Institutions vs. Majors: Evidence from The College Scorecard*

Shaun Dougherty[†], Matthew Guzman[‡], James Thomas[‡‡]

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Abstract

This paper uses the Field of Study dataset from The College Scorecard and a two-way fixed effect model to decompose median earnings five years after graduation into contributions from institutions and majors. Majors explain more variation in earnings than institutions, with a one standard deviation increase in major-specific contributions yielding a 26.6% larger gain than a comparable increase in institution-specific contributions. Using the two-way fixed effect estimates, we also rank institutions net of major composition and majors net of institution composition. Elite schools dominate the top of the institutional rankings, while STEM fields consistently lead among majors. When restricting the analysis to accessible institutions, majors remain the stronger determinant of earnings, and a set of high-value but often overlooked public universities emerges.

1 Introduction

The financial return to higher education has come under intense scrutiny as students and families face rising tuition costs and growing debt burdens.[1] Policymakers, too, are increasingly

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[†]Lynch School of Education, Boston College. Email: shaun.dougherty@bc.edu

[‡]Michigan State University. Email: guzman27@msu.edu

[‡‡]Federal Trade Commission. Email: jthomas2@ftc.gov

[1]For instance, a recent Pew survey found that only 22% of US adults feel a four-year degree is worth it for students who have to take out loans.

focused on which aspects of higher education deliver value—both to ensure accountability for public funds and to inform households making college choices.[2]

Against this backdrop, two factors stand out in shaping students' financial outcomes: the institution they attend and the field of study they pursue. While both institutions and majors are recognized as important determinants of earnings, existing evidence provides little clarity on how much each matters relative to the other. Furthermore, some institutions may appear to have high-earning graduates because they confer many degrees in high-paying fields, while some majors may seem lucrative mainly because they are concentrated at selective universities. Without a careful accounting of these overlapping influences, families and policymakers lack clear guidance on the relative importance of where and what students study, and on which colleges and majors consistently deliver high value.

To address this issue, this paper uses the Field of Study data from The College Scorecard to descriptively decompose institution-major specific median earnings into contributions from institutions and majors. We provide both an analysis of the relative importance of institutions and majors in determining earnings, rankings that identify high-value institutions net of major composition and high-value majors net of institution composition.

The Field of Study data are ideal for their quality, breadth, fine major categorizations, and relatively long earnings horizons. The data represent all federally funded students at Title IV institutions and are based on administrative enrollment and tax records. Furthermore, they finely categorize majors by 4-digit CIP codes and report median earnings five years after graduation, reducing sensitivity to early-career fluctuations.

We begin with an Analysis of Variance (ANOVA) showing that majors explain 46.5% of the variation in median earnings while institutions explain 22.8%. Next, we use a two-way fixed effects decomposition to show that a one standard deviation increase in major-specific contributions to earnings is 26.6% larger than a comparable increase in institution-specific contributions. These decompositions are descriptive in nature and thus only suggestive of causal effects; however, because sorting into universities is institutionalized by competitive admissions policies, our descriptive decompositions likely understate the importance of majors relative to institutions. As such, our analysis suggests that what you study—not where—is the most important factor determining earnings.

Following this decomposition, we use our two-way fixed effects model to rank institutions net of major effects and majors net of institution effects. Our institution rankings reinforce the strong earnings potential of elite institutions. Amherst College tops the rankings, followed by Yale, Princeton, MIT, and other Ivy-Plus universities and elite liberal arts

[2] See the U.S. Department of Education's 2023 Gainful Employment and Financial Value Transparency Rule, as well as congressional proposals such as the College Transparency Act.

colleges. Furthermore, our major rankings corroborate the earnings power of STEM degrees, with 16 of the top 20 majors coming from STEM fields.

While it is useful to document the earnings contributions of elite institutions, such exclusive institutions are not practical options for most students. Furthermore, while our major rankings net of institution effects reinforce the earnings power of STEM degrees, highly selective institutions may distort these rankings if major effects are heterogeneous across institution tiers. To consider the relative importance of institutions and majors in a way that is relevant to a broader set of students, we repeat our analysis restricting to "accessible" institutions, defined by less selective admissions and lower net costs.

Our restricted institution rankings highlight several high-value colleges that serve a broader student population, including San Jose State University, which tops our rankings despite having inclusive admissions and an average annual net price of $14,603, and Sonoma State University, which ranks 3$^{\text{rd}}$ and has inclusive admissions and an average annual net price for low-income families of only $1,831. These institutions are less visible in our overall rankings—where they place 56$^{\text{th}}$ and 108$^{\text{th}}$ respectively—illustrating the importance of separately considering colleges that serve a broader set of students. Our restricted major rankings and institution-major decompositions remain broadly consistent with our unrestricted analysis, implying that our conclusions about the relative importance of majors and the highest-value majors are not driven by exclusive institutions.

Our paper relates to a long line of academic literature on the financial returns to college majors and institutions.[3] The papers most similar to our work are Mabel et al. (2020) and Muse & Muse (2024). Mabel et al. (2020) use institution-level median earnings from the College Scorecard to assess the importance of majors and institutions, finding that majors appear slightly more important in explaining earnings variation. We build upon their work by using more recent institution-major level data from the College Scorecard, which provide finer major categorizations and allow us to estimate institution-specific earnings effects rather than relying on broad proxies for institutional quality.

Muse & Muse (2024) use the Field of Study data from the College Scorecard and a Cross-Classified Multilevel Model (CCMM) to examine the relative importance of majors and institutions in determining earnings, finding that majors play the larger role. We build on their work by estimating a two-way fixed effects model, which enables us both to assess the relative importance of majors and institutions and to rank institutions net of major effects and majors net of institution effects. In addition, we extend their analysis by repeating our

[3]Notable contributions not mentioned in the body include, but are not limited to: Altonji (1993), Altonji, Blom, et al. (2012), Andrews, Imberman, et al. (2024), Andrews, Li, et al. (2016), Arcidiacono (2004), Beffy et al. (2012), Black & Smith (2004, 2006), Bleemer & Quincy (2025), Hershbein & Kearney (2014), Hoxby (2009), Kirkbøen et al. (2016), and Zhang et al. (2024).

decomposition for accessible universities, providing insights that apply to institutions serving a broader range of students.

Our paper also connects to literature on post-secondary opportunities for students who may not be able to attend highly selective institutions.[4] A prominent example is Chetty, Friedman, et al. (2020), which ranks universities according to their "mobility rate"—a measure that combines the share of students who are low-income with the share of those students who reach high-income status as adults. Our analysis is complementary, focusing on accessible institutions and ranking them by their contributions to median earnings, net of major composition.

The remainder of the paper is organized as follows. Section 2 describes the Field of Study data from the College Scorecard and their suitability for decomposing median earnings into institution and major effects. Section 3 presents decomposition and ranking results for all comprehensive Title IV institutions. Section 4 repeats the analysis for "accessible" institutions that serve a broader range of students. Section 5 concludes.

2 Data

To understand the relative importance of institutions and majors in determining earnings, we use the Field of Study data from The College Scorecard. This dataset reports median earnings by institution and four-digit CIP codes for majors.[5] Institution-major-specific earnings are computed by merging administrative enrollment records from the Department of Education's National Student Loan Data System (NSLDS) with U.S. Department of Treasury tax records. We analyze the 2014-15, 2015-16 pooled graduating cohort for which median earnings five years after graduation (2020 and 2021) are available.

One advantage of this dataset is that it includes all Title IV-eligible institutions.[6] As such, it allows for a comprehensive analysis of the near-universe of higher-education institutions in the United States. Additionally, because enrollment and earnings information come from administrative records, they are free from the nonresponse bias and recall bias that affect survey data (Education, 2022, 2024).

Another advantage of the dataset is that it finely categorizes majors into four-digit

[4] Notable contributions not mentioned in the body include, but are not limited to: Bettinger et al. (2012), Card & Krueger (2005), Castleman & Page (2015), Dale & Krueger (2002, 2014), Dynarski et al. (2021), Eide, Hilmer, et al. (2016), Hoekstra (2009), Hoxby & Avery (2012), Loury & Garman (1995), Oreopoulos & Petronijevic (2013), Page & Scott-Clayton (2016), Pallais (2015), and Zimmerman (2014, 2019).

[5] Individuals who complete double or multiple majors majors are measured multiple times if the awards are completed in different four-digit CIP codes. If students complete multiple majors in the same four-digit CIP code, then they are only counted once.

[6] 2,669 bachelor's degree-granting institutions before sample restrictions.

CIP codes. Coarser categorizations such as two-digit CIP codes aggregate majors into broad categories, obscuring important differences in earnings potential. For example, within the two-digit "Social Sciences" category, students majoring in Economics (CIP 45.06) have median earnings of $75,535 five years after graduation, compared to $43,324 for those majoring in Anthropology (CIP 45.02)—a difference of more than $30,000 that would be lost under a coarser classification. Given that our main objective is to compare the relative importance of majors and institutions in determining earnings, capturing the full variety of majors is therefore paramount.

A final advantage of this dataset is that it reports median earnings five years after graduation. By this point, most graduates have completed the transition from initial job placements and early training, reducing short-term fluctuations in income. This measure therefore avoids penalizing majors whose earnings are temporarily depressed at career entry, and it offers a more stable indicator of longer-run earnings potential than some alternative data sources.[7]

While the Field of Study dataset has many strengths for our analysis, it also has important limitations. First, it does not include any measures of student characteristics by institution-major, such as average SAT scores, average high school GPA, or demographic shares. Without such controls, we can only describe earnings differences across institutions and majors, not identify causal effects. Because better prepared students disproportionately sort into higher-earning institutions and majors, these descriptive comparisons almost certainly overstate the causal impact of institutions and majors on earnings.[8]

A crucial question for our analysis is whether this selection bias has a larger effect on earnings differences across institutions or across majors. Causal studies consistently show that descriptive estimates greatly overstate the returns to attending more selective institutions, while the gap between descriptive and causal estimates is typically smaller for majors.[9] This pattern is intuitive: positive sorting into colleges is institutionalized through competitive admissions, whereas sorting into majors largely reflects students' own choices. The implication is clear—without controls for student characteristics, descriptive comparisons likely understate the importance of majors relative to institutions.

[7]For example, the NCES Baccalaureate and Beyond survey measures earnings one, four, and ten years after graduation, but the one-year follow-up is most frequently used due to better coverage and lower attrition. Similarly, the National Survey of Recent College Graduates collected earnings data for individuals within one to two years of degree completion.

[8]See Altonji, Arcidiacono, et al. (2016) for a review.

[9]Dale & Krueger (2002), Dale & Krueger (2014), Mountjoy & Hickman (2021), and Ge & Isaac (2022) find that causal effects of attending more selective colleges are small relative to descriptive differences, although Chetty, Deming, et al. (2025) finds large causal effects of attending an Ivy-Plus institution on extreme right-tail outcomes. For evidence on majors, see Bleemer & Mehta (2022), Kirkbøen et al. (2016), and Hastings et al. (2013), who document large causal effects of field of study choice.

Another limitation of the Field of Study dataset is that it reports median earnings only for students who received Title IV federal grants or loans. Because Title IV recipients disproportionately come from middle- and lower-income families, their earnings are not fully representative of all college graduates. At the same time, this restriction enhances internal validity by reducing unobserved heterogeneity: focusing on a more homogeneous group of students mitigates one channel through which sorting into institutions and majors can confound earnings comparisons. Although other sources of selection bias remain, limiting the sample to Title IV students likely moves our descriptive estimates closer to the causal effects.

An additional limitation of the Field of Study dataset is that it covers only graduates with earned income who are not enrolled in graduate school.[10] Evidence from other studies suggests that non-working graduates outside of graduate school are negatively selected and concentrated in lower-earning institutions and majors, whereas those enrolled in graduate school are positively selected and disproportionately from higher-earning institutions and majors.[11] As such, excluding these students likely understates the variance in median earnings across institutions and majors. That said, the excluded share is probably small, so this limitation is unlikely to alter our main conclusions.[12]

A final limitation of the Field of Study dataset is that it excludes non-graduates and does not track students who change majors. Information on intended major is rarely collected and often unreliable, so accounting for major changes is generally not feasible. Nonetheless, this omission matters for interpretation. Existing evidence shows that most switches are from higher-earning to lower-earning majors, and that switchers are negatively selected relative to their initial major but positively selected relative to their final major.[13] As a result, median earnings by final major likely overstate the earnings of both high- and low-earning initial majors, with ambiguous effects on the variance across majors. Similarly, studies show that non-graduates are negatively selected and disproportionately enrolled at lower-earning institutions, so excluding them tends to understate the variance in earnings across

[10] The dataset reports the number of graduates without earned income who are not enrolled in graduate school, but not the number enrolled in graduate school.

[11] See Carnevale et al. (2012), Eide, Brewer, et al. (1998), and Meijia & Johnson (2025) for evidence that non-working graduates are negatively selected, and see Baum & Steele (2017) and Mullen et al. (2003) for evidence that graduate students are positively selected.

[12] Graduates without earned income who are not enrolled in graduate school comprise only 6.5% of the total number of graduates who are not enrolled in graduate school. Further, Baum & Steele (2017) find that although 39% of bachelors degree recipients enroll in some graduate program within four years of graduating, the vast majority of these graduates pursue masters degrees or certificates, which generally last 1-2 years. Only 7.4% of bachelors degree recipients enroll in longer professional or doctoral degree programs within 4 years, implying that the share of bachelors recipients who are enrolled in graduate school five years after graduating is likely small.

[13] See Arcidiacono (2004), Arcidiacono et al. (2016), Astorne-Figari & Speer (2019), and Stinebrickner & Stinebrickner (2014)

institutions.[14]

For U.S., bachelor's degree-granting institutions, the complete Field of Study dataset for the 2014-15, 2015-16 pooled graduating cohort includes 2,414 institutions, 390 four-digit CIP code major categories, and 67,693 institution–major pairs at main campuses.[15] To construct our analysis sample, we first remove 44,812 institution–major pairs whose median earnings are privacy-suppressed because they include fewer than 16 graduates. Although this exclusion eliminates a substantial number of pairs, each suppressed cell represents very few graduates. As a result, the remaining pairs still account for at least 70.5% of students—and likely substantially more.[16]

After removing institution–major pairs without median earnings, the dataset contains 295 four-digit CIP code major categories. However, only 91 of these are offered widely enough—at more than 50 institutions—to support meaningful comparisons. To avoid drawing spurious conclusions from rare majors, we reclassify those below the 50 institution threshold into the "Other" category ending in 99 within the same two-digit CIP code.[17] This reclassification yields 127 four-digit CIP codes, of which 110 meet the threshold. We drop the remainder. As before, although this removes a non-trivial number of CIP codes, they account for only 1.16% of the graduates who remain after excluding institution–major pairs without median earnings.

Finally, to focus on institutions that provide meaningful variation for decomposing median earnings into institution and major effects, we exclude institutions with median earnings in two or fewer two-digit CIP codes. This removes 24.30% of the remaining institutions; however, because these institutions have fewer majors, they comprise only 3.19% of the remaining institution-major pairs. Most are specialized schools with limited academic diversity, though some are small institutions with few Title IV students, where many majors have privacy-suppressed median earnings.[18] In Appendix 1, we repeat our analysis using lower thresholds for uncommon majors and specialized institutions. Although some of these majors and institutions then enter our rankings, our main conclusions about the relative

[14] See Bound et al. (2010) and Stinebrickner & Stinebrickner (2012).

[15] While the Field of Study dataset contains rows for branch campuses, earnings data for these are duplicated from those of their respective main campuses. As these branch campuses observations do not provide additional information for earnings cohorts, we remove them from the analysis.

[16] Privacy-suppressed pairs have at most 15 graduates. In the extreme case where every suppressed pair has exactly 15 graduates, suppressed pairs represent 70.5% of students. However, most suppressed pairs likely have many fewer graduates, implying that the true share is likely much smaller.

[17] For example, majors such as "Fishing and Fisheries Science and Management" (CIP code 03.03) and "American Sign Language" (CIP code 16.16) are reclassified to "Natural Resources and Conservation, Other" (CIP code 03.99) and "Foreign Languages, Literatures, and Linguistics, Other" (CIP code 16.99).

[18] For example, Pomona College has majors in 39 4-digit CIP codes spanning 17 two-digit codes. However, only one of those four-digit codes has non-suppressed median earnings (Economics, 45.06).

importance of institutions and majors in determining earnings remain unchanged.

3 Results: All Institutions

To analyze the relative importance of institutions and majors across the higher education landscape, we begin by analyzing all comprehensive Title IV eligible institutions offering bachelor's degrees. In the following section, we restrict to "accessible" and "more accessible" institutions to provide insights that are relevant to a broader array of students.

3.1 Linear Decomposition

To begin, let $j = 1, \ldots, J$ denote comprehensive Title IV institutions and let $k = 1, \ldots, K$ denote majors grouped by 4-digit CIP codes. To decompose median earnings five years after graduation into contributions from institution quality and major marketability, we use the following linear two-way fixed effects model:

$$Y_{jk} = \alpha_j + \beta_k + \epsilon_{jk} \tag{1}$$

Y_{jk} represents median earnings 5 years after graduation for students who earned a bachelor's degree from institution j in major k, α_j and β_k represent institution and major fixed effects respectively, and ϵ_{jk} is the residual.

Table 1 reports an analysis of variance (ANOVA) based on this model, reporting the share of variance in median earnings that is jointly explained by institution and major effects, the marginal shares explained by adding institution (major) effects to a model with only major (institution) effects, and the share of variance that is captured by the residual term $\epsilon_{jk.}$

Most notably, results show that although adding institution effects to the model explains an additional 22.8% of variance in median earnings, adding major effects to the model explains an additional 46.5% of variance. This illustrates that while both factors are important, majors explain substantially more variance in median earnings than institutions.

To build on this analysis of variance, we estimate the fixed effects α_j and β_k and compare their distributions. Figure 1 displays kernel density plots of the distributions of $\hat{\alpha}_j$ and $\hat{\beta}_k$ that are centered around the average value of Y_{jk}. As such, $\hat{\alpha}_j$ represents predicted earnings of a student who graduates from institution j with an average major, and $\hat{\beta}_k$ represents predicted earnings of a student who graduates with major k from an average institution.

These plots illustrate that although institution effects have a long right tail, most institutions yield predicted earnings for graduates with an average major that are between \$50,000 and \$75,000. Comparatively, the distribution of major effects is somewhat bi-modal, with many low earning majors but a substantial number of higher earning majors.

The greater dispersion in major effects can also be seen directly—the standard deviation in major effects is \$15,414 while the standard deviation in institution effects is \$12,174. This implies that changing to a one standard deviation higher earning major while remaining at the same university is associated with an increase in earnings that is 26.6% greater than the increase associated with moving to a one standard deviation higher earning institution holding major fixed. This reinforces the finding from the analysis of variance that majors generally explain more variance in earnings than institutions.

3.2 Institution Rankings

In addition to facilitating a comparison of the relative importance of majors and institutions, estimates of $\hat{\alpha}_j$ and $\hat{\beta}_k$ can also be used to rank institutions by their effects on earnings controlling for the confounding effects of majors, and to rank majors by their effects on earnings controlling for institution effects. These rankings avoid overstating the value of institutions that disproportionately graduate students in high earning majors or majors that are over-represented at high earning institutions. As such, they provide more relevant information to students, families, and policy-makers.

Table 2 begins by listing the top 20 institutions along with their estimated fixed effects $\hat{\alpha}_j$.[19] The list is topped by Ivy-plus universities and elite liberal arts colleges, implying that these institutions' well known reputations for educating high earners have little to do with major composition.

In addition, to illustrate the range of institution effects, Table 2 also reports universities clustered around the 5th and 95th percentiles, with Greenville University and University of Richmond being the closest to the 5th and 95 percentiles respectively. We note that the difference between the institution effect for University of Richmond and for Greenville University is \$35,002. This implies that if a student moved from Greenville University near the bottom of the distribution to University of Richmond near the top while choosing the same major, her predicted earnings would increase by \$35,002. Remarkably, the long right tail of institution effects implies that if she moved again from University of Richmond to the very top Amherst College, her predicted earnings would increase an even larger amount.

[19] The complete ranking of all comprehensive Title IV institutions offering bachelor's degrees is provided in an online appendix.

3.3 Major Rankings

Having considered the effects of institutions on earnings, we now turn to the effects of majors. Table 3 reports the top 20 and bottom 20 majors grouped by 4-digit CIP code together with their estimated fixed effects $\hat{\beta}_k$.[20] Sixteen of the top 20 majors are in STEM fields, consistent with other work finding high returns to STEM degrees.[21]

At the other end of the major rankings are a range of majors in the humanities and arts. While there are many compelling reasons to study the humanities and arts, consistent with other literature, our decomposition shows that earnings five years after graduation is not among them.[22] As such, although we do not wish to discourage students from studying these fields, we do hope these statistics make them aware of the financial reality of completing degrees in the humanities and arts.

To further illustrate the relative importance of institutions and majors, recall that the difference between the 5th percentile institution effect for Greenville University and the 95th percentile effect for University of Richmond was \$35,002. Table 3 illustrates that this difference is approximately equal to the difference between Philosophy and Management Information Systems and Services (MISS); however, these majors represent the 13th and 88th percentiles—a smaller difference than Greenville University and University of Richmond. This illustrates that changing from Philosophy to MISS while remaining at the same institution is associated with the same earnings increase as moving from a 5th to 95th percentile institution while maintaining the same major. This is a remarkable finding given that students are generally free to change majors within institutions but face substantial barriers to changing institutions.

Put differently, our model predicts that a student graduating from Greenville University with a major in MISS will earn approximately as much as a student graduating from the much higher ranked University of Richmond who majors in Philosophy. This implies that for students who are unable to attend higher ranked institutions, high return majors can still yield earnings that are comparable to low return majors at less accessible institutions.

However, because of the long right tail in institution effects, the same difference between Philosophy and MISS is only equivalent to the difference between the 16th ranked Middlebury College and the top institution Amherst. As such, although a high earning major can boost earnings of students at 5th percentile institutions into the earnings distributions of 95th percentile institutions, they are much less effective at moving students into the distributions

[20] The complete ranking of all 4-digit CIP codes is provided in an online appendix.

[21] See Andrews, Imberman, et al. (2024) and Muse & Muse (2024). Also see Altonji, Arcidiacono, et al. (2016) for a review.

[22] See Altonji, Arcidiacono, et al. (2016), Andrews, Imberman, et al. (2024), and Zhang et al. (2024).

of the very top institutions.

4 Results: "Accessible Universities"

While the results in Section 3 identify the highest earning institutions across all comprehensive Title IV institutions, these institutions are also extremely exclusive. All of the top 20 universities in Table 2 except for the Dominican University of California are categorized as "more selective" according to the American Council on Education's undergraduate profile Carnegie classifications, and 86.4% of those in the top 5% of institutions are also categorized as more selective. In addition to exclusive admissions policies, many universities are very difficult to afford even with access to Federal student loans. While higher ranked institutions are not necessarily more expensive, high costs certainly make some universities inaccessible to many students.[23] Together, exclusive admissions policies and high costs imply that many of the top ranked universities in Table 2 are inaccessible to the vast majority of students.

Furthermore, while the major rankings presented in Table 3 illustrate the overall earnings power of different areas of specialization, it's not clear whether these rankings apply to more accessible institutions. Certain majors may be associated with very high earnings at top-tier exclusive universities but with more middling earnings at the institutions that are more accessible.

As such, this section replicates the analysis of Section 3 for subsets of comprehensive Title IV institutions that are "accessible" and "more accessible" based on admissions criteria and net price. This analysis compares the relative importance of majors and institutions and identifies high earning institutions and majors for the set of institutions that are available to a wider array of students.

4.1 Defining Accessibility

To identify "accessible" and "more accessible" institutions, we combine information on selectivity from Carnegie Classifications with affordability criteria based on net price from the Integrated Postsecondary Education Data System (IPEDS).[24] The Carnegie selectivity measure is based on multiple aspects of an institution's admissions process, including whether standardized test scores are required, the proportion of applicants who submit scores, and

[23] The correlation between $\hat{\alpha}_j$ and average net price is .42, implying that families generally pay more at higher value institutions. However, this is largely due to differences in student composition. The correlation between $\hat{\alpha}_j$ and average net price for low-income students is -0.01., implying that the lowest income families do not pay a premium for value.

[24] In this Section only, we drop the 0.61% of institution-major pairs that we are unable to match to IPEDS net price records.

the 25th percentile ACT or SAT scores of enrolled students. Based on these criteria, institutions are assigned to one of three categories—"more selective," "selective," or "inclusive".[25] The IPEDS net price variables report the average annual net price—defined as total cost of attendance minus grant and scholarship aid—for full-time, first-time undergraduate students receiving federal financial aid. Average net price is reported across all aided students and separately for five family income brackets. Importantly, for public institutions, net price measures are for in-state students.

Using these selectivity and affordability measures, we define "accessible" institutions as those that are not "more selective" according to Carnegie classification and that have an average net price across all aided students that is below median. This definition removes institutions that are more exclusive and generally higher cost but will include many institutions that are still not broadly accessible. Thus we also identify "more accessible" institutions as those that have an "inclusive" Carnegie classification and have a net price for families earning $0 - 30,000 that is in the bottom third of all institutions. This definition identifies institutions that are effectively open admission and are lower cost for the lowest income families.[26]

4.2 Linear Decomposition

To analyze the relative importance of majors and institutions among the set of universities that are available to a broader range of students, we repeat the analysis of variance and OLS estimation of Equation (1) using only accessible and more accessible institutions. Table 4 reports the marginal shares of variance in earnings explained by institution and major effects as well as standard deviations in the distributions of $\hat{\alpha}_j$ and $\hat{\beta}_k$.

Results show that, as in the full set of institutions, both majors and institutions have meaningful effects on earnings, but majors account for substantially more variation. Among accessible universities, majors explain 4.1 times as much variance in median earnings as institutions, and a one standard deviation increase in major effects corresponds to 1.7 times the earnings change associated with an equivalent increase in institution effects.[27] These

[25] "Four-year, higher part-time" institutions are not assigned a selectivity category in the Carnegie framework; we relabel them as "inclusive" to maintain consistency and reflect their typically open admissions policies.

[26] We experimented with absolute definitions of affordability based on whether a school's average net price by family income group minus federal loan limits was below a typical expected family contribution (EFC) for families in that income group. However, we found that too few institutions met these criteria.

[27] The factor of 4.1 versus factor of 1.7 discrepancy arises because we report the standard deviation in fixed effects but the ANOVA decomposes variance. If we square the fixed effect standard deviations, we see that the variance in CIP effects is 3.7 times larger than the variance in institution effects, which is consistent with the relative differences in the ANOVA.

differences are even larger than in the full sample, where majors explain only 2.0 times as much variance and the standard deviation ratio is 1.3. Among more accessible institutions, the relative importance of majors remains greater than in the full sample, though the contrast is somewhat smaller than among accessible institutions.

To explore this further, Figure 2 displays kernel density plots of $\hat{\alpha}j$ and $\hat{\beta}k$ for decompositions with only accessible and more accessible institutions. Comparing these to Figure 1 shows that restricting to accessible institutions removes the bimodality from the distribution of major effects but preserves its wide dispersion. Conversely, this restriction eliminates the long right tail of the institution-effect distribution, making it even more compressed. Together, these plots and decomposition statistics illustrate that restricting to accessible and more accessible institutions removes the highest-earning institutions while having limited effects on the importance of majors. This implies that among institutions that are more realistic for many students, the importance of majors relative to institutions is even larger than in the full set of comprehensive institutions.

4.3 Institution and Major Rankings

As in Section 3, in addition to assessing the relative importance of majors and institutions in determining earnings, the linear decomposition in Equation (1) can also be used to produce rankings of institutions and majors that control for the confounding effects of the other factor. In this subsection, we report these rankings for accessible and more accessible institutions to identify high value institutions that are realistic options for more students and to identify high and low earning majors at these institutions.

To begin, Table 5 reports the top 30 accessible universities by estimated institution effect $\hat{\alpha}_j$ together with their estimated institution effects, Carnegie selectivity classification, and average net price variables. Perhaps surprisingly, the top 30 accessible institutions includes a number of institutions that also meet our criteria for more accessible. As such, for brevity, we report only rankings for accessible institutions but print in bold the names of those institutions that also qualify as more accessible.[28]

While the estimated institution effects of top accessible institutions are more modest than those of the top overall institutions listed in Table 2, the rankings in Table 5 show there are many accessible (and even more accessible) institutions that yield sound predicted earnings. Some institutions of note are San Jose State University, which tops the rankings and is inclusive and relatively low cost; Sonoma State University, which has high predicted earnings and is inclusive and very affordable; and Michigan State University, which has high

[28]Full rankings of accessible and more accessible institutions are provided in an online appendix.

predicted earnings, is selective, and has an average net price of $129 for low income families. In the overall rankings in Table 2, these institutions rank 56th, 108th, and 224th respectively highlighting the importance of separately ranking accessible and more accessible universities to avoid obscuring high value institutions that are realistic options for many students.[29]

Next, Table 6 reports the top 15 and bottom 15 major categories ranked by major effects from a decomposition with only accessible institutions. For comparison, this table also includes each major's rank from decompositions with only more accessible institutions and across all comprehensive institutions. In general, major rankings are quite similar regardless of the set of institutions included in the decomposition. Engineering and Computer Science dominate all three rankings, Nursing is top 10 in all rankings, and the humanities and arts are at the bottom of all three rankings.

To explore this further, Figure 3 plots each major category's rank from a decomposition with all institutions to its rank from a decomposition with only accessible institutions. Majors clustered around the 45 degree line have similar rankings in both decompositions, while those that are significantly below (above) this line are particularly higher (lower) ranked in a decomposition with only accessible institutions.

Consistent with Table 6, Figure 3 shows that most majors lie close to the 45-degree line, indicating that major rankings are fairly similar whether measured across all institutions or only among accessible institutions. A few notable exceptions stand out, including Entrepreneurship—which ranks 43rd overall but 60th among accessible institutions—and Theology—which ranks 78th overall but 56th among accessible institutions.

Entrepreneurship's comparatively higher rank across all institutions is particularly striking. While this major provides solid opportunities to all students, benefits from entrepreneurship disproportionately accrue to graduates from more exclusive institutions. This may be because these graduates have greater access to social and financial capital, which are crucial complements to entrepreneurial training (Chetty, Friedman, et al., 2020; Martin, 2013). By contrast, While Theology does not generally produce high earnings, it appears to be relatively more lucrative for students who cannot access elite institutions.

Taken together, the evidence in Table 6 and Figure 3 confirms the well-documented pattern of high returns to STEM degrees and low returns to humanities and arts degrees across both all institutions and accessible institutions (Andrews, Imberman, et al., 2024; Muse & Muse, 2024; Zhang et al., 2024). At the same time, several notable exceptions highlight the importance of ranking majors separately by institution accessibility.

[29] Table 5 also identifies several "mega universities" including the University of Maryland - Global Campus, Colorado State University Global, Capella University, and Western Governors University. Recent research indicates that these primarily online universities may be accessible along other dimensions in addition to price as well. See Guzman et al. (2025).

5 Conclusion

The rising costs of higher education and growing debt burdens have intensified the need to understand what drives students' financial outcomes. To better inform families and policymakers, this paper uses the Field of Study dataset from The College Scorecard and a two-way fixed effects model to decompose institution-major specific median earnings into separate contributions from institutions and majors.

We find that majors account for substantially more variation in earnings than institutions. A one standard deviation increase in major-specific contributions to earnings is associated with a 26.6 percent larger gain than a comparable increase in institution-specific contributions, suggesting that what students study plays a larger role in shaping earnings than where they study. We also use the fixed effects estimates to construct rankings of institutions net of major composition and majors net of institution composition. These rankings show that elite liberal arts colleges and Ivy-Plus universities dominate the top of the institutional distribution, while STEM fields consistently rank among the highest-return majors. When restricting the analysis to accessible institutions defined by lower selectivity and cost, majors remain the stronger determinant of earnings, and a new set of high-value but less visible institutions emerges.

Although these descriptive decompositions provide useful benchmarks, they are ultimately limited by the data available. Most importantly, the College Scorecard does not provide observable measures of student characteristics at the institution-major level. Without measures such as average SAT scores, high school GPA, or demographic shares, our estimates cannot account for systematic sorting of students into institutions and majors. Expanding the Scorecard to incorporate such variables would enable much richer descriptive decompositions.

A second limitation is that the Scorecard only relates to majors at graduation. This allows us to measure the value of completed degrees in different fields but not the risks associated with starting in a given major. For many students and policy questions, decomposing outcomes by initial major would be more informative, since it would reflect both the rewards and risks of choosing a field. This is particularly important for STEM, where graduates earn high salaries but attrition rates are also high. Collecting high-quality information on intended major would be challenging in the U.S. context, where most students declare late, yet centralized efforts to do so would allow decompositions that speak to a wider array of policy concerns. Taken together, these opportunities for richer data would sharpen the guidance available to students and policymakers on what drives value in higher education.

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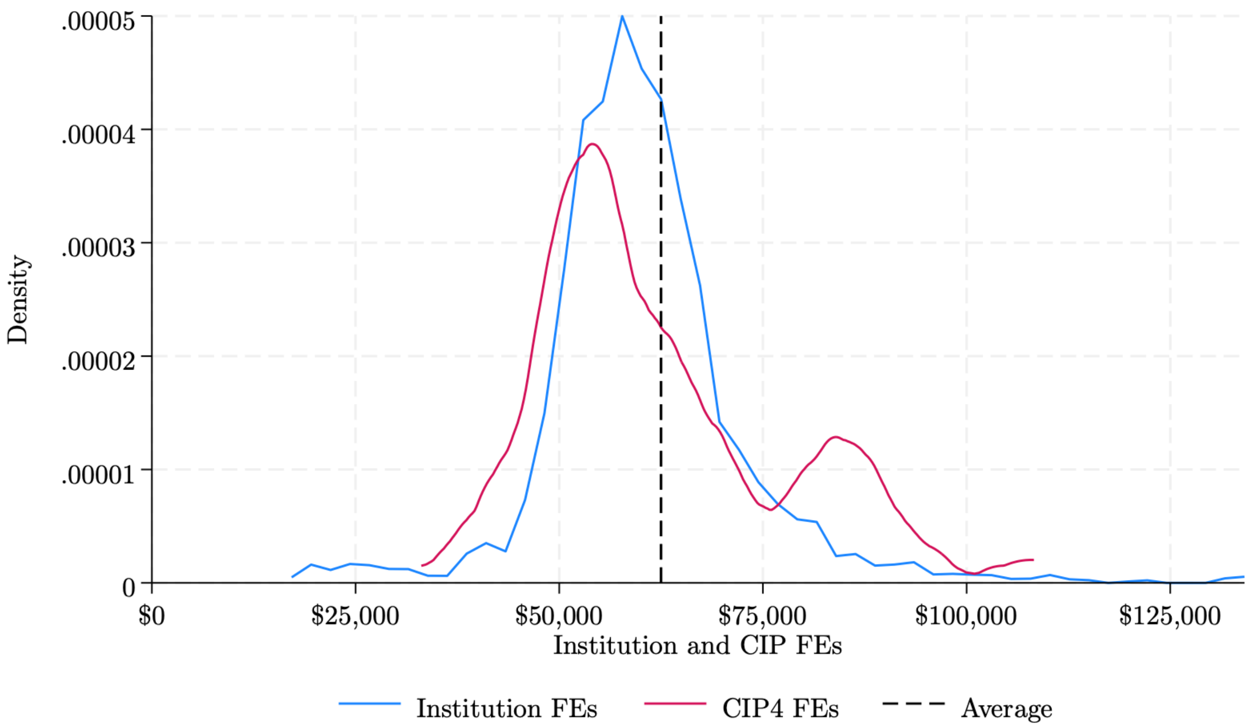
6 Tables and Figures

Table 1: ANOVA Comparing Institution and CIP Code Explanatory Power for Median 5-Year Earnings

Partial	Explained SS % of Total SS	df	F
Overall	78.84%	1,410	52.46
Institutions	22.84%	1,301	16.47
CIP Codes	46.54%	109	400.65
Residual	21.16%	19,858	
Total	100.00%	21,268	

Source: Twoway ANOVA of median earnings on institution and CIP code indicators. Partial sums of squares are reported as percentages of total sums of squares. Note that due to the partial interpretation of sums of squares and covariance between institution and cip codes, total percentages do not sum to 100%.

Figure 1: Kernel Density Plots of Institution and CIP Code Estimated Effects on Median 5-Year Earnings



Source: Kernel density plots of estimated institution and CIP code fixed effects using an Epanechnikov kernel. The dashed black line indicates the average of both estimated distributions, and these are mechanically equivalent.

Table 2: Ranking of Selected Institution Estimated Effects on Median 5-Year Earnings

Rank	Institution Name	Institution FE
1	Amherst College	$134,110
2	Yale University	$133,016
3	Princeton University	$132,315
4	Massachusetts Institute of Technology	$121,454
5	Stanford University	$114,586
6	Bowdoin College	$111,088
7	Harvard University	$110,800
8	University of Pennsylvania	$110,339
9	Swarthmore College	$106,929
10	Carnegie Mellon University	$106,515
11	Dominican University of California	$102,887
12	Dartmouth College	$102,726
13	University of Chicago	$102,013
14	Duke University	$100,305
15	Georgetown University	$100,033
16	Middlebury College	$98,059
17	Washington and Lee University	$97,292
18	Johns Hopkins University	$97,069
19	Brown University	$95,791
20	Santa Clara University	$93,876
63	Dickinson College	$81,106
64	Pacific Union College	$81,030
65	Massachusetts Maritime Academy	$80,967
66	**University of Richmond**	$80,706
67	Fairfield University	$80,677
68	Providence College	$80,568
69	Lafayette College	$80,339
1235	Fort Valley State University	$45,903
1236	Lindsey Wilson College	$45,883
1237	Saint Augustine's University	$45,791
1238	**Greenville University**	$45,704
1239	Shaw University	$45,696
1240	Crown College	$45,553

Source: Estimated institution fixed effects using Equation 1 for the top 20, 5$^{\text{th}}$ percentile, and 95$^{\text{th}}$ percentile institutions. Bolded institutions represent those that are exactly at the 5$^{\text{th}}$ and 95$^{\text{th}}$ percentiles.

Table 3: Ranking of Selected CIP Code Estimated Effects on Median 5-Year Earnings

Rank	CIP Name	CIP FE
1	Computer Engineering	$108,262
2	Computer Science	$107,679
3	Electrical, Electronics and Communications Engineering	$97,907
4	Industrial Engineering	$93,254
5	Computer and Information Sciences, General	$92,137
6	Chemical Engineering	$91,581
7	Aerospace, Aeronautical and Astronautical Engineering	$88,672
8	Mechanical Engineering	$88,087
9	Registered Nursing, Nursing Administration, Nursing Research and Clinical Nursing	$87,564
10	Engineering, Other	$86,849
11	Computer/Information Technology Administration and Management	$85,922
12	Engineering Technologies/Technicians, Other	$85,707
13	Biomedical/Medical Engineering	$84,645
14	**Management Information Systems and Services**	$84,385
15	Information Science/Studies	$83,775
16	Mathematics and Statistics, Other	$83,611
17	Computer and Information Sciences and Support Services, Other	$82,881
18	Civil Engineering	$82,552
19	Finance and Financial Management Services	$80,930
20	Business/Managerial Economics	$80,638
90	Parks, Recreation, Leisure, and Fitness Studies, Other	$50,503
91	Sociology	$50,415
92	Education, General	$50,338
93	Radio, Television, and Digital Communication	$50,127
94	History	$49,911
95	Human Services, General	$49,087
96	**Philosophy**	$48,562
97	Area Studies	$48,555
98	Rhetoric and Composition/Writing Studies	$46,516
99	Linguistic, Comparative, and Related Language Studies and Services	$46,271
100	English Language and Literature, General	$46,263
101	Ethnic, Cultural Minority, Gender, and Group Studies	$46,245
102	Human Development, Family Studies, and Related Services	$45,322
103	Ecology, Evolution, Systematics, and Population Biology	$43,996
104	Anthropology	$43,324
105	Visual and Performing Arts, General	$42,545
106	Fine and Studio Arts	$41,325
107	Film/Video and Photographic Arts	$41,157
108	Music	$40,392
109	Visual and Performing Arts, Other	$37,904
110	Drama/Theatre Arts and Stagecraft	$33,076

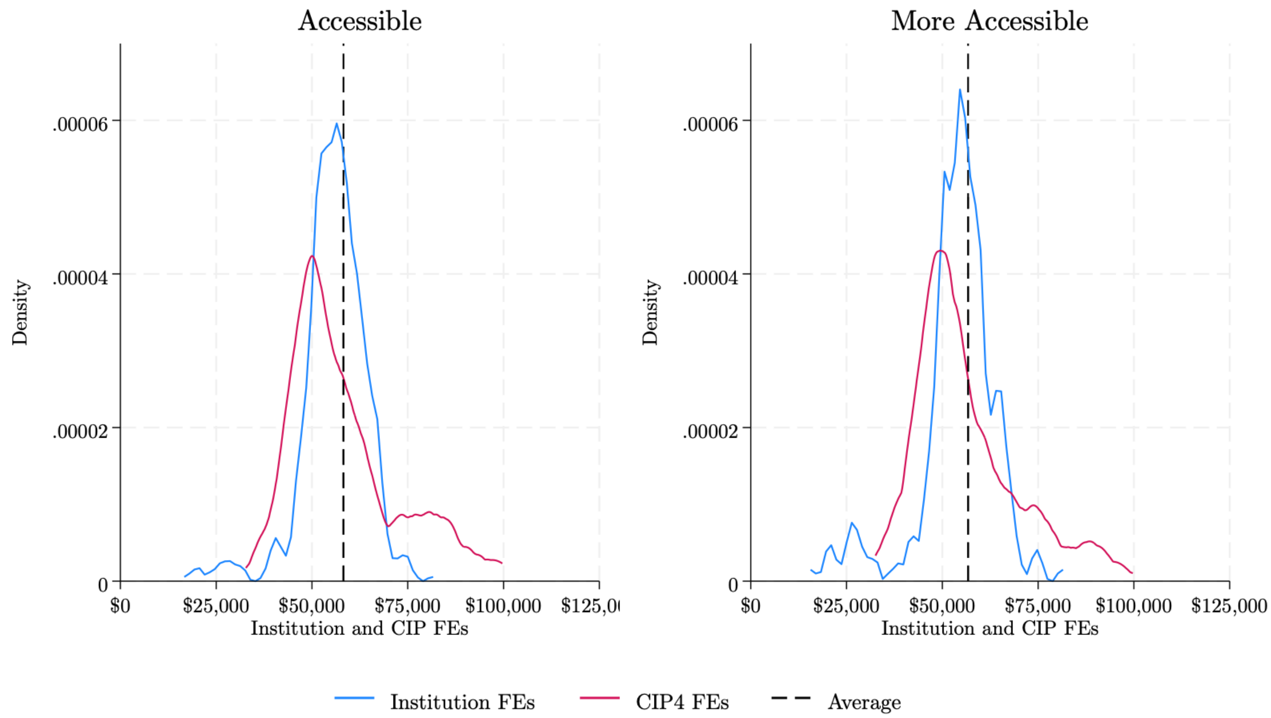
Source: Estimated CIP code fixed effects using Equation 1 for the top 20 and bottom 20 CIP codes. Bolded CIP codes represent those that have the same difference in estimated fixed effects as the 5^{th} and 95^{th} percentile institutions.

Table 4: ANOVA Comparisons of More Accessible and Accessible Institutions for Median 5-Year Earnings

	Accessible		More Accessible	
	Explained SS % of Total SS	Std. Dev of FE	Explained SS % of Total SS	Std. Dev of FE
Institution FE	14.91%	$8,374	21.50%	$10,268
CIP FE	61.12%	$14,513	56.53%	14,529

Source: Twoway ANOVA of median earnings on institution and CIP code indicators, separated by more accessible and accessible institutions. Partial sums of squares are reported as percentages of total sums of squares. Note that due to the partial interpretation of sums of squares and covariance between institution and CIP codes, total percentages do not sum to 100%.

Figure 2: Kernel Density Plots of Institution and CIP Code Estimated Effects for Accessible and More Accessible Institutions



Source: Kernel density plots of estimated institution and CIP code fixed effects using an Epanechnikov kernel separately for accessible and more accessible institutions. In each plot, the dashed black line indicates the average of the institution and major distributions, and these are mechanically equivalent.

Table 5: Ranking of Top 30 Accessible Institutions by Estimated Effects on Median 5-Year Earnings

Rank	Institution Name	Institution FE	Carnegie Classification	Net Price	Net Price for Low Income
1	**San Jose State University** (CA)	$81,634	Inclusive	$14,603	$10,225
2	Concordia College (NY)	$76,627	Inclusive	$16,641	$23,052
3	Virginia Military Institute (VA)	$75,418	Selective	$18,100	$10,705
4	**Sonoma State University** (CA)	$75,029	Inclusive	$7,055	$1,831
5	California State University-East Bay (CA)	$74,068	Selective	$12,631	$8,493
6	University of Maryland Global Campus* (MD)	$73,932	Inclusive	$16,228	$15,635
7	**University of Arkansas Grantham** (KS)	$73,893	Inclusive	$9,770	$9,745
8	**Colorado State University Global*** (CO)	$73,791	Inclusive	$12,351	$11,445
9	James Madison University (VA)	$72,887	Selective	$18,528	$13,588
10	George Mason University (VA)	$71,527	Selective	$18,841	$13,342
11	Charter Oak State College (CT)	$71,399	Inclusive	$9,697	$14,072
12	Simmons University (MA)	$70,471	Selective	$19,026	$12,476
13	St. Francis College (NY)	$70,235	Inclusive	$15,481	$12,759
14	**San Francisco State University** (CA)	$69,996	Inclusive	$13,641	$9,302
15	Oregon Institute of Technology (OR)	$68,959	Selective	$17,532	$10,568
16	Drew University (NJ)	$68,873	Selective	$17,033	$8,942
17	University of Massachusetts-Lowell (MA)	$68,823	Selective	$13,227	$7,628
18	Capella University* (MN)	$68,757	Inclusive	$17,840	$17,833
19	Fashion Institute of Technology (NY)	$68,402	Selective	$8,637	$6,172
20	**College of Staten Island CUNY** (NY)	$68,392	Inclusive	$6,818	$3,651
21	**California State University-Sacramento** (CA)	$68,238	Inclusive	$7,778	$3,878
22	**Western Governors University*** (UT)	$68,171	Inclusive	$10,336	$10,714
23	Purdue University-Main Campus (IN)	$68,010	Selective	$14,619	$3,709
24	University of Detroit Mercy (MI)	$67,858	Selective	$17,911	$13,356
25	Trident University International (CA)	$67,721	Inclusive	$13,916	$12,182
26	CUNY Queens College (NY)	$67,642	Selective	$4,777	$1,092
27	Ramapo College of New Jersey (NJ)	$67,550	Selective	$12,251	$6,453
28	University of Utah (UT)	$67,392	Selective	$11,112	$4,843
29	Michigan State University (MI)	$67,353	Selective	$8,738	$129
30	Towson University (MD)	$67,307	Selective	$11,076	$4,493

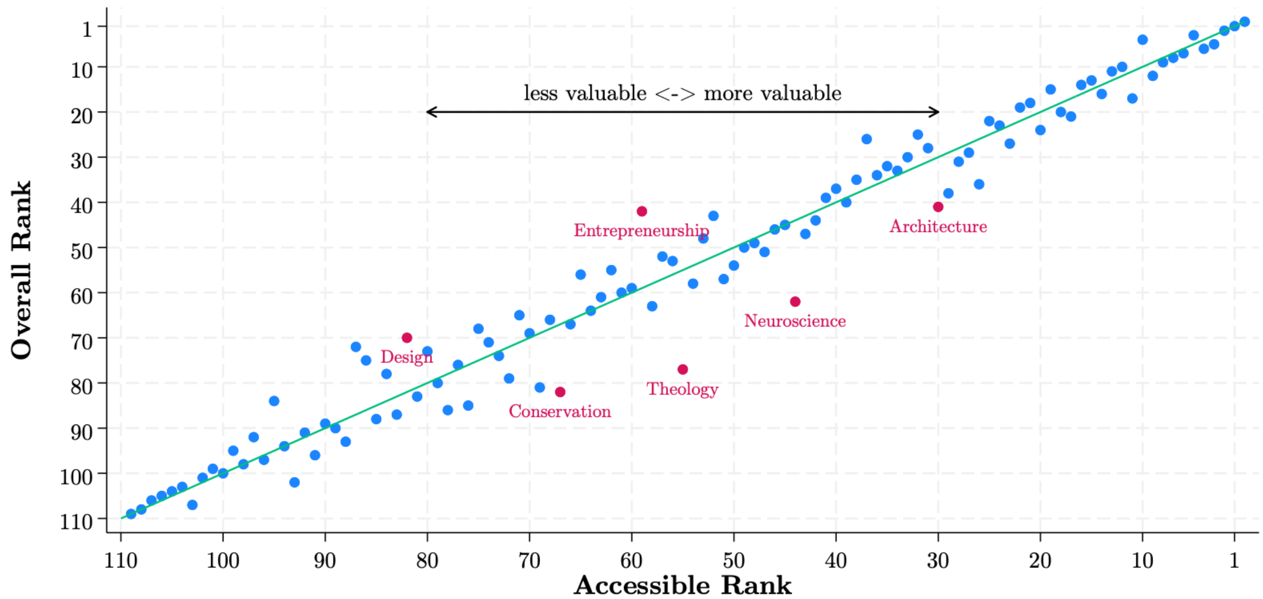
Source: Estimated institution fixed effects using Equation 1 on the accessible institution subsample. Top 30 institution effects are presented with their estimated fixed effects, Carnegie classifications, net prices, and net prices for low income students. Carnegie classifications and net prices are drawn from IPEDS HD and SFA tables. Bolded institutions represent those that meet the criteria for a more accessible institution as defined in the results section. Insititutions with an asterisk represent primarily online institutions, and this may represent another dimension of accessibility.

Table 6: Ranking of Top and Bottom 15 Majors by Estimated CIP Code Effect on Median 5-Year Earnings for Accessible Universities

CIP Name	Accessible CIP FE	Rank Among Accessible Universities	Rank Among More Accessible Universities	Overall Rank
Computer Engineering	\$99,686	1	1	1
Computer Science	\$96,072	2	3	2
Electrical, Electronics and Communications Engineering	\$95,614	3	2	3
Chemical Engineering	\$89,935	4	4	6
Aerospace, Aeronautical and Astronautical Engineering	\$88,482	5	8	7
Industrial Engineering	\$88,432	6	7	4
Mechanical Engineering	\$88,369	7	5	8
Registered Nursing, Nursing Administration, Nursing Research and Clinical Nursing	\$85,766	8	6	9
Engineering, Other	\$85,366	9	11	10
Biomedical/Medical Engineering	\$83,131	10	10	13
Computer and Information Sciences, General	\$82,866	11	13	5
Civil Engineering	\$82,038	12	9	18
Computer/Information Technology Administration and Management	\$81,636	13	15	11
Engineering Technologies/Technicians, Other	\$81,205	14	12	12
Computer and Information Sciences and Support Services, Other	\$78,273	15	16	17
Human Services, General	\$45,500	95	95	95
Graphic Communications	\$45,446	96	100	85
Rhetoric and Composition/Writing Studies	\$45,443	97	99	98
Radio, Television, and Digital Communication	\$44,870	98	98	93
Linguistic, Comparative, and Related Language Studies and Services	\$44,818	99	93	99
Philosophy	\$44,387	100	102	96
Ethnic, Cultural Minority, Gender, and Group Studies	\$44,353	101	94	101
English Language and Literature, General	\$43,706	102	97	100
Human Development, Family Studies, and Related Services	\$42,043	103	103	102
Music	\$40,668	104	104	108
Anthropology	\$40,337	105	101	104
Visual and Performing Arts, General	\$40,274	106	107	105
Fine and Studio Arts	\$38,895	107	106	106
Film/Video and Photographic Arts	\$38,693	108	105	107
Visual and Performing Arts, Other	\$37,916	109	108	109
Drama/Theatre Arts and Stagecraft	\$32,756	110	109	110

Source: Estimated CIP Code fixed effects using Equation 1 on the accessible institution subsample. Top 15 and bottom 15 CIP code effects are presented with their estimated fixed effects. Rankings among more accessible institutions and overall rankings are presented for comparison as well.

Figure 3: Scatterplot of Majors by Overall and Accessible Major Rankings



Source: Figure presents overall rankings of majors from Table 3 scattered against accessible rankings from Table 6. Majors plotted above the 45 degree line provide greater value overall, while majors plot below the line provide greater value for students at accessible institutions. While most majors provide relatively similar benefits to students at all institutions and at accessible institutions, those in red provide relatively different returns.

7 Appendix 1: Robustness Checks for Uncommon Majors and Specialization Definitions

In this appendix, we repeat our analyses of institutions and majors using lower thresholds in our definitions of uncommon majors and specialized institutions. While changing these definitions leads additional institutions and majors to enter our rankings, our finding that majors are relatively more important than institutions regarding earnings five-years post-graduation is substantively unchanged. The first panel of each of the following tables replicates the results of our main analysis. These are presented in Table 1. The subsequent panels in each table present the ANOVA results and standard deviations of fixed effects from models with different definitions of uncommon majors and specialized institutions.

Table A1: ANOVA Comparisons of Varying Definitions of Uncommon Major Threshold

	50-Institution Uncommon Major Threshold	
	Explained SS % of Total SS	Std. Dev of FE
Institution FE	22.84%	$12,174
CIP FE	46.54%	$15,414
	25-Institution Uncommon Major Threshold	
	Explained SS % of Total SS	Std. Dev of FE
Institution FE	22.22%	$12,079
CIP FE	47.09%	$15,580
	10-Institution Uncommon Major Threshold	
	Explained SS % of Total SS	Std. Dev of FE
Institution FE	21.74%	$12,034
CIP FE	47.31%	$15,790
	0-Institution Uncommon Major Threshold	
	Explained SS % of Total SS	Std. Dev of FE
Institution FE	21.40%	$12,020
CIP FE	47.54%	$16,862

Source: Twoway ANOVA of median earnings on institution and CIP code indicators. Partial sums of squares are reported as percentages of total sums of squares. Standard Deviations of FE from twoway fixed effect regression of institution and CIP code on earnings for the subsample meeting each definition.

Table A2: ANOVA Comparisons of Varying Definitions of Specialized Institution Threshold

	3 Two-Digit CIP Code Specialization Threshold	
	Explained SS % of Total SS	Std. Dev of FE
Institution FE	22.84%	\$12,174
CIP FE	46.54%	\$15,414
	2 Two-Digit CIP Code Specialization Threshold	
	Explained SS % of Total SS	Std. Dev of FE
Institution FE	23.16%	\$12,475
CIP FE	45.91%	\$15,397
	No Two-Digit CIP Code Specialization Threshold	
	Explained SS % of Total SS	Std. Dev of FE
Institution FE	23.24%	\$12,585
CIP FE	45.55%	\$15,385

Source: Twoway ANOVA of median earnings on institution and CIP code indicators. Partial sums of squares are reported as percentages of total sums of squares. Standard Deviations of FE from twoway fixed effect regression of institution and CIP code on earnings for the subsample meeting each definition.