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College Selectivity, Choice of Major, and Post-College Earnings

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ABSTRACT

College choice and choice of major are the most important decisions for future earnings. It is still unclear, however, what makes a greater difference—college or major—or whether a choice of college matters more for some majors, but not the others. Using cross-classified models and College Scorecard data, we show that a discipline is more consequential for future earnings than a college. The effect of STEM is substantial but is less pronounced at institutions with higher overall median earnings. The effect of college selectivity on earnings is more pronounced for non-STEM disciplines. Institutional characteristics—such as tuition, shares of graduates receiving different forms of financial aid, institutional size and location, and type of college—correlate with earnings of graduates. Racial and gender composition of an educational program correlate with expected earnings of its graduates even after control for other institutional and disciplinary characteristics. Models presented here provide a better understanding of the effect of college and major choices on future earnings.

KEYWORDS

College outcomes; earnings of college graduates; STEM; cross-classified model; College Scorecard

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1. Introduction

The value of educational attainment for future earnings is beyond any doubt. "Individuals with higher levels of education earn more, pay more taxes, and are more likely than others to be employed" (Ma et al., 2019: p.4). In 2018, bachelor's degree recipients working full time had $24,900 higher median earnings than high school graduates (ibid). Aside from these overall positive outcomes from attaining a college degree, payoff from higher education vary depending on a field of study (e.g., Julian, 2012; Herschbein & Kearney, 2014; Carnevale et al., 2015; cited by Kim et al., 2015) and an institution a student chose to attend (e.g., Black & Smith, 2006; Brewer et al., 1999; Witteveen & Attewell, 2017; cited by Quadlin et al., 2021). College choice and choice of a major are, therefore, the most important decisions for future earnings of a college graduate.

As evidenced in the report Economic Well-Being of U.S. Households in 2021 by the Division of Consumer and Community Affairs (DCCA), when people with bachelor's degrees look back on their education decisions, they frequently indicate that they would attend a different institution or choose a different field of study. Those who attended private for profit institutions are more likely to regret their choice of an institution than those who attended a private non-profit or a public school. And those who studied the humanities and arts or social and behavioral sciences are more likely to regret their choice of a field of study, than those who studied engineering.

With datasets like College Scorecard, information about earnings by college and by fields of study is now widely available to consumers and can help guide decisions about college and major choice. Rankings of institutions that are based on College Scorecard data emerge. For example, Itzkowitz (2022) uses data from the College Scorecard to rank U.S. colleges along a calculated economic-mobility index. At the same time, information about potential earnings might still be misleading, because wages are associated with myriad of factors that have to be considered. Data on earnings might favor institutions that enroll students who are destined to succeed. "The institutions that are always on the top of the rankings—places like Harvard, Princeton and Stanford Universities—enroll students who are destined to succeed . . . It should be no surprise (and not worthy of praise) that the students then do well" (Jaschik, 2018). For example, Equitable Value Explorer that was introduced on November 4, 2021 by Bill and Melinda Gates Foundation's Postsecondary Value Commission clearly illustrates that institutions with greater shares of Pell students have lower institutional performance on the economic value thresholds. Aside from the shares of Pell students, median earnings can be associated with multiple college characteristics that do not necessarily reflect quality of education—such as geographic location, the level of urbanization, size of an institution, institution's type, and cost of attendance—as well as with student body for this institution or a discipline—gender and racial composition, selectivity (or high school performance of a typical student), or percentage of students receiving loans.

Deming and Figlio (2016) caution against evaluating institutions on the basis of employment and earnings outcomes, partially because of the variation in average compensation by field of study. For example, based on data available on the Equitable Value Explorer web site, there is a positive correlation (0.46) between the median salary and the percentage of students in STEM disciplines suggesting that schools with a greater percentage of STEM students are likely to have a greater economic value. Similarly, Broady and Hershbein (2020) suggest that graduates with majors that emphasize quantitative reasoning tend to have highest earnings with engineering fields being in the top five earning majors. The lowest-earning majors, on the other hand, are majors that train students to work with children (ibid). Using institution-level College Scorecard data, Mabel et al. (2019) estimated that more than three-quarters of the variation in median earnings across institutions is explained by observable factors and that accounting for differences in major composition explains 20-30 percent of the variation in overall median earnings across colleges, even after controlling for selectivity and student composition (ibid). Evaluating institutions on the basis of earnings of graduates gives these institutions an incentive to deemphasize fields that are socially desirable but not lucrative (Deming & Figlio, 2016).

Overall, despite data availability and existing empirical studies, the financial advantages of selecting one institution over another institution or one discipline over another discipline remain unclear. By disentangling effects of fields of study and institutions, the study presented here seeks to contribute to a better understanding of factors affecting future earnings of bachelor's degree recipients. First, we look into the proportion of variance that is explained by institutions and by fields of study. Then, we consider the effect of disciplines and the list of disciplines associated with top earnings once institutions are controlled for. We test a hypothesis that the effect of STEM designation varies across institutions and consider institutions with greatest and smallest effects of STEM. Finally, we look into institutional characteristics and student composition of a program or an institution that are associated with earnings of graduates.

2. Theoretical framework

Human capital theory (Becker 1964) views education as an investment in human capital. An individual decides to invest in education if the expected benefit of college attendance outweighs its expected cost. Prior research on human capital and college attendance suggests that an individual is more likely to pursue a college degree if she anticipates higher earnings from having this degree. Individuals select colleges and majors based on expected earnings, on the one hand, and direct cost of attendance—tuition, fees, books, and living expenses—on the other hand (e.g., Paulsen, 2001). Because more selective colleges are frequently associated with higher direct costs of attendance, students from low-income families might choose less expensive educational options. At the same time, the tuition does not vary for different college majors within the same institution (Ma and Savas 2014): "engineering and computer science are more lucrative fields after graduation than English or history, but they usually charge the same tuition within the same institution" (p.225). Hence, students from disadvantaged families can choose these fields to improve their odds of securing a better paid job upon graduation.

From a sociological perspective (Bourdieu, 1984; 1986), students exchange their cultural—i.e., what we know—and social—i.e., who we know—capital for the economic capital—i.e., earnings or what we have. Individuals from privileged backgrounds are more likely to earn more because of their choice of institution, on the one hand, and because of the uneven returns from educational attainment, on the other hand. According to Bourdieu (ibid; cited by Manzoni & Streib, 2019), more privileged individuals tend to distance themselves from necessity, while less privileged individuals tend to make a virtue of necessity. Privileged individuals tend to attend more expensive and prestigious universities and choose majors that are not necessarily associated with higher pay. On the contrary, less privileged individuals tend to choose less selective institutions and majors that are associated with higher pay.

Institutions and fields of study are two main ways in which students are stratified within educational levels (e.g., Davies & Guppy, 1997; cited by Ma & Savas, 2014). Gerber and Cheung (2008) suggest four theoretical reasons for differences in earnings depending on an institution:

- *Human capital*: some institutions have greater efficiency in educating their graduates.
- *Signal effect*: education signals cost and leads to higher salary, assuming that the employer associates this education with quality (Spence, 1973).
- *Social capital*: attending a more selective institution might lead to acquiring connections with high-achieving individuals. Overall, selectivity indicators help to capture the composition of the student body that may affect the learning environment (see, for example, James et al., 1989; Witteveen & Attewell, 2017).
- *Selection effect*: those who attend a more selective institution are likely to have characteristics—socio-economic background and academic achievement—that lead to greater economic success.

Empirical studies generally suggest that attending a more selective institution is associated with greater pay. A particular focus of many empirical studies is on the selection effect noted above. Students with high ACT or SAT scores or other characteristics associated with admission to more selective colleges are more likely to go to selective colleges, on the one hand, and to make more money after graduation, on the other hand. With some exceptions, findings from such studies show a positive association between selectivity and future earnings even after accounting for endogeneity or selection bias. For example, Brewer et al. (1999) suggested that even after controlling for selection effects, attending an elite private institution led to substantial economic returns. Dale and Krueger (2002) found that overall, students who attended more selective colleges earned about the same as students of a comparable ability who attended less selective schools. At the same time, attending a more selective college was associated with increased earnings for students from low-income families. Hoekstra (2009) concluded that attending the most selective state university caused earnings to be approximately 20% higher for white men. Witteveen and Attewell (2017) suggested large earnings payoffs from attending a highly selective college both four and ten years after graduation with uneven returns for men and women, for different college majors, and for graduates with different family background characteristics.

Consistently with prior empirical studies, we assume that college selectivity is correlated with earnings. To measure college selectivity, we use an ACT or SAT equivalent scores, open admissions indicator, and admission rates (see Table 1). These selectivity indicators, however, are not available for many colleges in the Integrated Postsecondary Education Data System (IPEDS). Data might be missing for open admissions institutions; upper-division universities; branch campuses; or institutions that do not require test scores for admissions. To prevent omitting institutions with missing data on selectivity, we added binomial indicators for availability of test scores and admission rates. Aside from adding binomial indicators, we replaced missing test scores and admissions rates with averages by institution type—private non-profit, private for-profit, or public. We used a middle point between the 25th and 75th percentile of the tests. When the share of SAT takers was higher than the share of ACT takers, we used SAT scores. Otherwise, we used ACT scores. Using ACT Concordance Tables (2018), SAT test scores were converted to the ACT equivalent scores. (See Table 1 for descriptive statistics and descriptions of variables measuring selectivity in this study.)

Table 1. Variable descriptions and descriptive statistics.

Variable	Description	Mean (SD)	Mean (SD)
Institutional characteristics:	Selectivity (Source: IPEDS)		
Open admissions	Equals 1 if an institution is an open admissions institution	0.23 (0.42)	0.23 (0.42)
ACT information	Equals 1 if 25th and 75th percentile scores for either SAT or SAT tests are available	0.54 (0.5)	0.55 (0.50)
ACT or SAT Equivalent (middle point)	A middle point between the 25th and 75th percentile; a selection between ACT or SAT score is made based on the percentage of students taking the test. Missing values are replaced with means by institution type--private for profit, private non-profit, or public	22.51 (2.87)	22.52 (2.87)
Admission information	Equals 1 if an admission rate is available	0.72 (0.45)	0.73 (0.45)
Admission rate	Admission rates divided by 10; e.g. 1 corresponds to 10%	6.79 (1.71)	6.78 (1.71)
Institutional characteristics:	Location (Source: IPEDS)		
Far West	Equals 1 for AK, CA, HI, NV, OR, and WA	0.12 (0.32)	0.11 (0.32)
Great Lakes	Equals 1 for IL, IN, MI, OH, and WI	0.15 (0.36)	0.15 (0.36)
Mid East	Equals 1 for DE, DC, MD, NJ, NY, and PA	0.17 (0.38)	0.17 (0.37)
New England	Equals 1 for CT ME MA NH RI VT	0.07 (0.26)	0.07 (0.26)
Outlying areas	Equals 1 for AS FM GU MH MP PR PW VI	0.03 (0.16)	0.03 (0.16)
Plains	Equals 1 for IA KS MN MO NE ND SD	0.10 (0.31)	0.11 (0.31)
Rocky Mountains	Equals 1 for CO ID MT UT WY	0.04 (0.19)	0.04 (0.19)
Southeast	Equals 1 for AL AR FL GA KY LA MS NC SC TN VA WV	0.24 (0.43)	0.24 (0.43)
Southwest	Equals 1 for AZ NM OK TX	0.08 (0.28)	0.08 (0.28)
Institutional characteristics:	Institution's type (Source: College Scorecard)		
Private, for profit	Equals 1 for private for profit institutions	0.17 (0.38)	0.17 (0.38)
Private, non-profit	Equals 1 for private non-profit institutions	0.52 (0.50)	0.52 (0.50)
Public	Equals 1 for public institutions	0.31 (0.46)	0.31 (0.46)
Institutional characteristics:	urbanization (Source: IPEDS)		
Large city	Equals 1 if an institution is located inside a principal city with population of 250,000 or more	0.25 (0.43)	0.25 (0.43)

City, other	Equals 1 if an institution is located inside a principal city with population less than 250,000	0.26 (0.44)	0.27 (0.44)
Suburb	Equals 1 if an institution is located within a territory outside a principal city and inside an urbanized area	0.26 (0.44)	0.26 (0.44)
Town	Equals 1 if an institution is located within a territory inside an urban cluster	0.17 (0.37)	0.17 (0.38)
Rural	Equals 1 if an institution is located within rural territory	0.06 (0.23)	0.05 (0.22)
Institutional characteristics: size of an institution (Source: IPEDS)			
Size, under 1,000	Equals 1 if an institution's fall FTE enrollments is less than 1,000	0.27 (0.44)	0.26 (0.44)
Size, 1,000-4,999	Equals 1 if an institution's fall FTE enrollments is less than 5,000 and equal to or greater than 1,000	0.44 (0.50)	0.44 (0.50)
Size, 5,000-9,999	Equals 1 if an institution's fall FTE enrollments is less than 10,000 and equal to or greater than 5,000	0.12 (0.33)	0.12 (0.33)
Size, 10,000-19,000	Equals 1 if an institution's fall FTE enrollments is less than 20,000 and equal to or greater than 10,000	0.09 (0.28)	0.09 (0.29)
Size, 20,000 or more	Equals 1 if an institution's fall FTE enrollments is equal to or greater than 20,000	0.08 (0.27)	0.08 (0.27)
Institutional characteristics: Graduate degree offerings (Source: IPEDS)			
Master's degrees	Equals 1 if an institution offers Master's degrees	0.72 (0.45)	0.73 (0.44)
Doctoral degrees	Equals 1 if an institution offers doctoral degrees	0.37 (0.48)	0.38 (0.49)
Institutional characteristics: Tuition and fees; financial aid (Source: IPEDS)			
In-state tuition	In-state tuition and fees divided by 1,000	19.73 (12.46)	19.81 (12.46)
% Grants	Percentage of undergraduates receiving grants divided by 10	7.51 (1.75)	7.54 (1.73)
% Loans	Percentage of undergraduates receiving loans divided by 10	5.9 (2.02)	5.94 (1.97)
% Pell grants	Percentage of undergraduates receiving Pell grants divided by 10	4.37 (1.96)	4.37 (1.96)
Institutional characteristics: Inequality in the state (Source: American Community Survey, Gini Index by State)			
Gini coefficient (for the institution's state)	The Gini coefficient ranges from 0, indicating perfect equality (where everyone receives an equal share), to 1, perfect inequality (where only one recipient or group of recipients receives all the income).	0.48 (0.02)	0.48 (0.02)
Number of observations/institutions		2,212	2,151
Disciplinary characteristics: STEM (Source: College Scorecard)			
STEM	Equals 1 if a discipline is included in the U.S. Department of Homeland Security (DHS) STEM Degree Program List.	0.43 (0.5)	0.42 (0.5)
Number of observations/disciplines		312	311
Programs within institutions: Earnings (Source: College Scorecard)			
Earnings	Median earnings by four-digit CIP by institution	$40,097 ($14,566)	$39,578 ($14,625)
Ln(Earnings)	Natural logarithm of median earnings	10.54 (0.34)	10.52 (0.35)
Programs within institutions: demographic characteristics (Source: IPEDS)			
% Men	Percentage of male graduates divided by 10	4.40 (2.38)	4.43 (2.58)
% Women	Percentage of female graduates divided by 10	5.60 (2.38)	5.57 (2.58)
% American Indian	Percentage of American Indian graduates divided by 10	0.06 (0.26)	0.06 (0.28)
% Asian	Percentage of Asian graduates divided by 10	0.48 (0.80)	0.48 (0.85)
% Black	Percentage of Black graduates divided by 10	1.03 (1.66)	1.03 (1.74)
% Hispanic	Percentage of Hispanic graduates divided by 10	1.04 (1.54)	1.05 (1.59)
% Native Hawaiians/ Pacific Islander	Percentage of Native Hawaiians/ Pacific Islander graduates divided by 10	0.03 (0.15)	0.03 (0.18)
% White	Percentage of White graduates divided by 10	6.31 (2.46)	6.3 (2.56)
% Multiracial	Percentage of Multiracial graduates divided by 10	0.26 (0.35)	0.26 (0.44)
% Unknown	Percentage of graduates whose ethnicity is unknown divided by 10	0.46 (0.77)	0.46 (0.88)
% International	Percentage of international graduates divided by 10	0.34 (0.65)	0.33 (0.68)
Interaction of disciplinary and institutional characteristics: STEM and selectivity			
Stem X ACT or SAT Equivalent	Interaction of STEM indicator and ACT or SAT Equivalent	7.37 (11.2)	7.23 (11.15)
STEM X Admission rate	Interaction of STEM indicator and admission rates divided by 10	2.02 (3.21)	1.98 (3.19)
Number of observations/programs within institutions		31,580	29,352

The following theoretical reasons of pay differential by field of study are suggested by Kim et al. (2015):

- *Human capital*: differences in earnings across college majors are due to different types of skills acquired in college programs.

- *Skill-biased technological change* perspective explains higher pay for certain skills—such as computer programming—by high demand for these skills.
- *A social closure:* when higher education expands, the bar for higher education in general is lowered. At the same time, completing a degree in certain fields—such as engineering—remains highly competitive. Hence, a field of study becomes an important dimension of educational stratification.
- *Selection effect* reflects differences in abilities across fields of study, on the one hand, and student aspirations (i.e., students who choose more lucrative fields of study pursue higher salaries upon graduation), on the other hand.

Empirical studies documented that labor market returns vary across fields of study (e.g., Kim et al., 2015; Mabel et al., 2020; Quadlin et al., 2021). A common analytical strategy in previous studies was to divide college majors into a few broad categories. Thus, the level of specificity in these studies was rather broad, and, hence, had limited value for academic degree planning or for students' choice of majors. In our study, we emphasize the level of specificity of both colleges and disciplines by utilizing a cross-classified model with programs nested within disciplines and within institutions. Including a random intercept at a disciplinary level (or at a four-digit Classification of Instructional Programs [CIP] code) provides an opportunity to incorporate specific disciplines into a model of earnings of college graduates. Aside from including random effects for disciplinary differences, we include random intercepts for institutions thus allowing for institution-specific effects.

STEM disciplines are associated with higher financial rewards (e.g., Melguizo & Wolniak, 2012; Broady & Hershbein, 2020; Deming & Figlio, 2016). We include STEM indicator of a discipline to test a hypothesis that STEM fields are associated with higher pay. We use the U.S. Department of Homeland Security (2022) STEM Designated Degree Program List to distinguish between STEM and non-STEM disciplines.

Privilege might play different role depending on an individual's field of study (Stuber, 2005; cited by Manzoni & Streib, 2019). Due to emphasis on practical skills in science, technology, engineering, and math (STEM), cultural and social capital might be less important in these disciplines. For disciplines with less emphasis on practical skills, cultural and social capital are more important and, hence, non-STEM fields might be associated with greater pay differential depending on institution's prestige and selectivity. Prior research studies looked into a possibility that college and college selectivity matters for some disciplines, but not for others. Eide et al. (2016) suggest that major-specific earnings vary markedly by college selectivity, with the strongest differences among business majors and the weakest differences among science majors. Quadlin et al. (2021) also studied the effect of college selectivity within fields and concluded that recent college graduates in two majors—business and the social sciences—experience a selectivity premium. Both studies were based on a limited number of majors, however.

We expect that the effect of selectivity and the effect of an institution is greater in non-STEM disciplines than in STEM disciplines. For example, for a student who decides to become an engineer, the effect of college selectivity might be less substantial than for a student who chooses sociology. Hence, we allow the effect of STEM designation to vary across institutions and include an interaction effect of STEM and selectivity in our models.

Gender is a predictor of both field of study and wages (Charles & Bradley, 2009; England & Li, 2006; Jacobs, 1996; Kim et al., 2015; cited by Quadlin et al., 2021). Lower earnings of women might be partially attributed to disciplines and colleges they choose. On the one hand, women's STEM degree attainment falls behind their men counterparts; and the share of females varies greatly across STEM disciplines (see, for example, National Center for Science and Engineering Statistics, 2019; cited in Ro et al., 2021). On the other hand, females in general and especially women of color are more likely to choose a college that is closer to home, because family is an important factor in their college choice decision-making process (Ro et al., 2021).

Prior studies also show that STEM fields are associated with fewer Black and Latina/o students as well as with higher departure rates among underrepresented minority youth who initially declare STEM majors (e.g., Riegle-

Crumb et al., 2019). As shown by Cox (2016; cited by Ro et al., 2021), proximity to college is also an important factor for students of color, which leads to a lower probability of their enrollment in more selective schools.

In our study, we include the share of females as well as shares of students from different racial and ethnic groups as predictors of earnings (see Table 1 for variable descriptions and descriptive statistics). These variables are included at a level of a discipline within institution and are based on IPEDS completions by race and by gender. When data on the share of females or on racial composition were not available at a disciplinary level, we used institution-level data. When institution-level data were missing, we embedded average gender and racial composition at a disciplinary level. A multi-level approach and inclusion of college-level and discipline-level predictors and random effects allows to explore the association between gender and earnings and between race and earnings after control for academic disciplines and institutions.

Faber and Slantcheva-Durst (2021) explored the association between tuition, fees and financial aid, on the one hand, and earnings of graduates, on the other hand. They concluded that the college's share of students who received Pell grants has a negative association with earnings while the share of students who received federal loans had a positive association with earnings. Net tuition is also positively related to earnings (ibid). In our study, we include in-state tuition and the shares of undergraduates receiving grants, loans, and Pell grants.

Institution's location might also play a role in earnings upon graduation. " . . . a glance at the top 50 colleges shows high-mobility institutions concentrated around the country's largest and metropolitan regions. Economic activity in big, diverse cities like New York, Los Angeles, and Dallas means the efforts of learners and faculty and staff in places like CUNY and Cal State can see a return in the form of social mobility" (Cantwell, 2022). Kopecny and Hillmert (2021) show that the geographic location (and a regional market) of an institution helps explain some of the variation in wages by institutions. While regional differences have been found in some studies, the association between the level of urbanization and earnings of graduates has not been confirmed. For example, Kolte (2021) found that urban location of a college does not have a significant effect on earnings or job placement of graduates. To test the hypothesis about the effect of institution's location on earnings of graduates, we include region and level of urbanization in our models, see Table 1.

Delisle and Christensen (2020) show that the level of income inequality in the state (Gini coefficient) can be associated with high institutional economic mobility rankings. To test the hypothesis that graduates of institutions that are located in the states with higher inequality have higher earnings, we include a Gini coefficient for the state of the institution's location in our models.

Size of an institution may be related to college quality and, therefore, earnings of graduates in several ways. For example, Fitzgerald and Burns (2000) suggest that larger schools may offer broader curriculum and promote a more diverse student body than smaller schools. Larger institutions can also be in a better position to purchase equipment, which would be useful to students. At the same time, large enrollments may be associated with higher student to faculty ratio, and therefore, with fewer opportunities for interaction between students and faculty. In our study, we include size of an institution that is based on fall FTE enrollment (see Table 1). Our hypothesis is that the size of an institution has a positive effect on earnings of graduates.

The presence of graduate programs at an institution could be another factor affecting future earnings of baccalaureate degree holders. On the one hand, having graduate programs might attract research oriented faculty and provide more opportunities for undergraduate research. It may also "add a pool of cheap labor available to teach undergraduates" (James et al., 1989: p.248). At the same time, research and focus on graduate education "erodes support for undergraduate teaching among senior faculty" (Fitzgerald & Burns, 2000: p.13). Hence, we remain agnostic about the effect of graduate programs at an institution on future earnings of undergraduates. In order to capture graduate degree offerings, we include binomial indicators for master's degrees and for doctoral degrees at the institutional level (see Table 1).

Institutional control might also affect the quality of undergraduate education. "Private colleges and universities may be more efficient in their use of fiscal and other resources than are publicly controlled institutions. Private institutions may also be able to raise more money for student and faculty support from alumni since they may be more likely than public institutions to employ a staff of full-time fundraisers." (Fitzgerald & Burns, 2000: pp.13-14). Dummy variables that distinguish between public, private for profit, and private non-profit institutions are included in the analysis presented here.

3. Data

The College Scorecard--a publicly available dataset maintained by the U.S. Department of Education—is used as a source of data on earnings for this study. Until recently, College Scorecard earnings data were provided at the institutional level, without disaggregation by a discipline. More recent data releases, however, include median earnings of graduates one year and two years after entering repayment by four-digit Classification of Instructional Programs (CIP) code. (A four-digit disaggregation is more useful for prospective students and for campus administrators and yet, compared to the six-digit code, has fewer data points that have to be privacy suppressed due to small cell counts.) College Scorecard data are produced by matching federal financial aid data (based on the National Students Loan Data System) to IRS tax records. Only students who received federal aid are included. Graduates who worked, did not enroll in measurement year, and did not receive a higher-level credential are included to estimate median earnings. Our study is based on the data file that includes graduates entering repayment from July 1, 2015 – June 30, 2017 and earnings measured in 2017 and in 2018. The dataset includes all combinations of institutions and fields of study for which College Scorecard data on median earnings of baccalaureate degree recipients were available. Separate models are estimates for data on one and on two years after entering repayment.

For institutional characteristics, we merged the College Scorecard data with the Integrated Postsecondary Education Data System data (2014-15 access database). Fall 2014 and 2014-2015 academic year were chosen so that IPEDS data precedes the repayment for graduation cohorts included here. For Gini coefficient, we use American Community Survey data (U.S. Census Bureau 2015). (See Table 1 for variable descriptions and descriptive statistics.)

4. Logarithmic Transformation of the Dependent Variable and Cross-Classified Model

Income is a textbook example of a positively skewed distribution. And the distributions of medians at a college and disciplinary levels remain positively skewed. Skewness (and standard error of skewness) of median earnings is 1.243 (0.014) for data on one year after entering repayment and 1.209 (0.014) for two years after entering repayment. Logarithmic transformations are a common practice of transforming a highly skewed variable into one that is more approximately normal (Benoit, 2011). For data in this study, skewness (and standard error of skewness) of a natural logarithm of median earnings is 0.179 (0.014) one year after entering repayment and 0.128 (0.014) two years after entering repayment. Logarithmic transformation of the dependent variable also helps with interpretation of the regression coefficients. With natural logarithm of earnings as a dependent variable, a one unit increase in independent variable multiplies the expected median earnings by e to the power of a regression coefficient.

Given the nature of data—each institution might have multiple records associated with fields of studies and each field of study might have multiple records associated with institutions—a cross-classified model can be used to estimate the effects of institutions and majors on post-college earnings. A cross-classified model (Raudenbush et al., 2004; Raudenbush & Bryk, 2002) allows separating institutional and disciplinary effects on median earnings and to estimate variance in median earnings across institutions and across fields of study. A cross-classified model also provides an opportunity to test a hypothesis about varying effect of a discipline by institution and its characteristics. For example, the analysis presented here helps understand the difference in the effect of STEM designations on earnings depending on institutions.

In a cross-classified model, earnings Yid are nested within the cross-classification of an institution i and a discipline d. The unconditional model (model without predictors) estimating the natural logarithm of earnings is as follows:

$$\ln(Y_{id}) = \beta_{0id} + r \text{ (Level 1)}$$

Where earnings Y_{id} are within the cross-classification of an institution i and a discipline d.

$$\beta_{0id} = \gamma_{00} + u_{0i} + v_{0d} \text{ (Level 2)}$$

Where γ_{00} is an intercept, u_{0i} is a residual (also called random effect) for institutions and v_{0d} is a residual for disciplines. A variance component for institutions δ_i^2estimates the extent to which earnings vary by institution. A variance component for disciplines δ_d^2 estimates the extent to which earnings vary by disciplines. Finally, a variance component δ_r^2 estimates the extent to which median earnings vary at level 1 or at the cross-classification of institutions and disciplines. Using variance components, one can calculate the proportion of variance in logarithm of earnings that can be explained by institutions and by disciplines. The intraclass correlation coefficient ICC_i is an estimate of the proportion of variance in logarithm of earnings that can be explained at the institutional level:

$$ICC_i = \frac{\delta_i^2}{\delta_i^2 + \delta_d^2 + \delta_r^2}$$

The intraclass correlation coefficient (ICC_d) is an estimate of the proportion of variance in logarithm of earnings that can be explained at a disciplinary level:

$$ICC_d = \frac{\delta_d^2}{\delta_i^2 + \delta_d^2 + \delta_r^2}$$

A comparison between variances for the unconditional model and for the model with predictors can be also used later to evaluate a proportionate reduction of error (Kreft and De Leeuw 1998; cited in Bickel 2007, p.132), which is similar to the conventional coefficient of determination. For example, the reduction in predicting error at a disciplinary level can be estimated as follows:

$$PRE = 1 - \frac{\delta_d^2(Model\ with\ predictors)}{\delta_d^2\ (Unconditional\ model)}$$

The estimation of the cross-classified models in this study is carried out using HLM, a user-friendly multi-level software package.

5. Unconditional Models

A primary purpose of estimating an unconditional cross-classified model—or model without predictors—is to partition the sources of variability at each level of analysis. The unconditional models in Table 2 were estimated to partition variation among institutions (δ_i^2), disciplines (δ_d^2), and disciplines within institutions(δ_r^2).

Based on Models in Table 2, the expected value of a median salary is \$37,272 ($e^{10.526}$) one year after entering repayment and \$36,864 ($e^{10.515}$) two years after entering repayment. The proportion of variance in earnings that can explained at an institutional level is 22% one year after entering repayment and 21% two years after entering repayment. The proportion of variance that can be explained by a disciplinary level is 60% one and two years after entering repayment. Thus, the unconditional model clearly demonstrates that college majors are more consequential for student earnings than institutions they choose to attend.

Table 2. Cross-Classified Unconditional Models.

	Model 1: One year after entering repayment	Model 2: Two years after entering repayment
Intercept $\beta_0(SE(\beta_0))$	10.526(0.017)***	10.515 (0.018)***
Level 2:Institution (δ_i^2)	0.031	0.031
Level 2: Discipline (δ_d^2)	0.086	0.089
Level 1: Residual (δ_r^2)	0.027	0.028

****Significant at the 0.1% level.*

Based on random coefficients from Model 1 in Table 2, after control for institutions, the disciplines with the highest expected salaries include:

- Petroleum Engineering (CIPC 14.25; expected median $71,146 [$e^{10.526+0.647}$]; N=20 [20 institutions])
- Computational Science (CIPC 30.30; expected median $65,163 [$e^{10.526+0.559}$]; N=1)
- Electrical, Electronics and Communications Engineering (CIPC 14.10; expected median $64,546 [$e^{10.526+0.549}$]; N=288)
- Mining and Mineral Engineering (CIPC 14.21; expected median $64,529 [$e^{10.526+0.549}$]; N=10)
- Computer Engineering (CIPC 14.09; expected median $63,783 [$e^{10.526+0.538}$]; N=199)
- Naval Architecture and Marine Engineering (CIPC 14.22; expected median $62,790 [$e^{10.526+0.522}$]; N=6)
- Registered Nursing, Nursing Administration, Nursing Research and Clinical Nursing (CIPC 51.38; expected median $62,179 [$e^{10.526+0.512}$]; N=1,020)
- Construction Engineering Technologies (CIPC 15.10; expected median $62,056 [$e^{10.526+0.51}$]; N=43)
- Construction Engineering (CIPC 14.33; expected median $61,826 [$e^{10.526+0.506}$]; N=16)
- Industrial Engineering (CIPC 14.35; expected median $61,813 [$e^{10.526+0.506}$]; N=90)

Based on random coefficients from Model 2 in Table 2, after control for institutions, the disciplines with highest salaries include:

- Petroleum Engineering (CIPC 14.25; expected median $67,332 [$e^{10.515+0.602}$]; N=21)
- Marine Transportation (CIPC 49.03; expected median $64,821 [$e^{10.515+0.564}$]; N=6)
- Mining and Mineral Engineering (CIPC 14.21; expected median $64,675 [$e^{10.515+0.562}$]; N=9)
- Electrical, Electronics and Communications Engineering (CIPC 14.10; expected median $63,900 [$e^{10.515+0.55}$]; N=265)
- Mathematics and Computer Science (CIPC 30.08; expected median $63,548 [$e^{10.515+0.545}$]; N=4)
- Computer Engineering (CIPC 14.09; expected median $63,133 [$e^{10.515+0.538}$]; N=178)
- Construction Engineering (CIPC 14.33; expected median $62,486 [$e^{10.515+0.528}$]; N=13)
- Registered Nursing, Nursing Administration, Nursing Research and Clinical Nursing (CIPC 51.38; expected median $61,869 [$e^{10.515+0.518}$]; N=968)
- Naval Architecture and Marine Engineering (CIPC 14.22; expected median $61,564 [$e^{10.515+0.513}$]; N=5)
- Industrial Engineering (CIPC 14.35; expected median $61,475 [$e^{10.515+0.511}$]; N=82)

After control for disciplines, institutions with top five expected salaries one year after entering repayment included private non-profit institutions: California Institute of Technology, CA (expected median $64,123; N=3 [three programs]); Massachusetts Institute of Technology, MA ($62,592; N=14); Harvard University, MA ($61,642; N=16); Harvey Mudd College, CA ($61,124; N=4); and Yale University, CT ($60,693; N=13). Institutions with top five expected salaries two years after entering repayment included four private non-profit institutions—Massachusetts Institute of Technology, MA ($63,681; N=12); Harvard University, MA ($61,757; N=16); California Institute of

Technology, CA ($59,853; N=2); and Harvey Mudd College, CA ($59,149; N=3)—and one public college—Bismarck State College, ND ($60,243; N=1). An unusual finding for a public institution in North Dakota is associated with one program at this institution--Business Administration, Management and Operations (CIPC 52.02). Based on data from College Scorecard, graduates of this program have unusually high median starting salary. Colleges with lowest expected salaries both one and two years after entering repayment share the same location—Puerto Rico.

All but one discipline—nursing—in the top ten expected salaries for one and two years after entering repayment are STEM disciplines. Next, we add a binomial indicator of STEM in the model and explore how the effect of STEM designation varies across institutions. We will refer to this model as a STEM model.

6. A STEM Model

As expected, STEM disciplines are associated with higher starting salaries. Based on models in Table 3, salary for STEM disciplines is, on average 31% higher than ($e^{0.273}$ or about 1.31 times) the salary for non-STEM disciplines one year after entering repayment and 32% higher than ($e^{0.277}$ or about 1.32 times) the salary for non-STEM disciplines two years after entering repayment. The expected median earnings one year after entering repayment is $43,695 ($e^{10.412+0.273}$) for STEM disciplines and $33,256 ($e^{10.412}$) for non-STEM disciplines (see Model 1 in Table 3). The expected median earnings two years after entering repayment is $43,304 ($e^{10.399+0.277}$) for STEM disciplines and $32,827 ($e^{10.399}$) for non-STEM disciplines (see Model 2 in Table 3).

Table 3. Cross-Classified STEM Model.

	Model 1: One year after entering repayment	Model 2: Two years after entering repayment
Intercept $\beta_0(SE(\beta_0))$	10.412(0.021)***	10.399 (0.021)***
Level 2:Institution (δ_i^2)	0.032	0.034
STEM ($\delta_{\beta_1}^2$)	0.003	0.002
Level 2: Discipline (δ_d^2)	0.069	0.071
STEM $\beta_1(SE(\beta_1))$	0.273 (0.031)***	0.277 (0.032)***
Level 1: Residual (δ_r^2)	0.026	0.028

****Significant at the 0.1% level.*

STEM models include two random effects at the institutional level—for the intercept and for the STEM effect. Both the intercept and the effect of STEM vary across institutions. Interestingly, the correlations between these two random effects are -0.610 for Model 1 and -0.652 for Model 2. These negative correlations suggest that the difference between STEM and non-STEM disciplines is more substantial for colleges with lower median earnings. Because the dependent variable is the logarithm of earnings, the difference between STEM and non-STEM should be thought of as a percentage difference and not the dollar difference. The dollar difference between STEM and non-STEM majors might remain the same for colleges with higher and lower median earnings. Examples for the highest and lowest effects of STEM are provided below. For example, the expected difference between STEM and non-STEM earnings is $7,147 for graduates of Inter American University of PR-Guayama and $6,397 for graduates of the University of Miami, FL. But for Inter American University of PR-Guayama, graduates in STEM disciplines are expected to make 61% more than graduates in non-STEM disciplines; while for the University of Miami, FL, graduates in STEM disciplines are expected to make 18% more than graduates in non-STEM disciplines (see earnings one year after entering repayment in Table 4).

As noted above, a comparison between variances for the unconditional model and for the model with predictors can be used to estimate a proportionate reduction of error which is similar to the conventional coefficient of determination. While variance components at level one and at institutional level remained about the same, [1] variance component for a discipline went down. Based on models for one year after entering repayment, including fixed and random effects for STEM disciplines reduces the error of predicting median earnings at a disciplinary level by about 19.8%:

$$PRE = 1 - \frac{\delta_d^2(STEM\ Model)}{\delta_d^2\ (Unconditional\ Model)} = 1 - \frac{0.069}{0.086} = \ 0.198$$

Similarly, based on models for two years after entering repayment, including fixed and random effects for STEM disciplines reduces the error of predicting a median salary at a disciplinary level by about 20.2% ($1 - \frac{0.071}{0.089}$). Next, we will add institutional characteristics to the models.

Table 4. Cross-Classified STEM Model; Institutions with lowest and highest effects of STEM.

Institution	N	Stem	Non-Stem	Diff.	% Diff.
One year after entering repayment; lowest effects of STEM					
Fordham University, NY	28	$49,305	$41,812	$7,493	18%
Massachusetts Institute of Technology, MA	14	$71,624	$60,531	$11,093	18%
University of Miami, FL	40	$41,108	$34,711	$6,397	18%
Colgate University, NY	17	$57,095	$48,159	$8,936	19%
CUNY New York City College of Technology, NY	16	$43,579	$36,720	$6,858	19%
One year after entering repayment; highest effects of STEM					
Pontifical Catholic University of PR-Ponce, PR	17	$24,579	$16,256	$8,322	51%
University of Puerto Rico-Humacao, PR	7	$23,920	$15,518	$8,402	54%
Atenas College, PR	2	$19,560	$12,651	$6,909	55%
Inter American University of PR-Aguadilla, PR	2	$18,775	$12,043	$6,732	56%
Inter American University of PR-Guayama, PR	5	$18,959	$11,812	$7,147	61%
Two years after entering repayment; lowest effects of STEM					
Williams College, MA	14	$57,918	$47,538	$10,380	22%
Cornell University, NY	45	$56,501	$46,345	$10,155	22%
Villanova University, PA	28	$55,054	$45,049	$10,005	22%
Massachusetts Institute of Technology, MA	12	$73,367	$59,948	$13,419	22%
Georgetown University, DC	27	$61,624	$50,286	$11,338	23%
Two years after entering repayment; highest effects of STEM					
Inter American University of PR-Bayamon, PR	12	$21,619	$14,421	$7,197	50%
University of Puerto Rico-Aguadilla, PR	7	$18,918	$12,548	$6,370	51%
Inter American University of PR-San German, PR	4	$18,486	$12,204	$6,282	51%
University of PR-Ponce, PR	5	$17,081	$11,218	$5,863	52%
University of PR-Arecibo, PR	8	$18,434	$12,103	$6,331	52%

7. Institutional Characteristics and Median Earnings

Including institutional-level predictors (see Table 5) reduces the error of predicting median earnings at the institutional level by about 71% for one year after entering repayment:

$$PRE = 1 - \frac{\delta_d^2(Model\ with\ level\ 2\ predictors)}{\delta_d^2\ (Unconditional\ Model)} = 1 - \frac{0.007 + 0.002}{0.031} = \ 0.710$$

The proportionate reduction of error for predicting median earnings at the institutional level for two years

[1] The variance component for the institutional level went up slightly, which is possible. "... when we put in explanatory variables, the level 2 variance can increase" (Pillinger, n.d.).

after entering repayment is 77%:

$$PRE = 1 - \frac{0.006 + 0.001}{0.031} = 0.774$$

As expected, college selectivity is associated with greater earning potential. Attending an open admissions college is associated with 7.8% ($1\text{-}e^{-0.081}$) decrease in expected earnings one year after entering repayment and 6.9% ($1\text{-}e^{-0.071}$) decrease in expected earnings two years after entering repayment (see Table 5). One-point increase in ACT or ACT equivalent score is associated with 0.7% increase in expected earnings. And 10% increase in institution's admission rate leads to 0.4% decrease in expected earnings.

Table 5. Cross-Classified Models, Disciplines (level 2), Institutions (level 2), and Programs within Institutions (level 1).

	Models with level 2 predictors				Models with predictors at both levels			
	One-year after entering repayment		Two years after entering repayment		One-year after entering repayment		Two years after entering repayment	
	B (SE)	exp(B)	B (SE)	exp(B)	B (SE)	exp(B)	B (SE)	exp(B)
Intercept	10.508 (0.084)***		10.499 (0.084)***		10.493 (0.086) ***		10.513 (0.086) ***	
Institutional characteristics: Selectivity								
Open admissions	-0.081 (0.014)***	0.922	-0.071 (0.014)***	0.931	-0.08 (0.014) ***	0.923	-0.071 (0.014) ***	0.931
ACT information available	0.009 (0.007)	1.009	0.013 (0.007)	1.013	0.01 (0.007)	1.010	0.013 (0.007)	1.013
ACT or SAT Equivalent	0.007 (0.001)***	1.007	0.007 (0.001)***	1.007	0.007 (0.001) ***	1.007	0.007 (0.001) ***	1.007
Admission information available	-0.098 (0.014)***	0.907	-0.097 (0.015)***	0.907	-0.098 (0.014) ***	0.907	-0.098 (0.015) ***	0.907
Admission rate (10%)	-0.004 (0.002)*	0.996	-0.004 (0.002)*	0.996	-0.005 (0.002) **	0.995	-0.006 (0.002) ***	0.994
Institutional characteristics: location								
Far West	0.076 (0.009)***	1.079	0.062 (0.009)***	1.064	0.074 (0.009) ***	1.077	0.059 (0.009) ***	1.061
Great Lakes	0.054 (0.008)***	1.055	0.048 (0.008)***	1.050	0.052 (0.008) ***	1.053	0.044 (0.008) ***	1.045
Mid East	0.073 (0.008)***	1.075	0.07 (0.008)***	1.072	0.07 (0.008) ***	1.073	0.067 (0.008) ***	1.069
New England	0.093 (0.01)***	1.097	0.09 (0.01)***	1.095	0.089 (0.01) ***	1.093	0.086 (0.01) ***	1.090
Outlying areas	-0.523 (0.022)***	0.593	-0.606 (0.023)***	0.545	-0.481 (0.024) ***	0.618	-0.581 (0.025) ***	0.559
Plains	0.061 (0.009)***	1.063	0.06 (0.009)***	1.061	0.059 (0.009) ***	1.061	0.055 (0.009) ***	1.057
Rocky Mountains	0.007 (0.013)	1.007	0.012 (0.013)	1.012	0.005 (0.013)	1.005	0.006 (0.013)	1.006
Southwest	0.052 (0.009)***	1.053	0.058 (0.009)***	1.059	0.059 (0.01) ***	1.061	0.062 (0.01) ***	1.064
Institutional characteristics: institution type								
Private, for profit	0.062 (0.011)***	1.064	0.071 (0.012)***	1.073	0.058 (0.012) ***	1.060	0.071 (0.012) ***	1.074
Private, non-profit	-0.014 (0.009)	0.986	-0.013 (0.01)	0.987	-0.015 (0.01)	0.985	-0.013 (0.01)	0.987
Institutional characteristics: urbanization								
Large city	0.011 (0.011)	1.011	0.006 (0.012)	1.006	0.015 (0.012)	1.015	0.012 (0.012)	1.012
City, other	0.001 (0.011)	1.001	-0.004 (0.012)	0.996	0.005 (0.011)	1.005	0.001 (0.012)	1.001
Suburb	0.004 (0.011)	1.004	0.003 (0.012)	1.003	0.009 (0.011)	1.009	0.009 (0.012)	1.009
Town	-0.022 (0.011)	0.979	-0.022 (0.012)	0.978	-0.021 (0.011)	0.979	-0.02 (0.012)	0.980
Institutional characteristics: size of an institution								
Size, 1,000-4,999	0.022 (0.008)**	1.023	0.02 (0.008)*	1.020	0.023 (0.008) **	1.023	0.021 (0.008) **	1.021
Size, 5,000-9,999	0.039 (0.01)***	1.040	0.043 (0.01)***	1.044	0.04 (0.01) ***	1.041	0.044 (0.01) ***	1.045
Size, 10,000-19,000	0.046 (0.011)***	1.047	0.052 (0.011)***	1.054	0.045 (0.011) ***	1.046	0.052 (0.011) ***	1.053
Size, 20,000 or more	0.065 (0.012)***	1.067	0.071 (0.012)***	1.074	0.063 (0.012) ***	1.065	0.069 (0.012) ***	1.071

Institutional characteristics: graduate degree offerings								
Master's degrees	0.029 (0.007)***	1.029	0.027 (0.007)***	1.027	0.029 (0.007) ***	1.029	0.028 (0.007) ***	1.028
Doctoral degrees	-0.009 (0.006)	0.991	-0.015 (0.006)**	0.985	-0.008 (0.006)	0.992	-0.014 (0.006) *	0.986
Institutional characteristics: tuition and financial aid								
In-state tuition ($1,000)	0.002 (0.000)***	1.002	0.002 (0.000)***	1.002	0.002 (0.0004) ***	1.002	0.002 (0.0004) ***	1.002
% Grants (10%)	-0.019 (0.002)***	0.981	-0.015 (0.002)***	0.985	-0.02 (0.002) ***	0.980	-0.016 (0.002) ***	0.984
% Loans (10%)	0.006 (0.002)***	1.006	0.006 (0.002)**	1.006	0.006 (0.002) ***	1.006	0.006 (0.002) **	1.006
% Pell grants (10%)	-0.024 (0.002)***	0.976	-0.025 (0.002)***	0.976	-0.021 (0.003) ***	0.979	-0.02 (0.003) ***	0.980
Institutional characteristics: inequality in the state								
Gini coefficient	-0.091 (0.153)	0.913	-0.167 (0.153)	0.846	-0.027 (0.156)	0.973	-0.12 (0.157)	0.887
Disciplinary characteristics: STEM								
Stem	0.264 (0.031)***	1.303	0.269 (0.032)***	1.309	0.279 (0.042) ***	1.322	0.245 (0.043) ***	1.278
Programs within institutions: demographic characteristics								
% Women (10%)					-0.005 (0.001) ***	0.995	-0.006 (0.001) ***	0.994
% American Indian (10%)					0.0003 (0.005)	1.000	-0.0084 (0.004) *	0.992
% Asian (10%)					0.007 (0.002) **	1.007	0.005 (0.002) *	1.005
% Black (10%)					-0.002 (0.001)	0.998	-0.004 (0.001) ***	0.996
% Hispanic (10%)					-0.007 (0.001) ***	0.993	-0.006 (0.001) ***	0.994
% Native Hawaiians or Pac. Isl. (10%)					-0.007 (0.008)	0.993	-0.009 (0.007)	0.991
% Multiracial (10%)					-0.003 (0.003)	0.997	-0.006 (0.003) *	0.994
% Unknown (10%)					0.004 (0.002) *	1.004	0.001 (0.002)	1.001
% International (10%)					0.008 (0.002) ***	1.008	0.008 (0.002) ***	1.008
Interaction of disciplinary and institutional characteristics: STEM and selectivity								
Stem X ACT or SAT Equivalent					-0.002 (0.001) *	0.998	-0.001 (0.001)	0.999
STEM X Admission rate (10%)					0.004 (0.002) *	1.004	0.006 (0.002) ***	1.006
Variance components								
Level 2:Institution (δ_i^2)	0.007		0.006		0.007		0.006	
STEM ($\delta_{\beta_1}^2$)	0.002		0.001		0.002		0.001	
Level 2: Discipline (δ_d^2)	0.070		0.073		0.067		0.069	
Level 1: Residual (δ_r^2)	0.026		0.028		0.026		0.028	

****** Significant at the 0.1% alpha level; ** Significant at the 1% alpha level; * Significant at the 5% alpha level.*

Geographic region of college's location matters for median earnings after entering repayment. For example, compared to graduates of colleges in Southeast, graduates of colleges in Far West are expected to make 7.9% more one year after entering repayment and 6.4% more two years after entering repayment; and graduates in New England are expected to make 9.7% more one year and 9.5% more two years after entering repayment. Compared to graduates of Southeastern colleges, graduates of colleges located in outlying areas are expected to make 40.7% less one year and 45.5% less two years after entering repayment. We did not find evidence of the association between the level of urbanization and earnings or between Gini coefficient and earnings, however.

Compared to graduates of public institutions, graduates of private for profit institutions are expected to make 6.4% more one year and 7.3% more two years more after entering repayment.

Graduates of larger institutions are expected to make more. For example, graduates of institutions with 20,000 or more FTE enrollments make 6.7% more one year and 7.4% more two years after entering repayment than graduates of institutions with less than 1,000 FTE enrollments.

Those who earn their baccalaureate degrees at an institution with master's programs are expected to make

2.9% more one year after entering repayment and 2.7% more two years after entering repayment. At the same time, graduating from an institution with doctoral programs is not associated with higher pay. Moreover, based on model for two years after entering repayment, graduates from colleges with doctoral programs and no master's programs are expected to make 1.5% less. One should note, however, that colleges with doctoral and without master's degrees are unusual. Compared to graduates of colleges that do not offer graduate degrees, graduates of colleges with both master's and doctoral degrees are expected to make 2.0% more one year after entering repayment (based on $e^{0.029-0.009}$) and 1.2% more two years after entering repayment.

Models also provide evidence of association between tuition, fees, and financial aid, on the one hand, and earnings of graduates, on the other hand. $1,000 increase in in-state tuition is associated with 2% increase in expected earnings. 10% increase in the percentage of students receiving loans is associated with 0.6% increase in expected earnings. 10% increase in the proportion of students awarded federal (other than Pell), state, local, institutional or other grant aid is associated with 1.9% decrease in expected earnings one year after entering repayment and 1.5% decrease in expected earnings two years after entering repayment. And 10% increase in the percentage of Pell grant recipients is associated with 4.2% decrease in expected earnings one year after entering repayment (based on $e^{-0.019-0.024}$) and 3.9% decrease in expected earnings two years after entering repayment.

8. Models with predictors at a level of a discipline within an institution

Racial and gender composition at a program level (see models with predictors at both levels in Table 5) is correlated with median earnings of graduates even after control for institutional and disciplinary characteristics. Thus, a 10% increase in the share of women is associated with 0.5% decrease in expected earnings one year after entering repayment and 0.6% decrease in expected earnings two years after entering repayment. Programs with greater shares of Asian and international students are expected to have greater median earnings of graduates. At the same time, programs with greater share of Hispanic graduates are expected to have lower earnings of graduates.

One of the main hypotheses of this study is that institutional selectivity plays different role depending on a field of study. We hypothesized that earnings of graduates in STEM disciplines are affected by institutional selectivity to a lesser extent than earnings of graduates in non-STEM disciplines. We tested this hypothesis by including interactions between STEM designation and test scores and between STEM designation and admission rates. Model for one year after entering repayment in Table 5 shows a statistically significant interaction effects of STEM designation and test scores. Based on this model, one-point increase in ACT or SAT equivalent score is associated with 0.7% increase in earnings for non-STEM disciplines and with 0.5% increase in earnings for STEM disciplines. Models in Table 5 show statistically significant interaction effects of STEM designations and admissions rates. Based on the model for one year after entering repayment, a 10% increase in institutional admission rate is associated with 0.5% decrease in expected earnings for non-STEM disciplines and with only 0.1% decrease (based on $e^{-0.005+0.004}$) for STEM disciplines. Based on the model for two years after entering repayment, a 10% increase in institutional admission rate is associated with 0.6% decrease in expected earnings for non-STEM disciplines and no decrease in expected earnings for STEM disciplines.

These findings once again emphasize the importance of a discipline and STEM designation for future earnings as well as confirm the initial hypothesis about differences in effects of institutional selectivity on earnings depending on a field of study.

9. Conclusion and Implications

Two most important decisions college students make are decisions about an institution they are going to attend and a discipline they are going to study. Empirical studies show that that both choices are important for future earnings. At the same time, existing research is less clear about what is more consequential—a field of study or an institution—and about differential effect of college and college selectivity across disciplines. For example, does college selectivity affect future earning of an engineer as much as it affects future earnings of a sociologist? Do median earnings of more selective colleges have smaller differential in pay by field of study? Our research is aimed at addressing these questions as well as at exploring other college- and discipline-level characteristics on median earnings of graduates.

Based on the cross-classified unconditional models presented here, we conclude that a discipline is more consequential for future earnings than college. The proportion of variance in earnings by institutions is about 21%-22%, while the proportion of variance by academic disciplines is about 60%. The effect of STEM designation on future earnings is substantial, but this effect varies across institutions. Interestingly, the effect of STEM is less pronounced in institutions with higher overall median salaries. Note that, because of a logarithmic transformation of the dependent variable of median earnings, less pronounced effect does not necessarily translate into a smaller absolute difference in expected salaries but rather into relative differences. For example, graduates in STEM disciplines are expected to make 61% more than graduates in non-STEM disciplines at Inter American University of PR-Guayama. At the same time, graduates in STEM disciplines are expected to make only 18% more than graduates in non-STEM disciplines at the University of Miami, FL. Our study also shows that the effect of college selectivity is less consequential for STEM majors than for non-STEM majors. Overall, the answer to the question about which college to choose for a certain major if you want to increase your return on investment is “it depends.” For some majors, it might make sense to choose a school with lower tuition and cost of living. For other majors, it might make sense to attend the most selective school one can get into.

Exploring effects of other college and discipline-level characteristics on earnings holds few surprises. Consistent with observations of Faber and Slantcheva-Durst (2021), graduates of institutions with higher in-state tuition and greater shares of students receiving loans tend to make more, while graduates of colleges with greater shares of students receiving grants and Pell grants tend to make less. Consistent with Kopecny and Hillmert (2021), geographic location of an institution affects earnings of graduates. And, similar to Kolte (2021), we conclude that urban location of a college is not associated with higher earnings of graduates. Inequality in the state (as measured by Gini coefficient) is not associated with earnings. Graduates of larger institutions tend to make more. And the presence of graduate programs at an institution is associated with greater median earnings.

An unexpected finding of higher earnings of graduates of private for profit institution aligns with observations of Gilpin and Stoddard (2017) about these institutions being more responsive to labor market demands. Another explanation of higher earnings of graduates of private for profit institutions can by related to student demographics. As noted by several studies (see, for example, Cellini, 2021), students in these institutions are generally older and, therefore, are more likely to have work experience prior to graduating from college.

Finally, our study illustrates that, after control for an institution and a field of study, racial and gender composition of a program correlates with earnings of its graduates. Graduates of programs with greater shares of females and Hispanic students are expected to make less, while graduates of programs with greater shares of Asian and international students are expected to make more.

With nuanced information about expected salaries in specific disciplines within specific institutions, college students would have sufficient information to make educated choice when it comes to an institution and a major. Models presented here can also help institutions become more responsive to labor market demands and develop programs that would have greater chances of preparing their graduates for gainful employment.

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All the authors claim that the manuscript is completely original. The authors also declare no conflict of interest.

References

ACT (2018). *ACT / SAT Concordance.* Retrieved on May 26, 2022 at https://www.act.org/content/act/en/products-and-services/the-act/scores/act-sat-concordance.html

Becker, G. S. (1964). *Human Capital*. New York: Columbia University Press. www.nber.org/books/beck-5

Benoit, K. (2011). *Linear Regression Models with Logarithmic Transformations*. Methodology Institute, London School of Economics, 8p. Retrieved on March 10, 2022 at https://kenbenoit.net/assets/courses/ME104/logmodels2.pdf .

Bickel, R. (2007). *Multilevel Analysis for Applied Research: It's Just Regression*! New York: Guilford Press. https://doi.org/10.3138/cjpe.025.008

Black, D.A. and Smith, J.A. (2006). Estimating the Returns to College Quality with Multiple Proxies for Quality. *Journal of Labor Economics, 24(*3): 701-728. https://doi.org/10.1086/505067

Bourdieu, P. (1984). *Distinction*. Cambridge: Harvard University Press. https://books.google.com/books/about/Distinction.html?id=nVaS6gS9Jz4C

Bourdieu, P. (1988). *Homo Academicus*. Palo Alto: Stanford University Press. https://doi.org/10.1093/sf/68.4.1317

Brewer, D. J., Eide, E. R., & Ehrenberg, R. G. (1999). Does It Pay to Attend an Elite Private College? Cross-Cohort Evidence on the Effects of College Type on Earnings. *The Journal of Human Resources, 34(*1): 104-123. https://doi.org/10.2307/146304

Broady, K. and Hershbein, B. (2020). *Major Decisions: What Graduates Earn Over Their Lifetimes*. The Hamilton Project, Brooking Institution. Retrieved at https://www.brookings.edu/blog/up-front/2020/10/08/major-decisions-what-graduates-earn-over-their-lifetimes/ on March 22, 2022.

Cantwell, B. (2022). Against Social-Mobility Rankings. They tell a simple story: Harvard's bad, CUNY and Cal State are good. It's not that straightforward. The Chronicle of Higher Education. Retrieved on March 23, 2022 at https://www.chronicle.com/article/against-social-mobility-rankings .

Carnevale, A. P., Cheah, B., and Hansen, A. R. (2015). The economic value of college majors. Georgetown University Center on Education and the Workforce; 2015. Retrieved on May 23, 2022 at https://1gyhoq479ufd3yna29x7ubjn-wpengine.netdna-ssl.com/wp-content/uploads/The-Economic-Value-of-College-Majors-Full-Report-web-FINAL.pdf

Cellini, S. R. (2021). For-Profit Colleges in the United States: Insights from Two Decades of Research. (EdWorkingPaper: 21-398). Retrieved on May 22, 2022 from Annenberg Institute at Brown University at https://www.edworkingpapers.com/sites/default/files/ai21-398.pdf

Charles, M. and Bradley, K. (2009). Indulging Our Gendered Selves? Sex Segregation by Field of Study in 44 Countries. *American Journal of Sociology, 114(*4): 924-976. https://doi.org/10.1086/595942

Cox, R. D. (2016). Complicating conditions: Obstacles and interruptions to low-income students' college "choices." *The Journal of Higher Education, 87(*1), 1–26. https://doi.org/10.1353/jhe.2016.0005

Dale, S. B. and Krueger, A. B. (2002). Estimating the payoff to attending a more selective college: An application of selection on observables and unobservables. *The Quarterly Journal of Economics, 117(*4): Pages 1491–1527. https://doi.org/10.1162/003355302320935089

Davies, S., & Guppy, N. (1997). Field of study, college selectivity, and student inequalities in higher education. *Social Forces, 75*, 1417–1438. https://doi.org/10.2307/2580677

Delisle, J.D. and Christensen, C. (2020). *Economic Mobility Conundrums: A Closer Look at the Opportunity Insights University Rankings*. American Enterprise Institute. Retrieved at https://www.aei.org/wp-content/uploads/2020/06/Economic-Mobility-Conundrums.pdf?x91208 on May 19, 2022.

Deming, D.J. and Figlio, D. (2016). Accountability in US education: Applying lessons from K–12 experience to higher education. *Journal of Economic Perspectives, 30(*3): 33–56. https://doi.org/10.1257/jep.30.3.33

Division of Consumer and Community Affairs (DCCA). (2022). *Economic Well-Being of U.S. Households in 2021*. Retrieved on May 25, 2022 at https://www.federalreserve.gov/publications/files/2021-report-economic-well-being-us-households-202205.pdf .

Eide, E. R., Hilmer, M.J., Showalter, M. H. (2016). Is it where you go or what you study? The relative influence of college selectivity and college major on earnings. *Contemporary Economic Policy, 34(*1): 37-46. https://doi.org/10.1111/coep.12115

England, P. and Li, S. (2006). Desegregation Stalled. The Changing Gender Composition of College Majors, 1971-2002. *Gender & Society, 20(*5): 657-677. https://doi.org/10.1177/0891243206290753

Faber, A. and Slantcheva-Durst, S. (2021). The impact of community college attributes on the earnings of their students. *Community College Journal of Research and Practice, 45(*9): 687-700. https://doi.org/10.1080/10668926.2020.1798302

Fitzgerald, R.A. and Burns, S. (2000). *College Quality and the Earnings of Recent College Graduates*. U.S. Department of Education. National Center for Education Statistics, NCES 2000–043, Washington, DC. Retrieved at https://nces.ed.gov/pubs2000/2000043.pdf on May 18, 2022.

Gerber, T. P and Cheung, S. Y. (2008). Horizontal stratification in postsecondary education: Forms, explanations, and implications. Annual Review of Sociology, 34: 299-318. https://doi.org/10.1146/annurev.soc.34.040507.134604

Gilpin, G., & Stoddard, C. (2017). Does regulating for-profit colleges improve educational outcomes? Response to Cellini and Koedel. *Journal of Policy Analysis and Management, 36(*4): 953-956. https://doi.org/10.1002/pam.22011

Herschbein, B., Kearney, M. (2014). Major decisions: What graduates earn over their lifetime. *The Hamilton Project Report*. Retrieved on May 23 at http://hamiltonproject.org/papers/major_decisions_what_graduates_earn_over_their_lifetimes/

Hoekstra, M. (2009). The effect of attending the flagship state university on earnings: A discontinuity-based approach. *The Review of Economics and Statistics, 91(*4): 717–724. https://doi.org/10.1162/rest.91.4.717

Itzkowitz, M. (2022). Out With the Old, In With the New: Rating Higher Ed by Economic Mobility. Retrieved at https://thirdway.imgix.net/pdfs/override/Out-with-the-Old_In-with-the-New.pdf on May 20, 2022.

Jacobs, J.A. (1996). Gender inequality and higher education. *Annual Review of Sociology, 22*: 153 – 185. https://doi.org/10.1146/annurev.soc.22.1.153

James, E., Alsalam, N., Conaty, J.C., To, D.-L. (1989). College quality and future earnings: Where should you send your child to college? *The American Economic Review, 79(*2): 247-252. https://doi.org/10.17848/9780880995542.ch5

Jaschik, S. (2018). The 'U.S. News' Rankings' (Faux?) Embrace of Social Mobility. *Inside Higher Ed*. Retrieved on March 23, 2022 at https://www.insidehighered.com/admissions/article/2018/09/10/us-news-says-it-has-shifted-rankings-focus-social-mobility-has-it.

Julian, T. (2012). Work-life earnings by field of degree and occupation for people with a bachelor's degree: 2011. *American Community Survey Briefs 11-04*. 2012 Retrieved on May 23, 2022 at https://files.eric.ed.gov/fulltext/ED537269.pdf .

Kim, C., Tamborini. C.R, and Sakamoto, A. (2015). Field of Study in College and Lifetime Earnings in the United States. *Sociology of Education, 88(*4): 320–339. https://doi.org/10.1177/0038040715602132

Kolte, T. (2021). *Mapping your Future: Do College Locations Impact Future Earnings and Job Placement*? Retrieved on March 22, 2022 at https://escholarship.org/uc/item/41s579fx

Kopecny, S. and Hillmert, S. (2021). Place of study, field of study and labour-market region: What matters for wage differences among higher-education graduates? *Journal for Labour Market Research, 19(*55). https://doi.org/10.1186/s12651-021-00301-4

Kreft, I., & de Leeuw, J. (1998). *Introducing Multilevel Modeling*. Sage Publications, Inc. https://doi.org/10.4135/9781849209366

Ma, J., Pender, M., and Welch, M. (2019). Education Pays. *The Benefits of Higher Education for Individuals and Society*. College Board, 44 p. Retrieved on March 22 at https://research.collegeboard.org/media/pdf/education-pays-2019-full-report.pdf .

Ma, Y. and Savas, G. (2014). Which is more consequential: Fields of study or institutional selectivity? *The Review of Higher Education, 37(*2): 221-247. https://doi.org/10.1353/rhe.2014.0001

Mabel, Z., Libassi, C.J., and Hurwitz, M. (2019). The value of using early-career earnings data in the College Scorecard to guide college choices. (EdWorkingPaper: 19-111). Retrieved on March 22, 2022 from Annenberg Institute at Brown University: http://www.edworkingpapers.com/ai19-111

Manzoni, A. and Streib, J. (2019). The equalizing power of a college degree for first-generation college students: Disparities across institutions, majors, and achievement levels. *Research in Higher Education , 60*: 577–605. https://doi.org/10.1007/s11162-018-9523-1

Melguizo, T., Wolniak, G. C. (2012). The earnings benefits of majoring in STEM fields among high achieving minority students. *Research in Higher Education, 53(*4): 383-405 https://doi.org/10.1007/s11162-011-9238-z

National Center for Science and Engineering Statistics. (2019). *Women, minorities, and persons with disabilities in science and engineering*: 2019, (Report No. 19–304). National Science Foundation. https://ncses.nsf.gov/pubs/nsf19304/

Paulsen, M. B. (2001). The economics of human capital and investment in higher education. In M. B. Paulsen and J. C. Smart (Eds.), *The finance of higher education: Theory, research, policy, and practice* (pp. 55–94). New York: Agathon Press. https://books.google.com/books?hl=en&lr=&id=9O9NBAAAQBAJ&oi=fnd&pg=PA55&dq=info:VEDsFWnC4HoJ:scholar.google.com&ots=aOYnCsoULR&sig=vAr4uqUDEajvrGJaL14Vsrzbb3Y#v=onepage&q&f=false

Pillinger, R. (n.d.) *Random intercept models. A transcript of random intercept models presentation*. Retrieved on May 22, 2022, at http://www.bristol.ac.uk/cmm/learning/videos/random-intercepts.html .

Postsecondary Value Commission. (2021). *Equitable Value Explorer*. Retrieved on May 27, at https://equity.postsecondaryvalue.org/ .

Quadlin, N., Cohenb, E. D., VanHeuvelenc, T. (2021). Same major, same economic returns? College selectivity and earnings inequality in young adulthood. *Research in Social Stratification and Mobility, 75*: 1-12. https://doi.org/10.1016/j.rssm.2021.100647

Raudenbush, A. S., & Bryk, A. S. (2002). *Hierarchical linear models: Applications and data analysis methods*. Thousand Oaks, CA: SAGE Publications. https://us.sagepub.com/en-us/nam/hierarchical-linear-models/book9230

Raudenbush, A. S., Bryk, A. S., Cheong, Y. F., & Congdon, R. T. (2004). HLM 6: *Hierarchical linear and nonlinear modeling*. Lincolnwood: Scientific Software International. https://books.google.com/books/about/HLM_6.html?id=VdmVtz6Wtc0C

Riegle-Crumb, C., King, B., and Irizarry, Y. (2019), Does STEM stand out? Examining racial/ethnic gaps in persistence across postsecondary fields. *Educational Researcher, 48(*3), 133–144 https://doi.org/10.3102/0013189x19831006

Ro, H. K., Meng, Y., and Zhu, Q. (2019). STEM Bachelor's degree attainment among women of color in the United States. Using geographic analysis for gender and racial equity research. In Ro, H. K., Fernandez, F., and Ramon, E.J. (Eds.) *Equity in STEM in Higher Education: International Perspectives on Policy, Institutional Culture, and Individual Choice*, 62-84. Routledge. London; New York. https://doi.org/10.4324/9781003053217-65

Spence M. (1973). Job market signaling. *Quarterly Journal of Economics, 87*: 355–374 https://doi.org/10.2307/1882010

Stuber, J. (2005). Asset or liability? The importance of context in the occupational experiences of upwardly mobile white adults. *Sociological Forum, 20(*1), 139–166. https://doi.org/10.1007/s11206-005-1900-9

U.S. Census Bureau. (2015). *American Community Survey (ACS) 1-Year Estimates Detailed Tables*. Retrieved on February 22, 2022 at https://data.census.gov/cedsci/table?q=gini&g=0100000US%240400000&tid=ACSDT1Y2015.B19083

U.S. Department of Homeland Security (DHS). (2022), *DHS STEM Designated Degree Program List.* Retrieved on February 2022 at https://www.ice.gov/sites/default/files/documents/stem-list.pdf

Witteveen, D., Attewell, P. (2017). The earnings payoff from attending a selective college. Social Science Research, 66: 154-169. https://doi.org/10.1016/j.ssresearch.2017.01.005