{Y}_{k(i)}$	$\overline{\boldsymbol{X}}_{\boldsymbol{k(i)}}$	$\overline{Y}_{k(i)}$	$\overline{\boldsymbol{X}}_{\boldsymbol{k(i)}}$
First Stage Coefficients, Treatment = Log($\overline{Y}_{p(i)}$)				
Peers of peers' log(EMI)	0.426**		0.389**	
	(0.084)		(0.084)	
Share FTE part-time		0.537**		0.635**
		(0.196)		(0.171)
Share FTE graduates		0.874**		0.628**
		(0.328)		(0.238)
Share BA's female		-0.043		-0.189
		(0.272)		(0.264)
Share BA's Black or Hispanic		0.498*		0.518**
		(0.233)		(0.190)
Share BA's Foreign		-1.797**		-1.722**
		(0.204)		(0.197)
Log average UG FTE		-0.165		-0.154*
		(0.089)		(0.078)
First-stage F	48.16	24.31	63.17	27.06
School FEs	✓	✓	✓	✓
Year FEs	✓	✓	✗	✗
State-by-Year FEs	✗	✗	✓	✓
N Observations	42,903	42,903	42,877	42,877
N Clusters	1690	1690	1690	1690

Notes: * $p < 0.05$, ** $p < 0.01$. Standard errors clustered at the institution-level are in parentheses. All models are weighted by the base-year total number of BA degrees. Columns 1 and 3 present first stage estimates where the instrument for average peers' log EMI was the peers of peers' average log EMI, $\overline{Y}_k$. Columns 2 and 4 present first-stage estimates where the instruments are represented by $\overline{\boldsymbol{X}}_{\boldsymbol{k}}$ in the main text and include the average FTE undergraduate enrollment, average share of FTE part-time, graduate students, the share of BA's awarded to female students, Black or Hispanic students, and foreign students. All models also include controls for the institution's own and peers' average log undergraduate enrollment, share of a school's total enrollment that is part-time, share graduate students, the share of bachelor's degrees awarded to women, to students that were either Black or Hispanic, to foreign or international students.

Figure A4: Placebo Peer Estimate Distribution with Actual Peer Group Estimates



Notes: Each figure depicts estimates generated using 100 randomly drawn peer groups and resultant excluded peers of peers. The dependent variable for each set of estimates was the focal institution's actual log EMI. Figure A plots the elasticities obtained from re-estimating the linear-in-means model from Equation 6 and column one of Panel A in Table 4. Figure B depicts 100 placebo estimates of the IV GMM2S procedure in column 2 of Table 4, where the first stage regresses the placebo peers' average EMI onto the placebo $\overline{X}_{k(i)}$ covariate values from excluded peers. Figure C replaces the average first-degree peers' EMI with the average peers' of peers EMI, effectively the first stage of the IV procedure in section 6.

Table A4: Peer Institution Effects Sensitivity to Influential Peer Removal

	1	2	3	4	5	6
	OLS	2SLS	GMM 2S	OLS	2SLS	GMM 2S
Panel A. Removing Most Influential Peer From Each Peer List						
Peers' Log(Average EMI)	0.283**	1.960**	1.034**	0.200**	2.022**	1.068**
	(0.071)	(0.304)	(0.283)	(0.072)	(0.331)	(0.290)
Instrument(s)	-	$\overline{Y}_k$	$\overline{\boldsymbol{X}}_{\boldsymbol{k}}$	-	$\overline{Y}_k$	$\overline{\boldsymbol{X}}_{\boldsymbol{k}}$
First-stage F	-	96.39	29.89	-	85.66	30.90
School FEs	✓	✓	✓	✓	✓	✓
Year FEs	✓	✓	✓	✗	✗	✗
State-by-Year FEs	✗	✗	✗	✓	✓	✓
N Observations	42,976	42,812	42,812	42,950	42,786	42,786
N Clusters	1694	1683	1683	1694	1683	1683
Panel B. Removing 5% Most Influential Peers from the Full Sample						
Peers' Log(Average EMI)	0.264**	2.285**	1.416**	0.204**	2.346**	1.431**
	(0.062)	(0.437)	(0.293)	(0.0506)	(0.462)	(0.299)
Instrument(s)	-	$\overline{Y}_k$	$\overline{\boldsymbol{X}}_{\boldsymbol{k}}$	-	$\overline{Y}_k$	$\overline{\boldsymbol{X}}_{\boldsymbol{k}}$
First-stage F	-	43.61	23.10	-	45.44	25.28
School FEs	✓	✓	✓	✓	✓	✓
Year FEs	✓	✓	✓	✗	✗	✗
State-by-Year FEs	✗	✗	✗	✓	✓	✓
N Observations	41,972	32,880	32,880	32,954	32,856	32,856
N Clusters	1607	1602	1602	1608	1601	1601

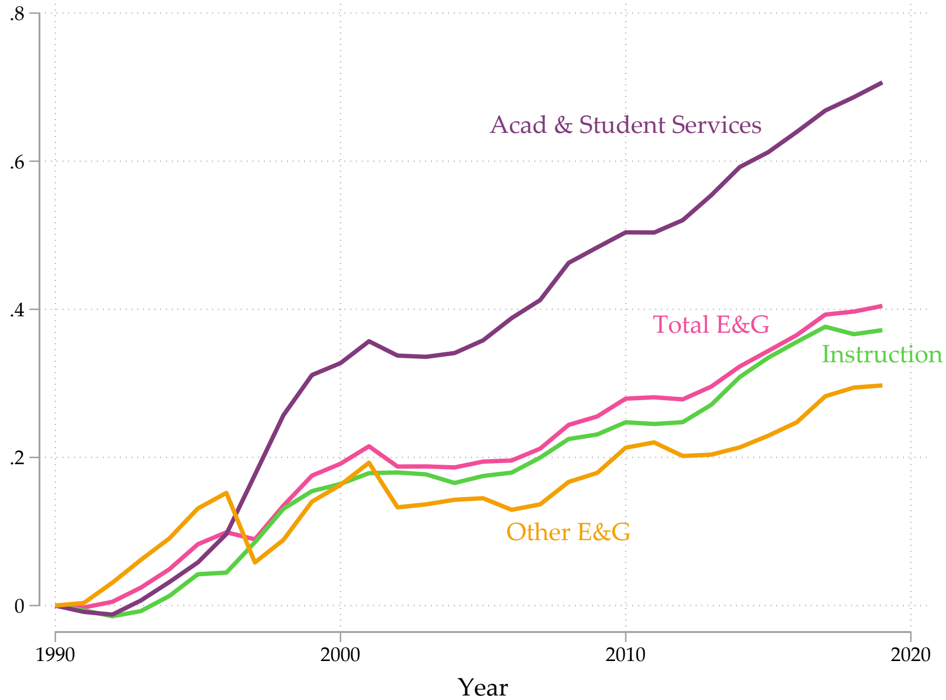
Notes: * $p < 0.05$, ** $p < 0.01$. Standard errors clustered at the institution-level are in parentheses. All models are weighted by the base-year total number of BA degrees. Panel A presents estimates analogous to Table 4 Panel A having removed the most influential peer from each college's peer list and subsequent excluded peer lists. Influence was determined by calculating the frequency at which a school is listed as a peer by another and ties were broken by Barron's Competitiveness Index and Undergraduate FTE enrollment (more competitive preferred to less and larger enrollment preferred to smaller). Columns 1 and 4 present traditional linear-in-means estimates including institution covariates and corresponding peer group averages. These controls include the log undergraduate enrollment, share of a school's total enrollment that is part-time, share graduate students, the share of bachelor's degrees awarded to women, to students that were either Black or Hispanic, to foreign or international students, and the number of years in the panel the school had awarded BA degrees and its quadratic. Column 2 and 5 instrument for peers' log(EMI) using the average peers of peers' log(EMI), Y. Columns 3 and 6 are estimated using a 2-stage generalized method of moments weighting procedure where excluded instruments are the control variable averages (X's) of all peers of peers, identified by $k(i)$. Panel B presents analogous estimates after removing the overall top 5% most influential peers in the dataset from both first and excluded peer lists.

Table A5: Relationship between peer institutions and the probability of new program introduction

	N Peers with program		Peer degree awards (100s)	
	1	2	3	4
Pr(Offered program in t | Not offered in t-1)				
1-year lag	0.001**	0.003**	0.0006**	0.002**
	(0.0001)	(0.0002)	(0.0001)	(0.0003)
Mean of dep var	0.009	0.008	0.009	0.008
Effect as percent	11.70%	40.60%	6.90%	25.50%
N Observations	1,914,198	1,910,611	1,914,198	1,910,611
Major-by-Year FE	✓	✓	✓	✓
School-by-Major FE	✗	✓	✗	✓

Notes: * $p < 0.05$, ** $p < 0.01$. Standard errors clustered at the institution-level in parentheses. Each pair of columns presents the effect of a treatment on the probability a school began awarding BA degrees in a particular major in the current year conditional on not having awarded degrees in that major in previous years. Peer treatment variables are lagged by one year in all cases. Columns 1 and 2 use the number of peers that award BA degrees in that major as the independent variable of interest. Columns 3 and 4 use the number of degrees awarded by peers in a given major in 100s. Peer lists are self-identified by the school in IPEDS between 2010-2019 and described in more detail in the main text.

Figure A5: Cumulative log change in Educational and General expenditures, by type 1990-2019



Notes: Source: IPEDS finance files, harmonized across years and institution types. All expenditures were adjusted to 2019 terms using the CPI prior to calculating changes. E&G excludes operation and maintenance of plant expenditures in this paper. The "Other" category includes research, institutional support, public service, and scholarship and fellowship expenditures

B. Data Appendix

B.1. IPEDS

As mentioned in the main text, the IPEDS sample is limited to all schools and years between 1990 and 2019 in which at least one bachelor's degree was awarded. This includes public, private non-profit, and for-profit colleges in all 50 states and Washington, D.C., but I exclude schools in Puerto Rico and other outlying islands and territories. These exclusions are made mainly because data on other constructs in the paper, like unemployment and state financial aid, are unavailable for these areas. I use institution identification number crosswalks from the Department of Education's College Scorecard dating from 2000 through 2019 to accommodate reporting changes within institutions' IPEDS identification numbers. This accounts for schools that merged with other schools either physically, or only for reporting purposes in IPEDS. I treat merged institutions as one entity so as not to inflate the contribution of net entry and exit in the changes to the EMI. Merging of institutions could be analyzed in more detail on its own to examine how major offerings and diversity changed after such events, though this is outside the scope of this particular paper.

The bachelor's degree completion data are reported at the 6-digit CIP-code level. Given the length of the panel, there are several vintages of codes that were used in reporting. The National Center for Education Statistics (NCES) typically introduces a new version of the codes each decade, with the exception of 1985. The 1985 version was also used by some institutions to report degrees in the 1990 and 1991 degree data from IPEDS. In order to make cross-decade comparisons of major diversity without artificially inflating majors due to the addition of new CIP codes over time, I harmonize CIP vintages to obtain a constant set of 4-digit CIP codes across all years of data. This typically involved a least-common-denominator approach to crosswalking codes that were added or changed: if one code was expanded to two separate codes, or vice versa, I use the less specific code across both years of data. With the harmonized list of 4-digit codes, I further collapse these to the 71 categories used in the main text. Hemelt et al. (2023) describes the aggregate codes in more detail. These categories are sufficiently detailed so as to preserve the CIP code organization structure, but broad enough to capture a large number of degrees while also eliminating issues of artificial field inflation, described in more detail in the next paragraph.

The harmonization of codes was most prominent in fields that went through significant change throughout the decades of interest. Computer Science, as one example, had just 6 4-digit CIP codes in 1985. By 2010, this nearly doubled to 11, reflecting the technological advances and increased number of occupations and tasks associated with this discipline. My harmonized version keeps the number at 6 codes, giving all new 4-digit codes in this area to the "Computer and Information Sciences, Other" catch-all code (11.99). The final major code collapses these all into 1, in many ways making the first step superfluous, but this may not always be the case. In general, this approach is conservative given the aims of this paper to quantify curricular diversification. It also bars against artificial inflation of diversity. Since new CIP codes are only released every decade, it is very likely colleges were awarding degrees in what eventually become "new" CIP codes, without any official designation. It is also very likely that colleges do not uniformly designate their degree awards across 4-digit CIP codes (let alone at the 6-digit level). For instance, some colleges transition to new codes slower than other colleges and the substantive differences across codes within the larger 2-digit codes are not usually denoted clearly by NCES. All these reasons should make it clear that examining major diversity at levels lower in code-specificity than I've done is difficult and potentially ill-advised, particularly when looking across a large group of institutions.

While some of the most central elements to this paper like degree completions, institution characteristics, and institutional expenditures and revenue are available for all 30 years, several other supplementary data elements are not available for all years and units of interest. I depict the years in which each data element was available in Figure B1. Some data elements from IPEDS were not collected until later in the panel, or were not collected on an annual basis. For example, six-year graduation rate cohorts start in 1991 (1997 collection year), omitting the 1990 base year of the panel. Information on the number of applicants, accepted students, and their test score information was first collected in 2002. The state of residence for incoming first-year students were collected every other year beginning in 1992.

FTE enrollment was not officially reported until 2004 onward. As FTE is a more precise estimate of enrollment for purposes of resource allocation I use fall enrollment counts of full- and part-time students in each year and institution to estimate FTE for all years in the panel. I assign weights of 1 to full-time students and 0.5 to part-time students and estimate the predictive power of this formula to capture the actual FTE estimates in the data when explicitly reported from 2004 to 2019. A linear regression of actual onto predicted FTE shows a coefficient of 0.97 and R-squared value of 0.96, suggesting this is a suitable prediction method. All references to FTE in the paper, regardless of year, use this formula-based FTE calculation to facilitate its use across all 30 years of interest.

B.2. The Cost Study at the University of Delaware

I use department-level data on instructional expenditures collected as part of the TCS in analyses of costs per credit hour after a new program introduction. These data are available for an unbalanced panel of institutions from 1998 through 2019. Hemelt et al. (2021) discusses the representation of these data in detail, though in general, participating institutions are more likely to be larger public research universities. In order to create a more balanced panel to analyze changes in average instructional costs within departments, I subset the full TCS dataset to institutions that participate for at least 12 consecutive years (out of 22). I chose 12 so as to allow estimation of an adequate number of pre- and post-period differences in the event study analyses. The results are generally robust to using different year thresholds for inclusion. The decision to limit to perennial participants decreases the number of schools available from 622 to 72, though nearly half of all schools in the sample (48 percent) participate just one or two years consecutively.

In Table B2 I provide basic descriptive statistics of the full IPEDS sample, compared to the perennial and non-perennial TCS samples. The sub-analysis of cost spillovers in Section 6 is performed using the perennial TCS participants who account for roughly 12 percent of all bachelor's degrees awarded between 1990 to 2019. In general, the perennial participants are overwhelmingly likely to be public (95 percent) and awarded from doctoral-granting institutions (95 percent). This is true of the rest of the TCS participants as well (77 and 83 percent respectively). In comparison, the full IPEDS sample of degrees awarded are 65 percent public and 74 percent doctoral granting across all years. The perennial participants also have higher average major diversity values with log average EMI values of 2.89 versus 2.49 for the full IPEDS sample. The samples are not markedly different in terms of demographic characteristics of their BA completers.

B.3. UNC System Microdata

The University of North Carolina System contains 16 public 4-year universities including the flagship, University of North Carolina at Chapel Hill (UNC-CH), two land-grant institutions,[29] a college devoted to the arts,[30] and five Historically Black Colleges or Universities (HBCU). Its undergraduate FTE enrollment in 2018 places it 9th among other states' public 4-year institution totals.[31] All but the UNC School of the Arts (15 out of 16) are perennial participants in TCS.

For this project, I use administrative records cataloging the dates new degree programs were

[29] North Carolina State University and North Carolina A&T University

[30] University of North Carolina School of the Arts

[31] Author's calculations.

approved by the UNC System to understand patterns in the lag between approval and first degree awards. Between 1990 and 2019 the UNC System introduced 73 new BA programs that went on to award degrees in subsequent years. Note, the number administratively is much higher because they include several new 6-digit CIP code programs and even specializations within these more specific codes. The 73 introductions I use each refer to the first time a new program within the 71 major categories from the main paper was introduced at a given school.

I merge these introductions with the IPEDS degree count data for each school and calculate the difference between the academic year of introduction and the year that major first awards degrees, as reported to IPEDS. The median and average difference are both 3 years with a standard deviation of 2.4. Overall, this suggests some heterogeneity across new programs. For instance, there are several programs that begin awarding degrees one and two years after introduction (49 percent of the programs). Yet, in trying to develop a rule for non-UNC programs, I preference the measures of central tendency and choose three years.

B.4. Department level analysis

This section provides additional details on the department-level program adoption analysis that used TCS and The University of North Carolina at Chapel Hill (UNC) microdata. To estimate the effects of program introduction on costs per credit hour, I use the aforementioned TCS sample of 72 perennial participants that reported data for 12 or more consecutive years (out of 22 max). I determine the academic years and majors in which new BA programs were introduced by these institutions taking the first year a bachelor's degree was awarded in IPEDS in a particular major and subtracting 3 years, assuming a constant phase-in period from a new program's origination and first degrees conferred, validated using the UNC system data capturing the exact date on which a new BA program was approved and link this to IPEDS degree awards.

I measure the similarity of majors to all other majors using administrative data from the UNC System, aggregating credits taken by students entering the 16 UNC public institutions between 2012 and 2015 and who completed their bachelor's degrees in 6 years or less between 2012 and 2020. I take each major, $m \in M$ in which a BA was completed during this time and I calculate the share of total credits in each major $p \in M$, including the major itself. Using this vector of shares, I generate a cosine similarity score between each focal major, m, and other majors $l \in M$,

$$Similarity_{m,l} = \frac{\sum_{p \in M} \left(\text{Share}_{m,p} \cdot \text{Share}_{l,p}\right)}{\sqrt{\sum_{p \in M} \text{Share}_{m,p}^2}\sqrt{\sum_{p \in M} \text{Share}_{l,p}^2}},$$

yielding a value between 0 and 1 for each m, l pair. Summary statistics of these similarity scores can be found in Appendix Table B1. Major pairs with values closer to one suggest high levels of overlap in the courses taken by students completing those degrees, where numbers close to zero imply high dissimilarity between the two majors in terms of the courses they take.

Majors with a similarity score of 0.25 or greater to a new program introduced in year t are considered "treated," while others with lower scores, or whose school had not yet introduced a new program to meet that similarity threshold remain untreated.[32]

The estimates presented in the main text in Figure 6 come from a dynamic TWFE event study given by,

$$\text{Log(InstExpPch)}_{m,i,t} = \sum_{\tau \neq -1} \beta_\tau^{es} \left(\text{Treated}_m 1\{t = \tau\}\right) + \mathbf{\Gamma X}_{\boldsymbol{m,t}} + \delta_{m,i} + \delta_t + \epsilon_{m,i,t}, \tag{8}$$

where the dependent variable is the log instructional expenditures per student credit hour taught in field m, at institution i, in year t. I include program and year fixed effects along with a control for the share of all credits taught at the graduate level.[33] To simplify estimation, I allow programs to be treated just once, though repeated treatment does occur by way of additional programs being added after the first one. In this setting, there is significant variation in the timing of "treatment" given the length of the panel and lack of uniformity in program adoption. To address bias in TWFE estimates due to differential treatment timing (e.g., de Chaisemartin & D'Haultfœuille, 2020; Goodman-Bacon, 2021) I also estimate event studies of the forms proposed by Sun & Abraham (2021) and Callaway & Sant'Anna (2021).

[32]This 0.25 threshold is roughly the mean similarity across major pairings. The threshold assumes majors below it to be unaffected by new majors in terms of costs. The main results are robust to using thresholds of 0.2 and 0.3 or to setting no similarity threshold at all and using not-yet treated units as a comparison group.

[33]Costs per credit hour cannot be determined separately for graduate and undergraduate credits.

B.5. Employment data

I obtain occupational employment for each state and year from 1997 through 2018 from the Occupational Employment and Wage Statistics (OEWS) survey and unemployment rates from the Local Area Unemployment Statistics (LAUS) from 1990 through 2019, both from the Bureau of Labor Statistics (BLS). I harmonize the OEWS occupation codes across different vintages of Standard Occupational Classification (SOC) codes using resources from the National Crosswalk Service,[34] and use it to create proxies for employer demand for different majors in each year. To map occupation codes to college majors, I use the NCES crosswalk of CIP to SOC codes, limiting to occupations that require at least a bachelor's degree.

This approach to mapping majors to occupations has limitations, though does have some precedent in the literature (e.g., Acton, 2021). It is not entirely clear how NCES made decisions about what occupations were related to each major. Furthermore, the binary designation of related or not related may give too little or too much weight to certain majors in trying to measure shocks in occupational demand. Other data-driven alternatives are feasible, but also have drawbacks. For example, Conzelmann et al. (2023) use industry employment shares and self-reported majors from the ACS to create industry-major mappings. I test this same approach with occupation creating vectors of shares from the ACS of individuals working in individual occupations who also reported obtaining bachelor's degrees in specific majors. Unfortunately, the ACS only has both occupation (or industry) and college major starting in 2009 and it is very likely that the mappings have changed significantly over time. This may not be an issue in shorter panels or some fields, like nursing where one occupation is stably related to a specific major. But over 30 years, more general occupations (e.g., General and Operations Managers) could have experienced non-trivial shifts in the underlying share of a given major that holds these positions.

Given these challenges, I preference the use of the occupational demand measures using NCES crosswalks to map occupational employment to majors. To summarize this process, I took the employment counts within each harmonized occupation code (SOC) and each state and year from 1997 through 2018. I assigned each observation to majors using the NCES crosswalk and then summed the employment counts across occupations, within each year, state, and major. Changes in employment within a given major reflect the effective employer demand across states and years. I describe further how this resultant dataset is used in the next appendix sections.

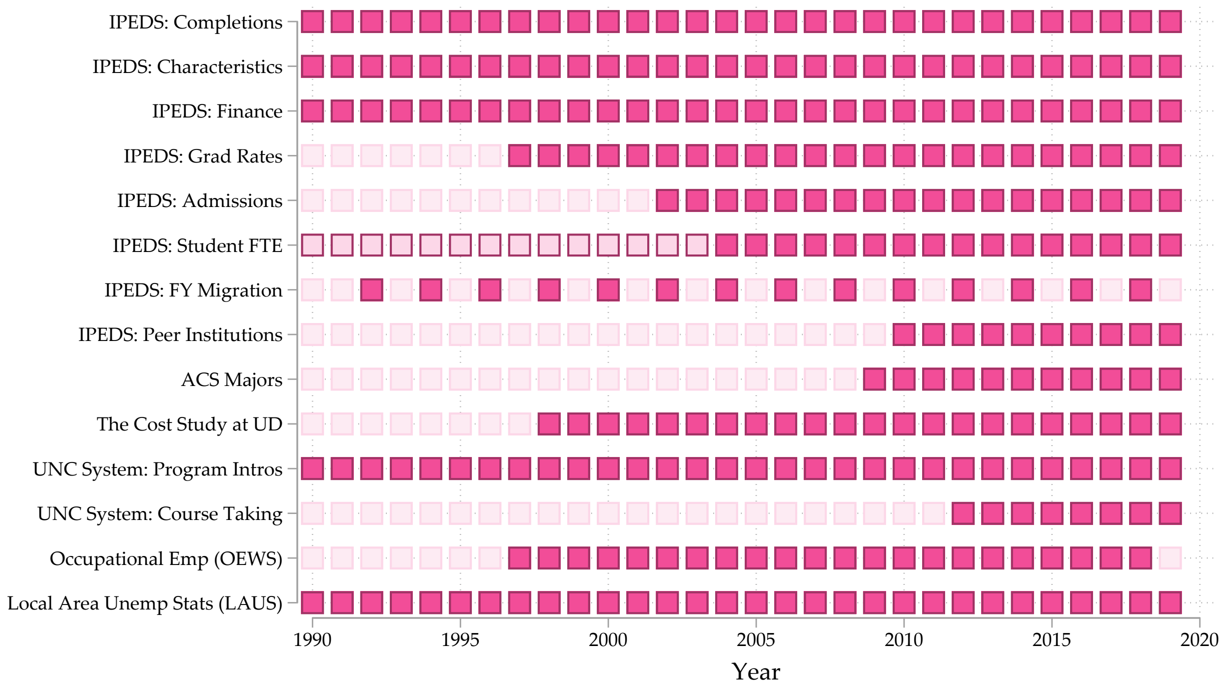
[34] https://widcenter.org/document/occcodes/

Table B1: Summary Statistics of Course Taking Cosine Similarity Across Majors

Major	Mean	SD	Max	Max Major	Min	Min Major
Architecture	0.084	0.090	0.756	Urban Planning	0.022	Nursing
Nursing	0.091	0.041	0.206	Other Allied Health	0.022	Architecture
Urban Planning	0.141	0.091	0.756	Architecture	0.041	Nursing
Engineering Technology	0.153	0.114	0.984	Construction Mgmt	0.042	Nursing
Aeronautical Engineering	0.153	0.121	0.995	Mechanical Engineering	0.036	Nursing
Applied Arts	0.153	0.053	0.306	English, Liberal Arts, Humanities	0.053	Nursing
Computer Engineering	0.156	0.123	0.997	Electrical Engineering	0.036	Nursing
Civil Engineering	0.159	0.063	0.344	Mathematics	0.042	Nursing
Construction Mgmt	0.160	0.116	0.984	Engineering Technology	0.040	Nursing
Mechanical Engineering	0.161	0.122	0.995	Aeronautical Engineering	0.038	Nursing
Special Educ & Teaching	0.162	0.085	0.634	Teacher Education	0.052	Architecture
Family & Consumer Sciences	0.162	0.056	0.292	Other, Miscellaneous	0.046	Architecture
Electrical Engineering	0.163	0.124	0.997	Computer Engineering	0.039	Nursing
Other Visual/Performing Arts	0.167	0.068	0.369	Teacher Education	0.069	Architecture
Social Work	0.173	0.068	0.348	Other, Miscellaneous	0.058	Architecture
Other Engineering	0.175	0.079	0.472	Systems Engineering	0.047	Nursing
Materials Science & Eng	0.184	0.092	0.552	Other Physical Sciences	0.048	Architecture
Rehab & Therapeutic Professions	0.194	0.083	0.394	Psychology	0.049	Architecture
Protective Services	0.200	0.106	0.797	Public Administration	0.065	Architecture
Agriculture	0.204	0.089	0.441	Biochem & Molecular Biology	0.047	Architecture
Hospitality Admin/Mgmt	0.209	0.131	0.658	Business	0.050	Architecture
Other Allied Health	0.209	0.073	0.371	Other, Miscellaneous	0.061	Architecture
Systems Engineering	0.210	0.088	0.475	Mathematics	0.055	Nursing
Chemical Engineering	0.213	0.107	0.503	Chemistry	0.045	Architecture
Biomedical Engineering	0.219	0.102	0.672	Other Physical Sciences	0.053	Architecture
Geography	0.228	0.098	0.499	Other, Miscellaneous	0.078	Nursing
Public Health	0.240	0.107	0.634	Allied Health	0.056	Architecture
Communication & Media Studies	0.247	0.105	0.557	Other, Miscellaneous	0.079	Nursing
Health & Medical Admin Services	0.248	0.110	0.720	Allied Health	0.062	Architecture
Fitness & Leisure Studies	0.248	0.098	0.613	Allied Health	0.059	Architecture
Computer & Info Science	0.251	0.124	0.771	Mgmt Info Systems & Science	0.067	Nursing
Public Policy	0.254	0.136	0.647	Other, Miscellaneous	0.074	Nursing
Public Administration	0.257	0.127	0.797	Protective Services	0.074	Architecture
Accounting	0.258	0.182	0.881	Business	0.062	Architecture
Allied Health	0.259	0.131	0.720	Health & Medical Admin Services	0.061	Architecture
Dietetics & Nutrition Services	0.266	0.132	0.622	Biology	0.052	Architecture
Psychology	0.267	0.109	0.515	Other, Miscellaneous	0.076	Architecture
Business	0.272	0.189	0.881	Accounting	0.064	Nursing
Teacher Education	0.273	0.106	0.634	Special Educ & Teaching	0.090	Architecture
Physics	0.278	0.123	0.698	Other Physical Sciences	0.069	Nursing
Microbiology	0.279	0.163	0.833	Biochem & Molecular Biology	0.057	Architecture
Geological & Earth Sciences	0.280	0.113	0.747	Atmospheric Sci & Meteorology	0.092	Architecture
Poli Sci/Gov & Intl Relations	0.283	0.141	0.753	Other, Miscellaneous	0.085	Nursing
Sociology	0.288	0.131	0.753	Human Resources Mgmt & Services	0.093	Architecture
Marketing	0.289	0.178	0.874	Business	0.074	Nursing
Finance	0.291	0.181	0.860	Business	0.074	Nursing
Philosophy & Religion	0.293	0.116	0.665	Other, Miscellaneous	0.096	Architecture
Atmospheric Sci & Meteorology	0.293	0.120	0.747	Geological & Earth Sciences	0.081	Nursing
Other Education	0.295	0.105	0.602	Teacher Education	0.084	Architecture
Natural Resources	0.295	0.107	0.526	Other, Miscellaneous	0.077	Architecture
Statistics	0.298	0.119	0.829	Mathematics	0.078	Architecture
Other Physical Sciences	0.308	0.148	0.698	Physics	0.079	Architecture
Mgmt Info Systems & Science	0.316	0.179	0.852	Finance	0.080	Architecture
Foreign Lang & Linguistics	0.320	0.137	0.696	Other, Miscellaneous	0.119	Nursing
Biology	0.320	0.174	0.898	Biochem & Molecular Biology	0.063	Architecture
Economics	0.321	0.151	0.841	Human Resources Mgmt & Services	0.085	Nursing
Chemistry	0.323	0.173	0.913	Biochem & Molecular Biology	0.065	Architecture
Biochem & Molecular Biology	0.334	0.186	0.913	Chemistry	0.065	Architecture
Human Resources Mgmt & Services	0.336	0.165	0.841	Economics	0.097	Nursing
Other Social Sciences	0.342	0.154	0.870	Other, Miscellaneous	0.116	Architecture
Pharm Sciences & Admin	0.350	0.170	0.900	Chemistry	0.091	Architecture
Mathematics	0.361	0.134	0.829	Statistics	0.106	Nursing
English, Liberal Arts, Humanities	0.376	0.137	0.877	Other, Miscellaneous	0.140	Nursing
Other, Miscellaneous	0.435	0.163	0.877	English, Liberal Arts, Humanities	0.148	Nursing

Notes: Summary statistics were generated by the Cosine Similarity of each major pair using the share of courses taken across majors by students who completed BAs in the focal major at UNC public 4-year institutions between 2012 and 2020.

Figure B1: Data source availability matrix, 1990-2019.



Notes: Student FTE was imputed for years 1990 through 2003 counting full time students as 1 and part-time students as half. See text for further details.

Table B2: Descriptive statistics of TCS samples and full IPEDS sample institutions

	Full IPEDS Sample		TCS Perennial		TCS Other	
	Mean	SD	Mean	SD	Mean	SD
Avg Log(EMI)	2.49	0.66	2.89	0.29	2.66	0.46
Control: Public	0.65	0.48	0.95	0.21	0.77	0.43
Control: Private nonprofit	0.32	0.46	0.05	0.21	0.23	0.43
Control: For-profit	0.04	0.19	-	-	-	-
Highest degree offering: Bachelor's	0.07	0.60	0.00	0.23	0.03	0.47
Highest degree offering: Master's	0.19	0.39	0.05	0.21	0.14	0.35
Highest degree offering: Doctorate	0.74	0.44	0.95	0.21	0.83	0.38
Share BA's awarded: Women	0.57	0.13	0.56	0.06	0.57	0.09
Share BA's awarded: Black	0.09	0.15	0.07	0.11	0.08	0.12
Share BA's awarded: Hispanic	0.08	0.10	0.07	0.12	0.07	0.11
Share BA's awarded: Foreign/Intl.	0.04	0.05	0.02	0.02	0.03	0.04
Share BA's (1990-2019)	1.00		0.12		0.43	
Number of Institutions	3,236		72		550	

Notes: TCS=The Cost Study at the University of Delaware. The perennial sample includes institutions in the main IPEDS analytic sample that participated 15 or more consecutive years in TCS between 1998 and 2019. Other institutions in TCS participated fewer than 15 consecutive years but were also part of the main IPEDS analytic sample.

C. Alternative explanations for major diversification

C.1. Graduate Education Spillovers

To understand possible effects from graduate program spillovers on the undergraduate EMI, I first create an analogous graduate EMI for the combined master's and doctoral degrees awarded by each institution and year as well as the (log) count of all graduate degrees awarded in a year from IPEDS. I report a series of regression results to test whether lagging indicators of these graduate degree diversity measures are related to the undergraduate EMI. Because schools need to be awarding graduate degrees to have a value for the EMI and total degrees, this is a test of the intensive margin of graduate spillovers. In each specification, I control for demographic and enrollment characteristics of the focal institution, and add various peer measures to test sensitivity of their relationships to the EMI and the main results in section 5.

The results in Table C1 show an elasticity of about 0.1 between the graduate and undergraduate EMI. That is, shown in Panel A, a 10 percent increase in the graduate EMI was associated with a 1 percent increase in undergraduate EMI the following year. In Panel B, The (log) growth in graduate degrees at an institution had a much smaller effect on the undergraduate EMI. This suggests that diversity of graduate degrees, not just increases in their number, is more highly correlated to the undergraduate EMI. This is consistent with the small effects of an institution's enrollment growth on the EMI discussed in the main text.

In either measurement, peer effect estimates are still significantly larger and aligned with the models from the main text that do not control or account for graduate degrees. Despite using lagged values, the patterns seen here still cannot definitively rule out simultaneity or reverse causality, whereby undergraduate major diversification causes graduate program diversification, or that the institution strategically diversified its graduate and undergraduate degrees during the same period of time. This does not rule out spillover effects from graduate education, but without credible exogenous variation to move either the graduate or the undergraduate major diversity independently, it is difficult to identify such effects. Yet, from this analysis, it seems unlikely graduate program spillovers would provide a stronger mechanism than peer effects, if they exist.

I also examine the extensive margin of graduate education and its relationship to the undergraduate EMI. If spillovers exist between the two levels, then I would expect schools who expand into graduate education to have larger or faster rates of undergraduate major diversification than schools that remain concentrated on delivering bachelor's degrees. To test this, I track the highest

Table C1: Graduate Degrees and Major Diversification

	1 OLS	2 OLS	3 GMM2S
Panel A. Graduate Degree Diversity, Outcome=Log(EMI)			
Log(Graduate EMI_{t-1})	0.116**	0.108**	0.088**
	(0.018)	(0.018)	(0.016)
Log(Peers' Average EMI_t)		0.252**	1.064**
		(0.086)	(0.269)
Instrument(s)	-	-	$\overline{X}_{k(i)}$
First-stage F	-	-	21.02
School FEs	✓	✓	✓
Year FEs	✓	✓	✓
Peer controls	✗	✓	✓
N Observations	29,928	29,921	29,824
N Clusters	1287	1287	1282
Panel B. Graduate Degree Awards, Outcome = Log(EMI)			
Log(Graduate Degrees_{t-1})	0.037**	0.028*	0.010
	(0.012)	(0.012)	(0.011)
Log(Peers' Average EMI_t)		0.262**	1.183**
		(0.088)	(0.296)
Instrument(s)	-	-	$\overline{X}_{k(i)}$
First-stage F	-	-	20.44
School FEs	✓	✓	✓
Year FEs	✓	✓	✓
Peer controls	✗	✓	✓
N Observations	29,928	29,921	29,824
N Clusters	1287	1287	1282

Notes: * $p < 0.05$, ** $p < 0.01$. Standard errors clustered at the institution-level are in parentheses. All models are weighted by the base-year total number of BA degrees. Panel A presents estimates for the one year lag of the graduate degree EMI on the log undergraduate EMI. Panel B is interested in the relationship between the one year lag of the log number of graduate degrees awarded on the log undergraduate EMI. All models control for logged undergraduate enrollment, share of a school's total enrollment that is part-time, share graduate students, the share of bachelor's degrees awarded to women, to students that were either Black or Hispanic, to foreign or international students, and the number of years in the panel the school had awarded BA degrees and its quadratic. Columns 2 and 3 add the same controls averaged across the institution's peers. And column 3 instruments for peers' average EMI using the average control values of excluded peers, as in the main text, $\overline{X}_{k(i)}$.

degree offerings of each school over time and identify switching institutions that expanded from baccalaureate education into master's or doctoral programs. Schools become treated if they begin offering a master's or doctoral degree of any type, including professional practice degrees (e.g., law). Institutions that only ever offer bachelor's degrees or lower serve as the comparison group ("stayers").

I start with a dynamic TWFE specification,

$$\text{Log}(\text{EMI}_{i,t}) = \sum_{\tau \neq -1} \beta_{\tau}^{es} \left(\text{Treated}_i 1\{t = \tau\}\right) + \mathbf{\Gamma X}_{i,t} + \delta_i + \delta_t + \epsilon_{i,t}, \tag{C1}$$

where each β_{τ}^{es} yields an estimate of the difference between treated and untreated units at that time relative to when "switchers" first added graduate degrees. In this setting, there is significant variation in the timing of "treatment" given the length of the panel and lack of an event that would induce institutions to begin offering graduate degrees at the same time. To address differential treatment timing, I also estimate event studies as proposed by Sun & Abraham (2021) and Callaway & Sant'Anna (2021).

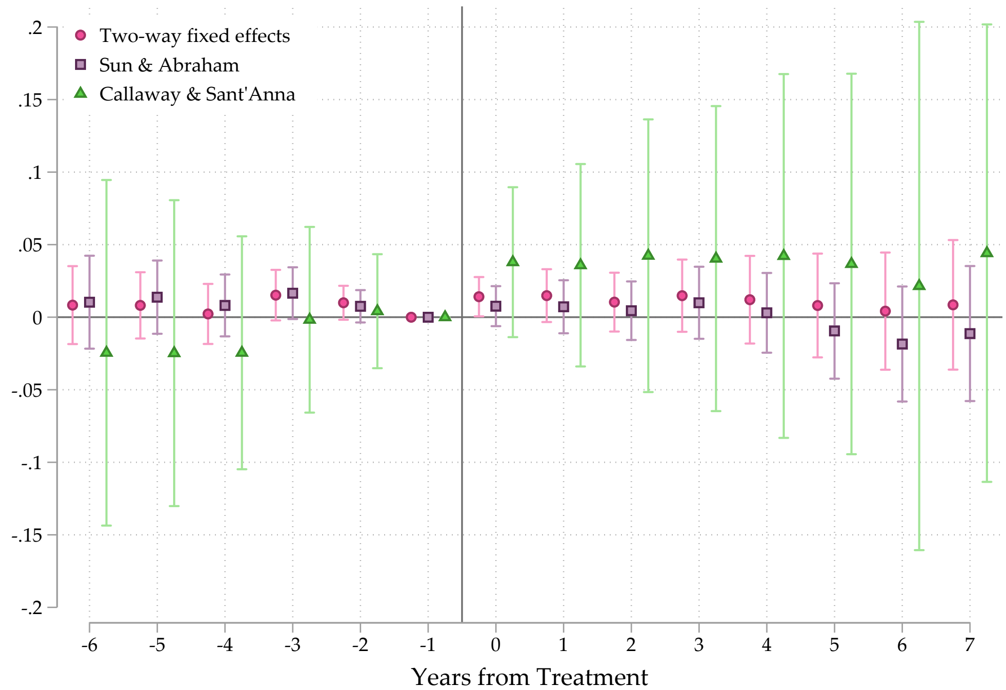
I plot relative-treatment timing estimates for pre- and post-treatment periods for all three estimators in Figure C1. Regardless of the estimator, the main conclusion is the same. Adding graduate education does not lead to increases in the bachelor's degree EMI compared to bachelor's degree institutions who did not add the capacity for graduate programs. Even 7 years post-treatment, the EMI remains roughly the same as "stayers." The Callaway & Sant'Anna (2021) specification yield positive though increasingly imprecise estimates over time, none of which exclude zero in the 95 percent confidence interval.

While the analyses of graduate education spillovers do not completely rule out a role for them in explaining the undergraduate EMI they do suggest this is not likely a main driver. Schools that added capacity for graduate programs or grew their existing graduate programs did experience larger increases in the EMI, but this could simply reflect overall institutional priorities for diversification of programs, not that graduate education caused diversification in undergraduate majors. More concretely, expanding into graduate education did not lead to increases in the undergraduate EMI compared to institutions remaining committed to baccalaureate education.

C.2. Declining state support

The Oaxaca-Blinder decomposition in Section 4.2 suggested some role for state support in major diversification, particularly among less selective public institutions. I test whether the share of total

Figure C1: Event Study Estimates of Effect of Graduate Program Introduction on Log(EMI).



Notes: Timing is relative to the first year in which institutions began offering graduate degrees. Comparision institutions are those who offered a bachelor's degree (and lower) throughout the panel. Estimates are weighted by BA degrees awarded in each year.

non-hospital revenue generated from state appropriations and financial aid to students or the (log) level of this state support per FTE had an effect on changes in the EMI. The level of appropriations is more commonly used in the literature to test effects of state support on outcomes, though in the case of major diversity, it is plausible that the share of revenue generated from state sources might matter as well to institutional decisions. Particularly public non-selective institutions, who tend to rely more heavily on state support, but whose levels of support per FTE may not reflect this, could make curricular decisions based on changes to these shares.

The results in Table C2 show a positive relationship between state support and major diversification, albeit small in the aggregate. Schools receiving support from the state in the form of appropriations or financial aid awarded to students saw a decline in their EMI by 0.2 percent for every 10 percent decline in state support.[35] These relationships among the full sample of institutions shrink and become imprecise when accounting for peer effects.

[35] The majority of state support goes to public institutions, however, over 70 percent of private institutions and even 56 percent of for-profit institutions receive some form of state aid. The amounts per FTE are substantially smaller at non-public institutions. Public colleges received over 12 thousand dollars per FTE, while private nonprofit and for-profits received 920 and 474 dollars per FTE on average, respectively (2019 dollars).

The lack of an average relationship fails to capture the importance of state support for moderately and less selective public institutions (e.g., regional public universities). Among public institutions that were classified below the top two Barron's competitiveness categories (Most and Highly competitive), the relationship between state support and major diversification is stronger by an order of magnitude. A 10 percent decline in state support led to a 1 percent decline in major diversity. This relationship is relatively stable even after adding peer effects. Worth noting is the point estimate in the IV peer effects model for this group of institutions is smaller than for the full sample, at about 0.85. Though strong, this suggests declining state support may have limited the extent to which these schools could improve their educational offerings in response to investments being made by institutions in other parts of their peer networks.

C.3. Changes in the business cycle and employer demand

An emerging strand of recent literature ties major choice and colleges' prioritization of certain fields to changes in the business cycle and employer demand for different skills (e.g., Blom et al., 2021; Conzelmann et al., 2023; Weinstein, 2022; Acton, 2021). It is plausible that college responses to shifts in demand for different fields over time led to major diversification. I test this notion in two ways. First, I create an effective unemployment rate faced by each college in a given year based on time-varying state unemployment rates and the share of a college's incoming first-year students attending the school from each state. I use the first year a college reported migration data to IPEDS after awarding bachelor's degrees. The use of a base-year set of shares, rather than allowing the shares to change over time is common in shift-share instrument designs (e.g., Chakrabarti et al., 2020) to bolster an argument for exogeneity of the shares themselves (Goldsmith-Pinkham et al., 2020). The measure of effective unemployment can be expressed as,

$$\widehat{EffUnemp}_{i,t} = \sum_{s} \frac{FY_{i,s,t_0}}{FY_{i,t_0}} \cdot ln\left(Unemp_{s,t}\right),$$

for each school, i and year, t. Results of regressing the log EMI on this construct are in Panel A of Table C3. The elasticity estimates centers around 0.1 but are very noisy. Adding peer constructs does not change this and the preferred peer effect estimates are similar to those in the main paper specifications as well. Though not shown, estimates using the lagged value of employment as an instrument to accommodate potential concerns for measurement error in this setting does not improve the precision of the estimates.

Unemployment across all job types and occupations likely captures a shock to student demand

Table C2: State Support and Major Diversification

	Full Sample			Public, Less Selective		
	1	2	3	4	5	6
	OLS	OLS	GMM2S	OLS	OLS	GMM2S
Panel A. State share of total revenue, Outcome=Log(EMI)						
Log(State Share$_t$)	0.015**	0.011*	0.006	0.161**	0.116**	0.070*
	(0.006)	(0.005)	(0.006)	(0.036)	(0.033)	(0.031)
Log(Peers' Average EMI$_t$)		0.293**	1.273**		0.164*	0.851*
		(0.058)	(0.308)		(0.080)	(0.394)
Instrument(s)	-	-	$\overline{X}_{k(i)}$	-	-	$\overline{X}_{k(i)}$
First-stage F	-	-	23.82	-	-	18.58
School FEs	✓	✓	✓	✓	✓	✓
State-by-Year FEs	✓	✓	✓	✓	✓	✓
Peer controls	✗	✓	✓	✗	✓	✓
N Observations	35,832	35,776	35,693	12,802	12,758	12,754
N Clusters	1570	1567	1559	486	484	482
Panel B. State appropriations and aid per FTE, Outcome = Log(EMI)						
Log(State support per FTE$_t$)	0.016**	0.013*	0.007	0.187**	0.149**	0.103**
	(0.006)	(0.006)	(0.006)	(0.041)	(0.041)	(0.037)
Log(Peers' Average EMI$_t$)		0.293**	1.269**		0.168*	0.822*
		(0.058)	(0.308)		(0.079)	(0.385)
Instrument(s)	-	-	$\overline{X}_{k(i)}$	-	-	$\overline{X}_{k(i)}$
First-stage F	-	-	23.65	-	-	18.21
School FEs	✓	✓	✓	✓	✓	✓
State-by-Year FEs	✓	✓	✓	✓	✓	✓
Peer controls	✗	✓	✓	✗	✓	✓
N Observations	35,942	35,886	35,801	12,879	12,835	12,829
N Clusters	1575	1572	1563	491	489	486

Notes: * $p < 0.05$, ** $p < 0.01$. Standard errors clustered at the institution-level are in parentheses. All models are weighted by the base-year total number of BA degrees. Columns 1-3 present estimates on the full sample, while columns 4-6 are run only on public institutions outside the top 2 most competitive categories by Barron's measure (most and highly competitive). Panel A presents estimates for the log share of total revenue from state appropriations and aid on the log EMI. Panel B is interested in the relationship between the (level) log of state appropriations and aid per FTE on the log EMI. All models control for logged undergraduate enrollment, share of a school's total enrollment that is part-time, share graduate students, the share of bachelor's degrees awarded to women, to students that were either Black or Hispanic, to foreign or international students, and the number of years in the panel the school had awarded BA degrees and its quadratic. Columns 2-3 and 5-6 add the same controls averaged across the institution's peers. And columns 3 and 6 instrument for peers' average EMI using the average control values of excluded peers, as in the main text, $\overline{X}_{k(i)}$.

for 4-year education rather than employment shocks colleges' may use to make curricular decisions to prioritize existing or start new programs. Employment shocks to certain fields vary significantly across time and location suggesting the use of a different type of demand measurement. I recruit OEWS major-specific employment shifts derived from occupational employment counts by state described in Appendix section B to create a measure of relative demand for majors for each school and year. Similar to unemployment, I first re-weight the employment counts for each major (mapped from occupational counts) by the same base-line shares from the IPEDS migration files,

$$E_{m,i,t} = \sum_{s} \frac{FY_{i,s,t_0}}{FY_{i,t_0}} \cdot OccEmp_{m,s,t}.$$

I then subset the full set of possible major offerings, M, into two mutually exclusive groups, r and r^C, where r contains all majors that a school offered at time, t, and r^C is its complement, containing all other majors. I posit that relative increases in demand for the majors in r^C will drive up major diversification, holding the demand for current majors in r constant. In other words, stronger employment growth in fields more closely linked with majors not offered by a college creates an incentive for that school to add new programs experiencing stronger demand. Formally, I define this relative demand measure to be,

$$\begin{aligned} \widehat{RelDemand}_{i,t} &= \log\left(\frac{\overline{E}_{r^C}}{\overline{E}_r}\right) \\ &= \log\left(\frac{1}{N_{r^C}} \sum_{m \in r^C} E_{m,i,t}\right) - \log\left(\frac{1}{N_r} \sum_{m \in r} E_{m,i,t}\right). \end{aligned} \tag{C2}$$

This equates to the log average predicted occupational employment in majors not offered divided by the average occupational employment of majors currently offered. An increase in this value suggests that the demand for majors not offered was higher relative to an institution's current majors.

I estimated the relationship between relative demand and the EMI in Panel B of Table C3. Colleges responded to a 10 percent increase in relative demand with a 1 percent increase in major diversity, a relationship that is consistent after including peer measures. This result suggests colleges consider the employment demand for majors when deciding whether to start new programs. Though the strength of this relationship is still a tenth that of peer effects, it is fairly precise.

Table C3: Employer Demand and Major Diversification

	1 OLS	2 OLS	3 GMM2S
Panel A. Effective unemployment rates, Outcome=Log(EMI)			
Log(Effective unemployment$_{t-1}$)	0.110	0.120	0.135
	(0.099)	(0.099)	(0.094)
Log(Peers' Average EMI$_t$)		0.207*	1.112**
		(0.082)	(0.263)
Instrument(s)	-	-	$\overline{X}_{k(i)}$
First-stage F	-	-	26.17
School FEs	✓	✓	✓
State-by-Year FEs	✓	✓	✓
Peer controls	✗	✓	✓
N Observations	40,583	40,499	40,394
N Clusters	1640	1636	1626
Panel B. Relative occupational demand, Outcome = Log(EMI)			
Log(Relative demand$_{t-1}$)	0.102**	0.104**	0.114**
	(0.027)	(0.025)	(0.023)
Log(Peers' Average EMI$_t$)		0.186*	1.063**
		(0.084)	(0.332)
Instrument(s)	-	-	$\overline{X}_{k(i)}$
First-stage F	-	-	23.18
School FEs	✓	✓	✓
State-by-Year FEs	✓	✓	✓
Peer controls	✗	✓	✓
N Observations	31,565	31,501	31,410
N Clusters	1626	1624	1616

Notes: * $p < 0.05$, ** $p < 0.01$. Standard errors clustered at the institution-level are in parentheses. All models are weighted by the base-year total number of BA degrees. Panel A presents estimates for the one year lag of the effective unemployment rate for each institution on the log undergraduate EMI. Panel B is interested in the relationship between the undergraduate EMI and the one year lag of the relative demand for majors the schools did not offer divided by the demand for their existing majors. All models control for logged undergraduate enrollment, share of a school's total enrollment that is part-time, share graduate students, the share of bachelor's degrees awarded to women, to students that were either Black or Hispanic, to foreign or international students, and the number of years in the panel the school had awarded BA degrees and its quadratic. Columns 2 and 3 add the same controls averaged across the institution's peers. And column 3 instruments for peers' average EMI using the average control values of excluded peers, as in the main text, $\overline{X}_{k(i)}$.