What good are skills, anyway? Estimating the returns to specific skills in a college education

T.J. Rakitan
PhD student
Department of Economics
Iowa State University
Ames, IA 50011
trakitan@iastate.edu

and

Georgeanne M. Artz
Assistant Professor
Department of Economics
Iowa State University
Ames, IA 50011
gartz@iastate.edu

***Selected Paper prepared for presentation at the 2015 Agricultural & Applied Economics Association and Western Agricultural Economics Association Annual Meeting, San Francisco, CA, July 26-28***

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## Abstract

How does the labor market reward the specific skills learned by college students? We use a novel data set that combines earnings, demographic and college transcript data for over 5,000 graduates of a large university to investigate how their skill development has been compensated during their experience in the labor market. Using student academic records to generate measures of skills acquisition in the areas of mathematics and communication, among others, we estimate the contribution of our skills acquisition measures to graduates' later incomes. We find that, consistent with established literature, the significance of even broad categories of skills diminishes as controls are added, although female graduates experience significant returns to quantitative coursework. These results are robust to different specifications, including controlling for innate ability via proxy measures.

## Introduction

Surveys of agricultural industry representatives find that skills in communications, interpersonal interactions, critical thinking and quantitative analysis rank among the most desired skills and characteristics in recent college graduates, while industry-specific knowledge ranks lower (Boland and Akridge 2004; Norwood and Henneberry 2006). In a similar vein, Artz, Orazem and Kimle (2014) show that the returns to development of specialized skills and knowledge while obtaining an undergraduate degree vary considerably. While teaching more specialized, industry-specific knowledge and skills can reward the minority of students who land jobs in the agriculture industry, it can hurt the majority of majors who find work in other sectors. These authors suggest that developing skills that retain value outside of agriculture, such as communication and business skills, provide graduates some insurance against risks arising from career changes, sector-specific changes or shocks, or economic circumstances.

Yet designing a curriculum to provide both sufficient breadth and depth can be challenging. Should undergraduate agribusiness programs require more math courses to shore up critical thinking and quantitative analysis skills? Should they include more writing in the curriculum? What aspects of the program will need to be eliminated in order to do so? Having a more informed sense of how particular skills, both specialized and general, are rewarded in the job market post-college can help guide decisions about curricular reform. In this paper, we aim to quantify the returns to sets of skills by characterizing majors as vectors of required general and applied skills, including mathematical skills and communication skills. We then examine how those skills are rewarded in the job market.

**Literature**

Basic cognitive skills are an important determinant of earnings (Tyler, Murnane and Willett 1999). Quantitative skills, in particular, have a positive impact on wages, especially for women, and the returns to these skills has risen over time (Grogger and Eide 1995; Levine and Zimmerman 1995; Murnane, Willett and Levy 1995, Mitra 2002). One mechanism through which higher math ability may increase earnings is through educational attainment; higher math ability in high school increases the likelihood of attending college (Murnane et a 1995, Taber 2001).

However, despite evidence that employers value communication skills, less is known about the role of verbal skills. Song, Orazem and Wohlgemuth (2008) find that individuals with higher verbal skills are more likely to pursue graduate studies, while those with higher math ability are more likely to enter the job market upon completing a bachelor's degree. Although not the main focus of his analysis, Tabor's results (2001) show that higher AFQT mathematics scores consistently raise earnings for college graduates across cohorts. While higher AFQT word knowledge scores raise the likelihood of attending college, in the earnings regressions, the coefficients are generally negative, but only significant in the 1982-1984 cohort. For individuals with a high school education, higher math ability raises earnings in two of the three cohorts, and higher verbal ability raises earnings in the 1988-1990 cohort.

An advantage of our dataset is that all the individuals have earned at least a bachelor's degree, so selection into college is controlled for by the sample.

**Data and Methods**

Our analysis uses a survey of Iowa State University alumni graduating between 1982 and 2006. Data were collected using a 2007 stratified random sample survey of 25,025 Iowa State University (ISU) alumni graduating between 1982 and 2006 resulting in 5,416 usable responses. The survey asked respondents a variety of questions about their careers subsequent to graduation in addition to individual demographics and family background. Survey responses were matched to student records containing information about majors, coursework, academic outcomes, and extracurricular activities while at ISU. Our data has a rich set of controls for academic success, family background and curricular diversity, increasing the confidence that our results reflect returns to skills learned in the major and not to differences in abilities of individuals across majors.

Not surprisingly, there is wide variation in the earnings reported by alumni across the six colleges of Iowa State. Figure 1 shows the distribution of personal income by college among those alumni working full time. The highest earnings are reported by graduates of the College of Engineering and the College Business. Half of business alumni and 70 percent of engineering alumni report earning at least $75,000 a year. Alumni from the College of Human Sciences report the lowest earnings, and only 28 percent of these graduates report earning at least $75,000 annually.

We are interested in exploring the extent to which these differences can be tied to the skills learned in the various college curricula. We decompose earnings into the sum of skill-set valuations, controlling for observable characteristics of individual students. Our identification strategy relies on variation in levels of attainment in each skill area, using variation in credits taken by individual students, as well as variation in students' academic performance within each class. Our use of data on students' academic outcomes in each of their classes helps to control for students' innate ability—we would expect more-able students to excel academically regardless of the course in which he or she has enrolled, while less-able students will tend to earn lower grades.

**Skills Measured**

At the college level, we assume that individual skills are developed as the result of coursework undertaken by a student. In our dataset, we observe individual classes taken by each survey respondent, as well as the number of credit-hours associated with each class and the grade the student received. From this, we can generate a general measure of how “skilled" the student is with respect to the material covered in each class.

Since we observe specific classes, we can choose a level of aggregation at which to estimate skills returns. The least disaggregated level of observation groups each course by type. For example, calculus can be thought of as a “pure" mathematics class, as can other courses in theoretical mathematics and statistics. However, coursework in the computer science fields, as well as the engineering disciplines might be thought of as “applied mathematics." Similarly, coursework in psychology, sociology and even some courses in economics can be considered “social science" coursework. By using this kind of broad categorization, we can generate first-approximation measures of skill types. Table 1 provides our categorization of skill sets.

This categorization scheme is straightforward, but we do not observe syllabus information for each class. As a result, we cannot guarantee that any *a priori* categorization of courses precisely captures the skill emphasized by each course. For example, while economics is largely considered a “social science," the economist's toolkit draws heavily from real analysis and applied statistics. Thus, it may not be reasonable to group economics with disciplines that study similar subject matter (e.g. psychology, sociology) if dissimilar skills are emphasized.

Additionally, lower-level classes are often introductory, meaning that they serve best as guides to the basics of a given discipline rather than skill incubators. Upper-level classes, on the other hand, require that students are already prepared with an understanding of the basics and can generally be thought of as imparting skills very directly related to the discipline of the course. In theory, the level of difficulty—i.e. the level of intensity of skills taught—rises as the course level increases. However, this is still consistent with more credits in a given category indicating greater development of those skills.

Disaggregating further would allow us to decompose wages into effects of classes from individual university departments. This specification has the advantage of allowing department designations to do the work of specifying courses that are thematically related to each other. Even if an individual department offers a wide variety of courses, the skills emphasized in each course must be consistent with the emphasis of the department, saving the analyst from improper *ad hoc* groupings. An additional advantage is that this allows us to track skills developed within any major curriculum, including interdisciplinary programs that require high-level coursework from several different departments.[1]

Table 2 illustrates the variation in courses taken, quality points (course grade points earned multiplied by the number of credits) and grade point average across colleges for the various skill sets. While some colleges place more emphasis on certain skills sets—for example, Engineering and Design—others are more balanced in their course offerings. The bottom panel of Table 2 shows the average grade point average by college and skill set. A simple regression of GPA for each skill set on the set of college dummies allows us to test for differences across colleges (Agriculture and Life Sciences (CALS) is the base). The asterisk in the table indicate that the mean for the college is significantly different that the mean for CALS. There is some evidence of sorting here; for example alumni from the college of Engineering have higher average GPAs in applied math; design majors have higher grades in art and liberal arts and sciences alumni have higher GPAs in humanities and social sciences. There are unconditional means however; in the analysis that follows we include a large set of controls for individual background and ability that may control for this selection.

**Empirical Specification**

Since our wage equation is reduced-form, we must include both labor-supply and labor-demand measures. Our empirical specification takes the form

$$y_i = \alpha + \beta_{\gamma}^{'}\gamma_i + \beta_X^{'} X_i + \beta_{\theta}^{'}\theta + \beta_{job}^{'} J_{ii} + \epsilon_i$$

[1] When estimated, these results led to many omissions due to few observations of individual classes—e.g. due to low enrollment in obscure courses. Furthermore, interpretation is difficult with over 300 unique department or course designators, so we have not included estimates at this disaggregated level. We hope to incorporate a pared-down version of this level of disaggregation in future work.

where $y_i$ is the natural logarithm of individual $i$'s income; $\gamma_i$ is a measure of individual skills cultivated by individual $i$; $X_i$ is a matrix of characteristics of individual $i$, including experience or job tenure, age, and other demographic characteristics, but not including controls for the innate ability of the student; $\theta_i$ is a vector of measures of individual $i$'s innate ability; and $J_i$ is a vector of characteristics of the job in which individual $i$ was working at the time of the survey.

The wage information contained in our dataset is censored; that is, wages are reported as falling between cutoff points. As such, our estimation follows a latent-variable approach, ordered probit, to estimating earnings. Our interest is in the vector $\beta_\gamma$, which estimates the returns to specific skills cultivated by individual students.

In the context of our latent-variable framework, we will estimate the probability that individual $i$ has income within a certain interval, and we will examine both the vectors of estimated coefficients and the marginal effects of additional skill attainment on subjects' income interval. This is given as the change in the estimated probability of belonging to a certain income category as skill attainment changes, scaled by the estimated coefficient corresponding to the marginal skill.

**Estimation**

We use ordered probit estimation, estimated by maximum likelihood. We restrict our sample to employed individuals, and include a dummy variable for part-time status. As in the established literature, there exists the possibility that wage differences attributed to specific skills may in fact be due to differences in innate ability, i.e. that bias may arise due to selection into the development of certain skills over others. We address this possible selection bias using a “selection on observables” approach, including proxy measures, including high school rank,[2] as well as measures of ability developed during college, such as cumulative GPA.  The earnings estimation has a hedonic interpretation, controlling for industry, experience and other non-skill factors, allowing us to isolate a reduced-form relationship between measures of investment in specific skills and annual earnings.  We estimate the model for all alumni combined, and then separately for men and women.

**Results**

Tables 3 through 6 list our results.  Our ordered probit estimations show that several skill categories have statistically significant impacts on log earnings, but significance decreases (and sometimes is lost entirely) as more controls are added to the right-hand side.  We estimated the model using both number of credits completed in each skill category (Table 3) and quality points obtained in each skill category (Table 4).  There are differences in these two measures.  Focusing on model 4, which includes all the individual-level controls except the industry of the individual’s current job,[3] Table 3 suggests that having an increasing number of credits in art, life sciences, physical sciences and humanities lowers earnings.  In contrast, for the corresponding model in Table 4, the coefficients on quality points earned in each of these skill categories are insignificant.  Meanwhile, having more quality points in math and statistics has a significantly positive impact on earnings.  This suggests that it is not just the number of credits, but also the quality of the learning that occurs in the courses that matters.

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[2] Our data set includes additional measures such as ACT and SAT scores, whether the student was a National Merit Scholar and information on high school extracurricular activities.  However, for many individuals these data are missing – we hope to incorporate these measures in future work.

[3] It is possible that the individuals’ choices of jobs are correlated with innate ability.  However, our controls include years of experience in the workforce (but not at current job) as well as indicators of academic success, which proxy for intelligence.

Tables 5a and 5b report the estimation results separately by gender. While additional art, life sciences and physical sciences credits reduce earnings for men, for women, additional math credits raise earnings, even after controlling for college major and a host of individual ability and background characteristics. This finding is interesting, and consistent with previous studies. The results are weaker when you use quality points instead of credits, but the positive returns to more math, and applied math, for women remains statistically significant.

Table 6a reports the direction and significance of the marginal effects of the skill sets by income level, controlling for individual traits, ability and job characteristics. These indicate the effect of an additional credit in the skill set on the probability of having income in a particular range. For example, having more art credits lowers the probability of being in the top three earnings categories. Additional math credits are positively associated with earning more than $60,000 annually. Much of the action, so to speak, is in the highest income categories; having more applied math and math and statistics credits increase the probability of high earnings, while more credits in communications, sciences and social sciences reduces this probability.

While many of the marginal effects are significant, they are very small in practical terms. For example, an additional credit of applied mathematics, such as a mechanical engineering class, is associated with an increase of 0.000034 in the probability of having income between $150,000 and $249,999. Similarly, the marginal effects of mathematics and statistics courses are largely significant, but an additional credit of mathematics or statistics only decreases the probability of earning less than $25,000 per year by 0.00092. Projecting linearly and using the fact that a typical class at Iowa State is 3 credits, this implies that an extra 3-credit math course can be expected to lower the probability of making less than $25,000 per year by about 0.027

and can be expected to raise the probability of earning between $150,000 and $249,999 per year by 0.00056.

However, when we restrict the regression to females only, we see statistically-significant marginal effects for mathematics credits across nearly all levels of income. We report these results in Table 6b, using the same convention as Table 6a. Though the statistical significance of these effects is robust to controls for individual characteristics and ability, we report the results for which we have used our full set of controls. Worth noting is that this is not the case for applied math credits. This could be due to very few female students at ISU having taken large quantities of coursework that emphasized applied mathematics. Indeed, the average of applied math credits earned by female ISU alumni is about 12.4, while the average number of applied math credits earned by male graduates is about 35.9. Dividing average skillset quality points by average credits earned yields an approximation of the average GPA for applied math; interestingly, graduates of both sexes have quite similar applied-math GPAs (around 2.8).

Again, despite the statistical significance of these marginal effects, our estimated changes to the probability of entering any given income category are quite small. All else equal, we would expect that a female student who takes an additional 3-credit math class at ISU experiences a decrease of 0.00278 in the probability of earning less than $25,000 and an increase of 0.00175 in the probability of earning between $100,000 and $150,000.

Also worth noting is that when we restrict the regression to males only, mathematics coursework has no effect. That is, mathematics credits do not have a statistically significant impact on the probability of earning income within any given range for male ISU graduates. Again comparing average credits taken and average quality points, male graduates took, on average, 18.8 credits of mathematics and/or statistics, while female graduates took about 12.7. These averages are much closer together than the average applied math credits taken by ISU graduates, and the standard deviations of math credits taken by both male and female students are also lower than their applied-math counterparts. This could mean that there is less variation overall in math credits taken, which may confound the identification of the effect of mathematics and statistics classes on earnings.

**Summary**

These preliminary results suggest that, consistent with previous research, quantitative skills are more highly rewarded in the job market, but only for women. Controlling for a wide range of individual characteristics, including college of major, we find evidence that higher levels of math credits in college are positively associated with higher earnings for women.

Findings from this analysis can more concretely guide curricular reform. For example, if the returns to math-related skills are more highly valued in the job market relative to other skills, it provides justification for enhancing quantitative requirements. In particular, college curricula may place emphasis on non-quantitative coursework, while the majority of mathematics and statistics courses remain in the realm of “free elective” classes. In particular, this could indicate systematic differences in the preparedness of students to perform difficult quantitative work as compared to their readiness to undertake difficult communication tasks.

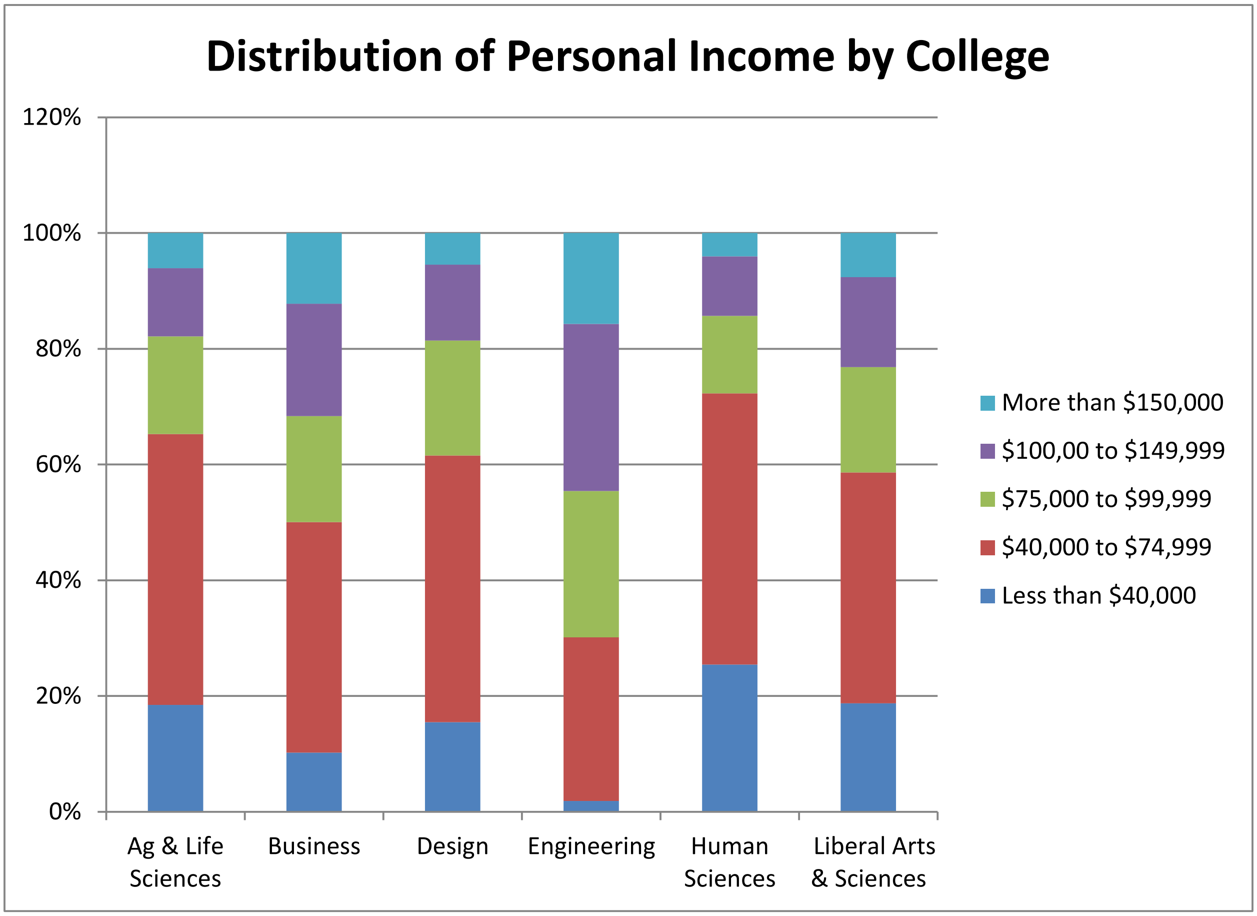
**Future Directions**

In future work, we plan to investigate the possible role of selection into college major and its impact on our estimates. We will use a Heckman-type selection procedure that uses pre-college measures to predict a student's major, and conditional on this we carry out a second-stage wage estimate in which predicted ability measures are included. While selection can occur at various levels, we specifically consider students' selection into particular majors based on their pre-college attributes. We base this choice on the premise that majors represent an “average" difficulty with respect to certain skills—for example, a major in Communications Studies will require students to master higher-level communications skills, while a major in Electrical Engineering will require students to master more difficult levels of mathematics. Conditional on the student's chosen major, however, we can examine how students' innate ability to handle the difficulty of the skills emphasized by the major—which might be thought of as a “tolerance" for difficulty—is distributed about the average difficulty of the major.

Additionally, we will explore potential expansions to our data that will allow us to account for a wider variety of labor-demand-side factors that may impact how the market values particular skills. Our data also allow us to explore how various skills components of individual majors are rewarded within and outside their “home” industries. We will be able to assess which skills are more general or transferrable across industries and which are major-specific and heavily discounted outside of agriculture. The potential implication is that majors that heavily weight those skills may want to explore adding additional weight to skills that are more highly rewarded outside the industry.

We can also examine if there are differences between upper and lower courses, with the idea that higher level courses teach more major specific material, while lower level courses are more general education oriented.

**Figure 1.**



Distribution of Personal Income by College
120%
100%
80%
60%
40%
20%
0%
Ag & Life Sciences
Business
Design
Engineering
Human Sciences
Liberal Arts & Sciences
More than $150,000
$100,00 to $149,999
$75,000 to $99,999
$40,000 to $74,999
Less than $40,000

Table 1: Broad "Skill" Categories

| Class Category | Examples of Included Courses |
|---|---|
| Art | Art, Design, Dance, Landscape Architechture, Music and Theatre |
| Applied Mathematics (APMATH) | Engineering (all), Computer Science, Materials Science, Transportation Planning/Logistics |
| Communications (COM) | Communications Studies, Speech/Communication, Foreign Languages (all) |
| Humanities (HUM) | Classical Studies, Philosophy, Religious Studies, History |
| Life Sciences (LIF) | Animal Ecology, Biomedical Science, Biology, Botany, Ecology/Evolutionary Biology, Horticulture, Microbiology, Veterinary Medicine |
| Mathematics (MAT) | Mathematics and Statistics |
| Physical Sciences (PHY) | Chemistry, Physics, Geology, Meteorology |
| Social Sciences (SOC) | Economics, Sociology, Criminal Justice, Psychology, Political Science |
| Other | All non-categorized courses |

Table 2. Average Number of Credits, Quality Points and Average GPA by Skill Type Across Colleges

| | Agriculture & Life Sciences | Business | Design | Engineering | Human Sciences | Liberal Arts & Sciences |
|---|---|---|---|---|---|---|
| *Average Number of Credits* | | | | | | |
| Applied Math | 10.4 | 7.5 | 6.1 | 73.2 | 3.8 | 12.2 |
| Communications | 14.2 | 16.7 | 14.7 | 11.6 | 16.8 | 25.2 |
| Math | 11.6 | 14.6 | 8.0 | 23.8 | 10.0 | 19.1 |
| Art | 2.4 | 3.0 | 76.9 | 2.1 | 9.1 | 6.2 |
| Humanities | 5.5 | 10.0 | 7.9 | 4.2 | 6.0 | 13.6 |
| Life Science | 50.4 | 2.8 | 5.8 | 1.8 | 18.1 | 13.8 |
| Physical Science | 14.1 | 5.3 | 5.0 | 20.2 | 8.3 | 20.5 |
| Social Science | 23.1 | 22.3 | 15.2 | 10.9 | 26.5 | 31.6 |
| *Average Quality Points* | | | | | | |
| Applied Math | 28.4 | 18.7 | 15.2 | 206.5 | 8.2 | 30.5 |
| Communications | 38.5 | 44.5 | 37.1 | 29.5 | 42.8 | 68.4 |
| Math | 28.0 | 34.7 | 14.8 | 58.5 | 21.8 | 46.1 |
| Art | 6.4 | 8.2 | 231.6 | 5.4 | 26.4 | 17.5 |
| Humanities | 14.9 | 27.3 | 20.1 | 11.7 | 14.6 | 39.0 |
| Life Science | 136.0 | 7.2 | 14.3 | 5.0 | 49.4 | 38.2 |
| Physical Science | 33.8 | 11.9 | 11.4 | 53.4 | 18.4 | 52.7 |
| Social Science | 63.9 | 61.0 | 38.0 | 33.4 | 70.3 | 88.8 |
| *Average GPA* | | | | | | |
| Applied Math | 2.73 | 2.77 | 2.55* | 2.88** | 2.50** | 2.66 |
| Communications | 2.72 | 2.69 | 2.54*** | 2.54*** | 2.59** | 2.70 |
| Math | 2.48 | 2.54 | 2.08*** | 2.53 | 2.43 | 2.42 |
| Art | 2.69 | 2.72 | 2.96** | 2.55 | 2.79 | 2.62 |
| Humanities | 2.73 | 2.77 | 2.51** | 2.77 | 2.58* | 2.88** |
| Life Science | 2.77 | 2.58** | 2.64 | 2.71 | 2.69 | 2.75 |
| Physical Science | 2.38 | 2.48 | 2.44 | 2.66*** | 2.34 | 2.53** |
| Social Science | 2.82 | 2.79 | 2.58*** | 3.10*** | 2.63*** | 2.95** |

Notes: Stars indicate the mean GPA for the college is significantly from the mean for CALS at the 10-percent (*), 5 percent (**) or 1 percent (***) level.

Table 3: Ordered Probit Earnings Regression - Skills Measured by Credits Obtained

| Variable | Model 1 | Model 2 | Model 3 | Model 4 | Model 5 |
|---|---|---|---|---|---|
| ART_credits | -0.00339*** | -0.00322*** | -0.00305*** | -0.00311*** | -0.00191* |
| | (0.000811) | (0.000775) | (0.00111) | (0.00113) | (0.00113) |
| APMATH_credits | 0.00407*** | 0.00342*** | -0.00165 | -0.00165 | -0.00284* |
| | (0.000787) | (0.000821) | (0.00157) | (0.00159) | (0.00164) |
| COM_credits | -0.00453*** | -0.000616 | 0.000468 | 0.000442 | 0.000959 |
| | (0.00168) | (0.00163) | (0.00167) | (0.00168) | (0.00166) |
| HUM_credits | -0.00284 | -0.00612** | -0.00564** | -0.00512* | -0.00249 |
| | (0.00256) | (0.00244) | (0.00266) | (0.00266) | (0.00258) |
| LIF_credits | -0.00505*** | -0.00411*** | -0.00184** | -0.00183* | -0.00176* |
| | (0.000780) | (0.000742) | (0.000918) | (0.000940) | (0.000947) |
| MAT_credits | 0.00669*** | 0.00205 | 0.00200 | 0.00245 | 0.00201 |
| | (0.00200) | (0.00206) | (0.00206) | (0.00204) | (0.00195) |
| PHY_credits | -0.00332** | -0.00326** | -0.00291* | -0.00321* | -0.00191 |
| | (0.00150) | (0.00154) | (0.00166) | (0.00168) | (0.00164) |
| SOC_credits | -0.00427*** | -0.00225** | -0.000942 | -0.000626 | 0.00123 |
| | (0.000978) | (0.000986) | (0.00103) | (0.00103) | (0.00107) |
| OTHER_credits | -0.000940 | -0.000899 | 0.000371 | 0.000602 | 0.00134 |
| | (0.00126) | (0.00120) | (0.00128) | (0.00130) | (0.00131) |
| Control for worker traits | No | Yes | Yes | Yes | Yes |
| Control for school background (college) | No | No | Yes | Yes | Yes |
| Control for ability indicators | No | No | No | Yes | Yes |
| Control for job sector | No | No | No | No | Yes |
| Observations | 4,756 | 4,756 | 4,756 | 4,733 | 4,733 |

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Table 4: Ordered Probit Earnings Regression - Skills Measured by Course Performance

| Variables | Model 1 | Model 2 | Model 3 | Model 4 | Model 5 |
|---|---|---|---|---|---|
| ART_QP | -0.00107*** | -0.000616*** | -0.000523 | -0.000506 | -9.73e-05 |
| | (0.000224) | (0.000224) | (0.000359) | (0.000358) | (0.000357) |
| APMATH_QP | 0.00177*** | 0.00172*** | 0.000661 | 0.000670 | 0.000136 |
| | (0.000261) | (0.000272) | (0.000522) | (0.000523) | (0.000544) |
| COM_QP | -0.00180*** | 1.89e-05 | 0.000545 | 0.000438 | 0.000418 |
| | (0.000597) | (0.000570) | (0.000577) | (0.000583) | (0.000587) |
| HUM_QP | -0.000992 | -0.00137* | -0.00123 | -0.00120 | -0.000260 |
| | (0.000873) | (0.000807) | (0.000889) | (0.000888) | (0.000869) |
| LIF_QP | -0.00183*** | -0.00109*** | -0.000104 | -0.000185 | -0.000240 |
| | (0.000286) | (0.000290) | (0.000372) | (0.000375) | (0.000376) |
| MAT_QP | 0.00134* | 0.00157** | 0.00137* | 0.00137* | 0.000912 |
| | (0.000688) | (0.000693) | (0.000709) | (0.000717) | (0.000693) |
| PHY_QP | -0.000605 | -0.000831 | -0.000315 | -0.000429 | 7.29e-05 |
| | (0.000548) | (0.000554) | (0.000601) | (0.000614) | (0.000604) |
| SOC_QP | -0.00158*** | -0.000267 | 0.000332 | 0.000368 | 0.000933*** |
| | (0.000338) | (0.000321) | (0.000340) | (0.000341) | (0.000356) |
| OTHER_QP | -5.35e-06 | -2.12e-06 | 0.000351 | 0.000400 | 0.000818* |
| | (0.000443) | (0.000416) | (0.000438) | (0.000440) | (0.000445) |
| Control for worker traits | No | Yes | Yes | Yes | Yes |
| Control for school background (college) | No | No | Yes | Yes | Yes |
| Control for ability indicators | No | No | No | Yes | Yes |
| Control for job sector | No | No | No | No | Yes |
| Observations | 4,615 | 4,615 | 4,615 | 4,598 | 4,598 |

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Table 5a. Ordered Probit Estimation of Earnings -- Impact of Credits by Skill Set by Gender

| | All Alumni | | | Male Alumni | | | Female Alumni | | |
|---|---|---|---|---|---|---|---|---|---|
| Number of Credits in: | (1) | (2) | (3) | (1) | (2) | (3) | (1) | (2) | (3) |
| ART | -0.003*** | -0.003*** | -0.002* | -0.004*** | -0.003** | -0.003* | -0.001 | -0.001 | 0.0004 |
| | (0.0008) | (0.001) | (0.001) | (0.001) | (0.001) | (0.002) | (0.001) | (0.00171) | (0.002) |
| Applied Math | 0.003*** | -0.002 | -0.003* | 0.002*** | -0.002 | -0.003 | 0.009*** | 0.004 | 0.001 |
| | (0.001) | (0.002) | (0.002) | (0.001) | (0.002) | (0.002) | (0.002) | (0.004) | (0.004) |
| Communication | -0.0006 | 0.0005 | 0.001 | -0.003 | -0.002 | 0.0004 | 0.002 | 0.003 | 0.002 |
| | (0.002) | (0.002) | (0.002) | (0.003) | (0.003) | (0.003) | (0.002) | (0.002) | (0.002) |
| Humanities | -0.0061** | -0.006** | -0.002 | -0.006* | -0.005 | -0.0003 | -0.007* | -0.009** | -0.007* |
| | (0.002) | (0.003) | (0.003) | (0.003) | (0.003) | (0.003) | (0.004) | (0.004) | (0.004) |
| Life Sciences | -0.004*** | -0.002** | -0.002* | -0.006*** | -0.004*** | -0.003** | -0.002** | -0.0001 | -0.001 |
| | (0.001) | (0.001) | (0.001) | (0.001) | (0.001) | (0.002) | (0.001) | (0.001) | (0.001) |
| Math and Statistics | 0.002 | 0.002 | 0.002 | -0.002 | -0.002 | -0.002 | 0.007* | 0.007* | 0.008** |
| | (0.002) | (0.002) | (0.002) | (0.002) | (0.002) | (0.002) | (0.004) | (0.004) | (0.004) |
| Physical Sciences | -0.003** | -0.003* | -0.002 | -0.004* | -0.004* | -0.003 | -0.002 | 0.0003 | 0.001 |
| | (0.002) | (0.002) | (0.002) | (0.002) | (0.002) | (0.002) | (0.002) | (0.002) | (0.002) |
| Social Sciences | -0.002** | -0.001 | 0.001 | -0.001 | -0.0004 | 0.001 | -0.002* | -0.0005 | 0.002 |
| | (0.001) | (0.001) | (0.001) | (0.001) | (0.002) | (0.002) | (0.001) | (0.002) | (0.002) |
| Other | -0.001 | 0.0004 | 0.001 | -0.002 | 0.000 | 0.002 | -0.002 | -0.001 | -0.002 |
| | (0.001) | (0.001) | (0.001) | (0.002) | (0.002) | (0.002) | (0.002) | (0.002) | (0.0021 |
| Observations | 4,756 | 4,756 | 4,733 | 2,851 | 2,851 | 2,836 | 1,842 | 1,842 | 1,836 |

Model 1 includes controls for experience, experience-squared, gender, graduate degree, marital status, rural background native English speaker and part-time work status. Model 2 adds controls for College of major, Model 4 adds family background measures – parent’s education, high school rank, and cumulative GPA and controls for industry of current job.

Table 5b. Ordered Probit Estimation of Earnings -- Impact of Quality Points by Skill Set by Gender

| | All Alumni | | | Male Alumni | | | Female Alumni | | |
|---|---|---|---|---|---|---|---|---|---|
| Number of Credits in: | (1) | (2) | (3) | (1) | (2) | (3) | (1) | (2) | (3) |
| ART | -0.001*** | -0.001 | -0.0001 | -0.001*** | -0.001 | -0.001 | -0.0001 | 0.000 | 0.0002 |
| | (0.000) | (0.0004) | (0.0004) | (0.0003) | (0.001) | (0.001) | (0.0004) | (0.001) | (0.001) |
| Applied Math | 0.002*** | 0.001 | 0.000 | 0.001*** | 0.001 | -0.0004 | 0.004*** | 0.002* | 0.001 |
| | (0.0003) | (0.001) | (0.001) | (0.0003) | (0.001) | (0.001) | (0.001) | (0.001) | (0.001) |
| Communication | 0.0002 | 0.001 | 0.0004 | -0.001 | -0.0004 | -0.0004 | 0.001 | 0.002* | 0.001 |
| | (0.001) | (0.001) | (0.001) | (0.0009) | (0.001) | (0.001) | (0.001) | (0.001) | (0.001) |
| Humanities | -0.001* | -0.00123 | -0.0003 | -0.001 | -0.0008 | 0.0001 | -0.002 | -0.002 | -0.002 |
| | (0.001) | (0.001) | (0.001) | (0.001) | (0.001) | (0.001) | (0.001) | (0.001) | (0.001) |
| Life Sciences | -0.001*** | -0.0001 | -0.0002 | -0.002*** | -0.001 | -0.001** | -0.0002 | 0.001* | -0.000 |
| | (0.0003) | (0.0004) | (0.0004) | (0.0004) | (0.001) | (0.001) | (0.000) | (0.001) | (0.001) |
| Math and Statistics | 0.001** | 0.001* | 0.001 | 0.001 | 0.0005 | -0.001 | 0.003** | 0.002* | 0.002 |
| | (0.001) | (0.001) | (0.001) | (0.001) | (0.001) | (0.001) | (0.001) | (0.001) | (0.00120) |
| Physical Sciences | -0.001 | -0.0003 | 0.000 | -0.001 | -0.001 | -0.001 | -0.0004 | 0.0004 | 0.0004 |
| | (0.001) | (0.001) | (0.001) | (0.001) | (0.001) | (0.001) | (0.001) | (0.001) | (0.001) |
| Social Sciences | -0.0003 | 0.0003 | 0.001*** | 0.001 | 0.001** | 0.001 | -0.0001 | 0.0001 | 0.0004 |
| | (0.0003) | (0.0003) | (0.0004) | (0.001) | (0.001) | (0.001) | (0.001) | (0.001) | (0.001) |
| Other | 0.000 | 0.0004 | 0.001* | -0.0004 | 0.000 | 0.001 | -0.0002 | 0.0001 | -0.000 |
| | (0.000) | (0.000) | (0.0004) | (0.001) | (0.001) | (0.001) | (0.001) | (0.001) | (0.001) |
| Observations | 4,756 | 4,756 | 4,733 | 2,851 | 2,851 | 2,836 | 1,842 | 1,842 | 1,836 |

Model 1 includes controls for experience, experience-squared, gender, graduate degree, marital status, rural background native English speaker and part-time work status. Model 2 adds controls for College of major, Model 4 adds family background measures – parent's education, high school rank, and cumulative GPA and controls for industry of current job.

Table 6a. Marginal Effects of Additional Credits by Income Level

| | Art | Applied Math | Commun-ications | Human-ities | Life Science | Math and Stats | Physical Sciences | Social Sciences | Other |
|---|---|---|---|---|---|---|---|---|---|
| Income levels | | | | | | | | | |
| Decline to state | + | + | | | + | | | | |
| $0 - $24,999 | | | | + | | - | | | |
| $25,000 - $39,999 | | | | + | | - | | | |
| $40,000 - $59,999 | | | | | | | | | |
| $60,000 - $74,999 | | | | - | | + | | | |
| $75,000 - $99,999 | | | | - | | + | | | |
| $100,000 - $149,999 | | | | - | | + | | | |
| $150,000 - $249,999 | - | + | - | | - | + | - | - | |
| $250,000 - $500,000 | - | + | - | | - | + | - | - | |
| More than $500,001 | - | + | - | | - | + | - | - | |

+ indicates a significant positive marginal effect; - indicates a significant negative marginal effect; here, significance is defined as a p-value less than 0.10.

Table 6b. Marginal Effects of Additional Credits by Income Level by gender:

| Income levels | Art | Applied Math | Commun-ications | Human-ities | Life Science | Math and Stats | Physical Sciences | Social Sciences | Other |
|---|---|---|---|---|---|---|---|---|---|
| **Male** | | | | | | | | | |
| Decline to state | + | | | | + | | | | |
| $0 - $24,999 | + | | | | + | | | | |
| $25,000 - $39,999 | + | | | | + | | | | |
| $40,000 - $59,999 | + | | | | + | | | | |
| $60,000 - $74,999 | + | | | | + | | | | |
| $75,000 - $99,999 | | | | | - | | | | |
| $100,000 - $149,999 | - | | | | - | | | | |
| $150,000 - $249,999 | - | | | | - | | | | |
| $250,000 - $500,000 | | | | | - | | | | |
| More than $500,001 | | | | | - | | | | |
| | | | | | | | | | |
| **Female** | | | | | | | | | |
| Decline to state | | | | + | | - | | | |
| $0 - $24,999 | | | | + | | - | | | |
| $25,000 - $39,999 | | | | + | | - | | | |
| $40,000 - $59,999 | | | | | | | | | |
| $60,000 - $74,999 | | | | - | | + | | | |
| $75,000 - $99,999 | | | | - | | + | | | |
| $100,000 - $149,999 | | | | - | | + | | | |
| $150,000 - $249,999 | | | | - | | + | | | |
| $250,000 - $500,000 | | | | - | | + | | | |
| More than $500,001 | | | | | | | | | |

+ indicates a significant positive marginal effect; - indicates a significant negative marginal effect; here, significance is defined as a p-value less than 0.10.

**Table 7. Distribution of Income by Full-Time/Part-Time Work and Male/Female**

| Income levels | Full-time | | Part-time | | Men | | Women | |
|---|---|---|---|---|---|---|---|---|
| | N | % | N | % | N | % | N | % |
| Decline to state | 127 | 3.1 | 9 | 2.7 | 108 | 3.8 | 48 | 2.5 |
| $0 - $24,999 | 84 | 2.0 | 164 | 49.3 | 59 | 2.1 | 254 | 13.3 |
| $25,000 - $39,999 | 434 | 10.5 | 70 | 21.0 | 163 | 5.7 | 368 | 19.3 |
| $40,000 - $59,999 | 907 | 22.0 | 47 | 14.1 | 468 | 16.4 | 514 | 27.0 |
| $60,000 - $74,999 | 645 | 15.6 | 18 | 5.4 | 428 | 15.0 | 257 | 13.5 |
| $75,000 - $99,999 | 768 | 18.6 | 10 | 3.0 | 569 | 20.0 | 245 | 12.9 |
| $100,000 - $149,999 | 753 | 18.2 | 11 | 3.3 | 662 | 23.2 | 145 | 7.6 |
| $150,000 - $249,999 | 284 | 6.9 | 4 | 1.2 | 262 | 9.2 | 49 | 2.6 |
| $250,000 - $500,000 | 87 | 2.1 | 0 | 0 | 90 | 3.2 | 20 | 1.1 |
| More than $500,001 | 39 | 0.9 | 0 | 0 | 43 | 1.5 | 6 | 0.3 |
| Total | 4,128 | 100 | 333 | 100 | 2,852 | 100 | 1,906 | 100 |

Note: 80% (266 of 333) of part-time workers are women.

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