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The Importance of Skills and Majors in Determining Future Earnings

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The Importance of Skills and Majors in Determining Future Earnings

An AIR commissioned paper

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Introduction

Research in higher education has consistently found that the earnings of college graduates vary by their college major (Berger, 1988; Carnevale, Cheah, & Hanson, 2015; Finnie & Frenette, 2003; Hecker, 1996; Thomas & Zhang, 2005). Discussion of majors and earnings by the popular media, which regularly profiles students whose college major seemingly landed them at either extreme of the earnings spectrum (Korn, 2015; Stockwell, 2014; Strauss, 2016), has led to the development of a narrative where college majors completely determine individual income. The perceived connection between majors and future earnings is so strong that policy proposals have suggested public university funding be based on differential earnings associated with graduates of different majors (Kiley, 2013). However, most discussions on the relationship between college majors and earnings does not consider general cognitive skills, which are critical factors associated with labor market outcomes (Cawley, Heckman, & Vytlacil, 2001; Hanushek et al., 2015).

Against this backdrop, the purpose of this study is to better understand the relationship between majors and earnings, by examining within-major heterogeneity in earnings attributable to the role of general cognitive skills and how cognitive skills interact with knowledge obtained from different majors to affect earnings. Among graduates of the same major, it is possible for earnings to vary according to differences in general cognitive skills. For example, completion of an engineering major signifies mastery of specific, applicable curricula and can lead to earning levels that are on average higher than some other majors. But, there is no reason to believe that wages of engineering degree holders would be insensitive to variation in their cognitive skills. Similarly, while some majors, such as in the humanities, are not as well connected to particular occupations and may lead to lower streams of compensation, completers of these majors with advanced cognitive skills may reap additional earnings benefits compared to those with low cognitive skills. Also, individual earnings that are associated with cognitive skills may vary according to the type of content specific skills and knowledge that individuals possess. That is, the combination of general cognitive skills and different major-specific skills may lead to different levels of earnings.

Previous literature

Theoretical Framework: Re-introducing a Measure of Skill to Human Capital Theory

Human capital was originally theorized to describe the cognitive skills, knowledge and competencies of individuals or groups (Becker, 1962). In contrast to the concept of economic or material capital -- the money, tools and physical resources that allow for work and profit to be generated -- human capital describes resources like knowledge and skills of people needed for doing productive work and generating profits.

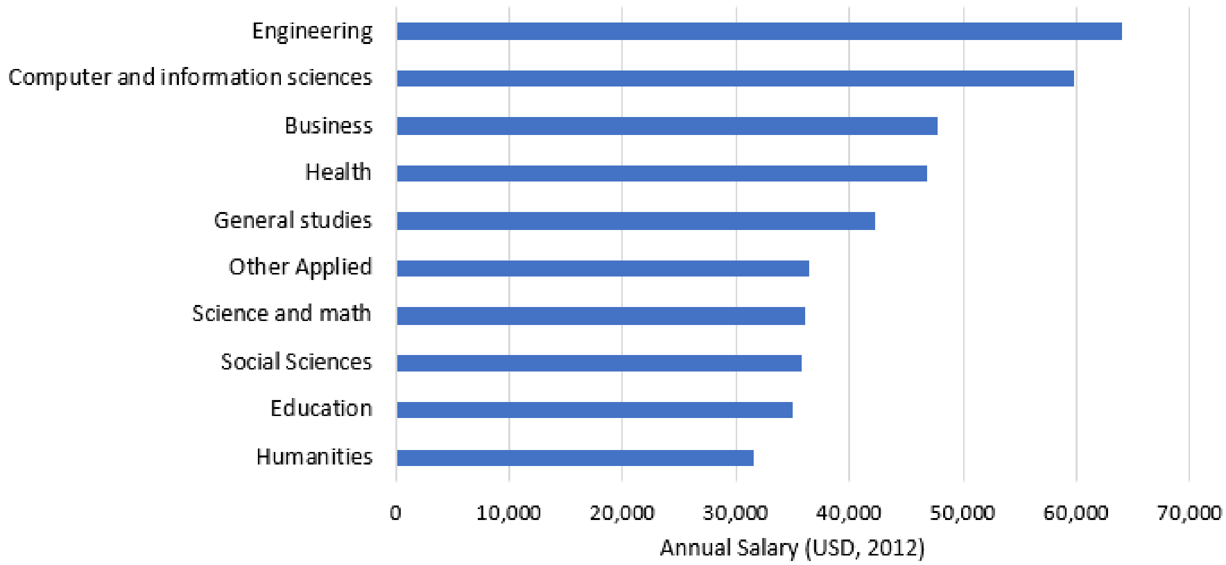
Gathering data on human capital (i.e. measuring individual cognitive skills, knowledge and competencies) is difficult, expensive and contested terrain. So, overtime, individual educational level became a proxy measure for human capital. The thinking here was simple: to attain a certain educational level, each individual is required to demonstrate that they have obtained a set of cognitive skills, knowledge and competencies. Therefore, educational level could be used as a (blunt) measure of human capital. This line of reasoning is so mainstream that many people inside and outside of the academic research community use *education level* and *human capital* interchangeably (see examples: Goldin & Katz, 1996; Johnson, 1997).

However, it is a truism that college graduates vary in their levels of skills, ability, and knowledge, however defined. This also applies to graduates of the same academic major. Therefore, accounting for direct measures of cognitive skills, compared to simply educational attainment level or major field of study alone, can more fully encompass the concept of human capital (OECD, 2013a). We seek to fully bring to bear the theory of human capital to the relationship between majors and earnings by including a variable accounting for literacy and numeracy skills to models of post-college earnings.

Earnings and majors

Often research examining the relationship between college major and the future earnings of college graduates contributes to an image of a “horse race” solely among majors—a ranking of majors by the highest return on investment in terms of labor market earnings (Berger, 1988; Carnevale, Cheah, & Hanson, 2015; Finnie & Frenette, 2003; Hecker, 1996; Thomas & Zhang, 2005). Estimates, for example, show that the median entry annual income for recent graduates of the highest earnings majors is between $41,000 and $50,000 and by mid-career is between $65,000 and $83,000 (Carnevale, Cheah, & Hanson, 2015). In the middle of the major-earnings pack are recent graduates of the social sciences, law and public policy, whose median salary is between $31,000 and $32,000 (Carnevale, Cheah, & Hanson, 2015). And at the low range of the salary continuum for recent graduates are people who majored in the arts, consumer services, and recreation, whose median annual earnings is $27,000 (Carnevale, Cheah, & Hanson, 2015). There is also evidence that a major can have lasting impact on lifetime earnings; while graduates in every field had wage growth over time, some majors, such as history, experience an average negative wage growth over the career (Thomas and Zhang, 2005). The pattern of differences in mean salaries is illustrated across 10 common college majors in Figure 1 with data from Baccalaureate and Beyond 2012, a nationally representative sample of recent college completers.

Figure 1. Mean annual salaries of recent college graduates by major (2012).



Source: Baccalaureate and Beyond 2012.

Completion of a college major is not the only benefit that students gain, there is continued general learning that can enhance advanced cognitive skills. While some past analyses question how much learning actually takes place in college, most assessments suggest that it can be substantial (Arum & Roksa 2011; Pascarella et al. 2011). Human capital theory indicates that garnering credentials and the skills that enhance job performance is incentivized, particularly in the professionalized parts of the American occupational structure (e.g. Autor 2014; Baker 2014; Becker 1962). Other studies indicate that the learning of literacy and numeracy, especially into higher levels, enhances overall cognitive functioning that can lead to better problem solving, reasoning, and working with complexity (Baker et al. 2012; Baker et al. 2015). In line with this previous literature, our analysis re-introduces cognitive *skills* into research on majors and occupational outcomes—there may be a horse race among majors, but there is likely one among cognitive skills as well.

Technological progress has greatly affected nearly every aspect of life, including how work is conducted in the work place, how people interact with friends and family, and how people go about their daily lives. Such social and economic changes stemming from technological changes have called for increased use of cognitive skills, particularly those pertaining to information-processing (OECD, 2013a). Skills are also important for individuals in light of globalization and the changes it has led to in terms of how goods are produced and traded across borders (OECD, 2017). Studies have empirically demonstrated that cognitive skill is positively associated with educational attainment and earnings (Cawley, Heckman, & Vytlacil, 2001). Even within a group of high-IQ individuals, pre-collegiate IQ has been shown to be associated with higher lifetime earnings (Gensowski, Heckman, & Savelyev, 2011). Using the PIAAC data, Hanushek et al. (2015) show that the economic returns to skills across the world, on average, are 18% for prime-age workers. Because of the difficulty of obtaining datasets with reliable measure of skills, very little previous work attends to the relationship between skills, majors and labor market outcomes.

Previous studies that have looked into skills, majors and earnings have used pre-college measure of skill such as SAT and ACT scores (Arcidiacono, 2004; Paglin & Rufolo, 1990; Wolniak, Seifert, Reed, & Pascarella, 2008). For example, compared to verbal scores, quantitative scores have a greater degree of association with sorting into majors and labor market outcomes (Arcidiacono, 2004; Paglin & Rufolo, 1990). Wolniak et al. (2008) use the ACT score to control for possible confounding effects in the relationship between major and earnings, and find that majors which offer narrowly-defined, specific set of knowledge (e.g., computer science) tend to have the highest earnings. Another measure of skill that has been employed to examine the relationship between major fields of study and earnings is the Armed Forces Qualification Test

(AFQT) score. For both men and women, the AFQT[1] score is found to be a statistically significant predictor of earnings, regardless of the selectivity of the institution from which they graduate (Monks, 2000). Other work uses the AFQT as a control for ability in examining the relationship between occupational specificity of the major and employment (Roksa & Levy, 2002). Although skill has been considered in previous research on college majors and labor market earnings, the skill measure, such as SAT/ACT or the AFQT has a measure of general aptitude and lacks relevance to the workplace. In contrast, the skill measures in PIAAC are designed to assess information processing skills that are relevant to various social and economic contexts, and in particular, expands the concept of cognitive skills by assessing numeracy and literacy used in digital environments (OECD, 2013a).

Our study contributes to the literature on the relationship between skills and earnings in a number of ways. We examine literacy skills and numeracy skills separately to see if these interact with major in different ways to predict earnings. There is a need for more research on the relationship between major and earnings including a direct measure of general cognitive skills. College majors have been treated as proxies for individual skills, but general skills that go beyond majors need to be considered. Most datasets do not collect both an indicator of what major field a person enrolled in *and* a measure of their cognitive abilities – so testing whether major or cognitive skills is driving labor market earnings is not possible. We hypothesize that by omitting measures of skills in models that use majors to predict labor market earnings, the explanatory power of major field choice has been overstated in the literature.

[1] The Armed Forces Qualification Test (AFQT) score is calculated using the cognitive test components of the Armed Services Vocational Aptitude Battery (ASVAB) tests, which are used to predict academic/occupational success in the military.

Research Questions

Do general cognitive skills explain within-major heterogeneity in earnings?

How do general cognitive skills interact with specific skills and knowledge acquired in majors to explain earnings?

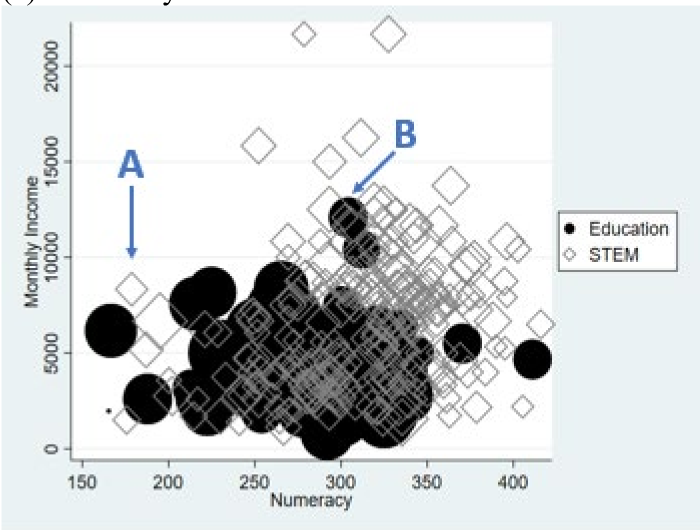
Hypothesis

Earnings, within a major, varies by literacy and numeracy skills.

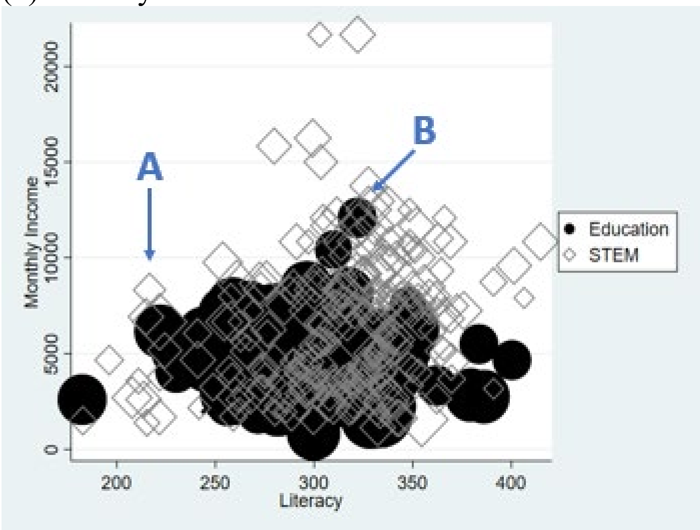
Along with majors verifying specific curricular knowledge, cognitive skills may propel college graduates to reap labor market returns. Applicable curricular knowledge learned through a specific major likely contributes to the labor market outcomes of graduates, but there are also likely to be general cognitive skills that are valued in the work place and thus are positively associated with employment and earnings, net of the effect of specific majors. For example, the STEM major with lower cognitive skills (person A, Figure 2 (a) and (b)), for both numeracy and literacy, does not necessarily out-earn the education major with more cognitive skills (person B, Figure 2 (a) and (b)).

Figure 2. Scatter plot of numeracy and monthly earnings by major (weighted values).

(a) Numeracy



(b) Literacy



Notes: Plots weighted by sampling weights. For both numeracy and literacy, the first plausible value was used. Although not shown, no major differences are found when drawing the scatter plot using the other plausible values or the average of the 10 plausible values.
Source: PIAAC 2012/2014, authors' calculations.

How specific skills acquired through majors interact with general cognitive skills to explain earnings varies by major.

In addition to general cognitive skills explaining earnings variation within graduates of the same major, it is also possible for the returns to cognitive skills to vary by major. In other words, there could be interactional effects between cognitive skills and major-specific skills. For example, it may be that numeracy skills are associated with relatively higher returns for STEM graduates compared to humanities graduates due to the type of tasks required in the workplace. That is, numeracy skills may be more highly valued for tasks in jobs held by STEM graduates compared to the type of work or tasks required by graduates of the humanities.

Data and Methods

As the purpose of this study is to understand the role individual skill plays in the relationship between academic major and labor market earnings for college graduates, the analytical sample includes only 4-year college or university graduates and above, between the ages 25 and 65. In order to observe only those with strong labor market commitments, the sample is limited to wage-earners who work full-time; those who are not self-employed and reported working at least 30 hours a week. Given that higher cognitive skill increases probability of employment, the restriction of the sample to full-time workers means that we likely underestimate the association between cognitive skills and earnings. However, such a sample restriction is used in order to diminish the influence of non-skill factors that may affect labor market commitment, such as health, and better capture the direct relationship between cognitive skills and earnings (Hanushek et al., 2015). Also, to limit the effect of outliers, those in the top 1 percent of the earnings distribution are excluded from the sample. For example, the average earnings of the top 1 percent more than doubles the average earnings of the next 1 percent. Respondents with missing values in any of the variables included in the regression models were dropped from the analysis.

The final working sample consists of 970 respondents. Descriptive statistics of the analytical sample can be found in Table 1.

The original PIAAC data contains 9 major fields of study[2]: For this study, to address concerns of small sample sizes, the original majors were re-classified into five categories.[3] The majors within the "Social Science" category were combined due to the similarities in the materials taught; "service" programs generally includes psychology, public policy, social work, and "general programs" tend to include various areas of the social sciences, such as political science, economics, and sociology. "STEM" was categorized based on the U.S. Dept. of Homeland Security's classification of STEM majors.[4]

Due to resource and time constraints, tests administered in most large-scale ability assessments like PIAAC are not long or comprehensive enough to accurately assess the ability of each tested individual. To assess the level of cognitive skills while accounting for such limitations, PIAAC utilizes plausible values, a method used to retrieve score distribution estimates through posterior distributions of respondent ability. A way to understand plausible values is to view them as representing the range of abilities that a respondent might have given his/her item responses, or random draws from an estimated distribution of a respondent's actual ability (Wu, 2005). For each skill domain, PIAAC assigned each respondent ten PVs, drawn from a posterior distribution through combining the scaled cognitive item responses with a latent regression model using background characteristic information. (OECD, 2013b).

[2] "general programs"; "teacher training and education science"; "humanities, languages, and arts"; "social sciences, business and law"; "science, mathematics and computing"; "engineering, manufacturing and construction"; "health and welfare"; "agriculture and veterinary" and "services."

[3] "Education" ("teacher training and education science"); "Humanities" ("humanities, languages, and arts"); "Social Science" ("general programs," "services," and "social sciences, business and law"); "STEM" ("science, mathematics and computing," "engineering, manufacturing and construction," and "agricultural and veterinary"); "Health" ("health and welfare").

[4] For details, refer to https://www.ice.gov/sites/default/files/documents/Document/2016/stem-list.pdf.

Table 1. Descriptive statistics for analytical sample (weighted)

Variable	Mean	Std. Dev.	Std. Err.	Min	Max
Monthly income (dollars)	6122.41	3573.19	25.70	247.00	21666.67
Numeracy	299.07	43.04	143.51	133.53	427.94
Literacy	307.28	38.02	162.90	149.83	425.60
Age	42.52	11.18	142.55	25	65
Work experience (yrs)	21.61	11.57	63.29	0	47
Variable	Percentage	Std. Dev.	Std. Err.		
Major					
Education	14.01%	0.35	9.57		
Humanities	13.50%	0.34	9.90		
Social sciences	35.85%	0.48	15.51		
STEM	25.42%	0.44	13.53		
Health	11.21%	0.32	10.88		
Female	50.92%	0.50	44.81		
Graduate school	40.80%	0.49	19.33		
Immigrant	18.55%	0.39	11.19		
Parent's education					
less than high school	5.62%	0.23	6.21		
high school	36.49%	0.48	18.97		
above high school	57.89%	0.49	31.85		
Race					
Hispanic	5.32%	0.22	7.93		
White	75.21%	0.43	44.37		
Black	8.26%	0.28	19.19		
Other	0.11	0.32	7.26		
N	970				

Note: Sampling weights applied in calculations of mean and standard deviation values.
Source: PIAAC 2012/2014, authors' calculations.

For the analysis we use a multiple regression based on the basic Mincer equation (Mincer, 1974). The main dependent variable is individual earnings, measured by the log of the respondents' monthly income, excluding bonuses, converted to 2012 US dollars. The main OLS equation to be estimated is as follows:

$$log(y_i) = \beta_0 + \gamma_{1j} Major_j + \beta_2 Skill_i + \beta_3 Gradschool_i + \gamma_{2j} Major_j * Skill_i + X_i + \varepsilon_i$$

where y_i is the monthly income of individual i. Monthly income is logged in our regressions in order to transform the income into a normal distribution, since earnings distributions tend to be skewed upwards due to a small number of high earners (Heckman & Polachek, 1974). Our main independent variables of interest are $Major_j$ and $Skill_i$. $Major_j$ is an indicator variable for major j. It is the academic major for one's highest educational degree, and among five different majors "teacher training and education science" (hereafter "education") is used as the reference group. $Skill_i$ is the PIAAC score for individual i, separately, for each skill variable (numeracy and literacy). The interaction between $Major_j$ and $Skill_i$ represents the degree to which returns to cognitive skills varies across majors. More specifically, it shows how the association between cognitive skills and earnings for graduates of a certain major differs compared to the cognitive skill-earnings association for the reference group (i.e. education majors). For each skill variable (numeracy and literacy), all ten plausible values are utilized, and the scores are standardized to have a mean of zero and standard deviation of one across the working sample. $Gradschool_i$ is a dummy variable with a value of one if the respondent's highest educational attainment exceeds a bachelor's degree (i.e. master's or doctoral degree), and zero otherwise. X_i is a vector of control variables for demographic and socioeconomic background of individual i, including work experience, gender, immigrant status, race, and parents' highest level of education. Also included in X_i is the degree of skill-use that takes place at work. This was added to account for that fact that utilization of skills in the work place could affect an individual's development of skills. For models with numeracy we add "numeracy at work," an index designed to measure the degree to which numeracy skills are used at work, and for models with literacy we add "read at work" and "write at work," which measure the extent to which reading and writing is required for one's work. ε_i is the error term. The squared value of work-experience is added to the model to account for the quadratic relationship between work experience and earnings; earnings tend to increase at a faster rate earlier in the career compared to later years (Heckman & Polachek, 1974). As the two skill domains are quite highly correlated (correlation of 0.8), rather than including numeracy and literacy simultaneously in the same models, we analyze the two skills separately. The high degree of correlation would make it difficult to distinguish one from the other. For all regressions, the *repest* macro for Stata was used, which incorporates the full set of replicate weights and sampling weights, and uses the Jackknife 2 method for the estimation of standard errors.

Limitations

This study has some obvious limitations. The measure of cognitive skills in this study reflects learning that takes place throughout the life course; it is a combination of learning done in formal educational settings, in the work place, and in informal everyday life. The skill measure does not differentiate between cognitive skills learned before, during, or after college. Data for earnings were collected at the same point in time as cognitive skills. Therefore, causal relationships cannot be established. While controlling for years of work experience and the degree of skill-use in the workplace would account for a portion of the skill development that takes place in the work place, this study is unable to fully disentangle the cognitive skill development that takes place before, during and after college., What we can establish is the association between cognitive skills (wherever they are developed) with earnings while accounting for college majors.

In addition, while cognitive skills and majors are important, they are by no means the only factors relevant to earnings and other labor market outcomes. Rumberger & Thomas (1993) show that for certain majors, institutional selectivity has a significant impact on earnings, however, due to data limitations we are not able to account for institutional selectivity in our analyses. Also, economic context matters; economic growth at both national and regional levels affect individual earnings and employment. Family status can also play a role, as factors like the number of dependents and marital status [5] can influence one's labor market choices and opportunities. Additionally, more intrinsic and personal factors like individual preference, interests, and motivation may affect one's earnings and occupation, net of the effects of academic major and cognitive skills. Although this study is unable to account for all such factors directly in the analyses, future research that incorporates them would enhance the understanding of the relationship among cognitive skills, major, and earnings.

Lastly, the sample size of 970 may be a relatively small sample, when considering the fact that it is to represent the labor market for those aged 25-65 in the U.S. Table A2. in Appendix A compares demographic characteristics of the analytical sample and those of U.S. census data. It is evident that the characteristics are generally similar.

Another limitation is that the variable for the respondent's academic major is that of his or her highest educational level. In other words, for those who have attained degrees in graduate school, the indicator variable for academic major may be different from the academic major that the respondent studied during his or her undergraduate years. This means that the variable design may not fully reflect the policy discussions on academic majors and earnings, which largely focus on undergraduate majors. We address this issue by controlling for graduate school attainment. We do not exclude graduate degree holders from the sample because of the drastic reduction in sample size that would result from such a restriction (approximately 40% of the working sample) and the

[5] Although PIAAC includes data on the employment status of spouses, due to a large number of observations with missing data (approximately 25% of the working sample), this study does not directly account for them.

strong association with earnings that graduate degrees have been shown to have in the labor market (Carnevale, Cheah, & Hanson, 2015).

Findings

Table 2 and Table 3 report the estimates of equation 1 for numeracy and literacy, respectively. The baseline findings (Model 1 in Table 2 and Model 1 in Table 3) confirm previous research on the economic returns to majors, that is, some fields of study are associated with higher earnings than others. Our regression models include a vector of individual characteristics, majors, cognitive skills, earnings, and major fields of study, with ‘education’ as the reference group. The field of study with the greatest earnings difference compared to education majors is ‘STEM.’ Compared to education majors (the omitted category), on average, STEM majors earn 34% more in monthly income. This model corroborates other studies concluding that college major is associated with earnings (Berger, 1988; Carnevale, Cheah, & Hanson, 2015; Finnie & Frenette, 2003; Hecker, 1996; Thomas & Zhang, 2005).

For both Tables 2 and 3, Model 2 adds the measure of cognitive skill to Model 1. Most of the coefficients for the majors are still significant with the addition of the cognitive skills variable. Furthermore, both numeracy and literacy, as an independent variable are significant predictors of monthly income at the $p = <.001$ level. Coefficient estimates for numeracy and literacy reveal that higher numeracy and literacy by a single standard deviation are associated with higher earnings of approximately 16.7% and 14.9%, respectively. Said another way, on average, workers who scored approximately 43 points higher on numeracy and 38 points higher on literacy (one standard deviation) earn 16.7% and 14.9% higher earnings compared to their peers who graduated with the same majors.

Model 3 adds controls for factors that may affect earnings, including gender, years of work experience, graduate school attainment, immigrant status, parents' level of education, and race. We see that differences in earnings across majors persist and cognitive skills maintains the positive and significant association with earnings. We also see that females, on average, earn less than males, that whites and Asians tend to earn more than Hispanics, and that those with graduate degrees earn more than non-graduate degree holders. The two coefficient estimates for the quadratic form of years of experience are statistically significant, but while it is positive for the first term, it is negative for the squared term. This reflects the fact that the relationship between earnings and experience is positive on average, but the growth rate of earnings, rather than occurring in linear fashion, declines with more years of experience (Mincer, 1974). While more recent studies have updated the modelling of wage growth using longitudinal data, we deemed that for this study, the cross-sectional nature of the PIAAC data makes it appropriate to incorporate a simple quadratic growth pattern of earnings.

Model 4 in Table 2 and Table 3 adds interaction terms between the cognitive skill measures and majors and include the full set of controls. The interaction between cognitive skills and majors allows us to see how the relationship between cognitive skills and earnings varies across majors; how the returns to cognitive skills is different for graduates of different fields of study. The results indicate that the association between cognitive skills and earnings are indeed different for different majors; compared to education majors, social science and STEM majors experience greater returns to cognitive skills. The returns to numeracy and literacy are the highest for social science majors; approximately 21 percentage points higher for numeracy and 16 percentage points higher for literacy, than that of education majors.

In Model 5 of Tables 2 and 3 we add the degree of skill-use for each domain. In regressions with numeracy we add "numeracy at work," and in regressions with literacy we add "read at work" and “write at work.” Adding the skill-use variables diminishes the size of the coefficients for the interactions between college major and skill domain, but the coefficients are still positive and statistically significant. If the frequency of using certain skills in the work place is positively associated with development of that skill, the skill-use variable could partially control for skill development that takes place in the work place.

Table 2. OLS Regression on monthly earnings – Numeracy

Dependent Variable: Log (Monthly Earnings)	(1)	(2)	(3)	(4)	(5)
Major					
Education (omitted)					
Humanities	0.104	0.041	0.144*	0.200**	0.229**
	(0.073)	(0.069)	(0.072)	(0.077)	(0.074)
Social sciences	0.327***	0.254***	0.340***	0.394***	0.378***
	(0.055)	(0.055)	(0.057)	(0.058)	(0.054)
STEM	0.342***	0.231***	0.309***	0.370***	0.323***
	(0.063)	(0.067)	(0.065)	(0.064)	(0.067)
Health and welfare	0.234**	0.231**	0.324***	0.384***	0.380***
	(0.084)	(0.083)	(0.069)	(0.083)	(0.083)
Numeracy (standardized)		0.167***	0.119***	-0.051	-0.020
		(0.025)	(0.026)	(0.045)	(0.038)
Numeracy at work					0.080***
					(0.021)
Female			-0.154***	-0.142**	-0.149***
			(0.044)	(0.043)	(0.042)
Work experience			0.032***	0.033***	0.033***
			(0.007)	(0.007)	(0.007)
Work experience^2			-0.001***	-0.001***	-0.001***
			(0.000)	(0.000)	(0.000)
Graduate school			0.260***	0.254***	0.228***
			(0.043)	(0.042)	(0.044)
Immigrant			0.018	0.019	0.026
			(0.065)	(0.065)	(0.064)
Parents' education					
Below high school (omitted)					
High school			-0.063	-0.069	-0.041
			(0.072)	(0.069)	(0.079)
Above high school			-0.038	-0.040	-0.008
			(0.079)	(0.074)	(0.081)
Race					
Hispanic (omitted)					
White			0.240*	0.247*	0.231**
			(0.100)	(0.100)	(0.088)
Black			0.172	0.182	0.172
			(0.100)	(0.104)	(0.109)
Other			0.143	0.155	0.160
			(0.112)	(0.109)	(0.100)

Major * Numeracy					
Education * Numeracy (omitted)					
Humanities * Numeracy				0.180*	0.093
				(0.074)	(0.069)
Social Science * Numeracy				0.210***	0.176***
				(0.054)	(0.048)
STEM * Numeracy				0.166**	0.130*
				(0.061)	(0.051)
Health * Numeracy				0.192	0.150
				(0.117)	(0.119)
Observations	974	974	974	974	925
R-squared	0.045	0.121	0.233	0.243	0.261

Notes: Least squares regression weighted by sampling weights.
Standard errors in parentheses. *** p<0.001, ** p<0.01, * p<0.05
Source: PIAAC 2012/2014, authors' calculations.

Table 3. OLS Regression on monthly earnings – Literacy

Dependent Variable: Log (Monthly Earnings)	(1)	(2)	(3)	(4)	(5)
Major					
Education (omitted)					
Humanities	0.104	0.048	0.138	0.174*	0.214**
	(0.073)	(0.071)	(0.072)	(0.078)	(0.073)
Social sciences	0.327***	0.275***	0.344***	0.379***	0.398***
	(0.055)	(0.052)	(0.057)	(0.058)	(0.056)
STEM	0.342***	0.284***	0.323***	0.363***	0.356***
	(0.063)	(0.064)	(0.064)	(0.063)	(0.062)
Health and welfare	0.234**	0.212**	0.310***	0.352***	0.353***
	(0.084)	(0.080)	(0.068)	(0.072)	(0.066)
Literacy (standardized)		0.149***	0.118***	-0.012	0.020
		(0.023)	(0.022)	(0.040)	(0.038)
Read at work					0.068**
					(0.025)
Write at work					0.044*
					(0.017)
Female			-0.186***	-0.176***	-0.167***
			(0.042)	(0.042)	(0.038)
Work experience			0.032***	0.033***	0.032***
			(0.007)	(0.007)	(0.007)
Work experience^2			-0.001***	-0.001***	-0.001***
			(0.000)	(0.000)	(0.000)
Graduate school			0.259***	0.256***	0.216***
			(0.042)	(0.041)	(0.045)
Immigrant			0.046	0.053	0.083
			(0.064)	(0.064)	(0.057)
Parents' education					
Below high school (omitted)					
High school			-0.039	-0.045	-0.045
			(0.071)	(0.070)	(0.082)
Above high school			-0.025	-0.030	-0.045
			(0.080)	(0.077)	(0.086)
Race					
Hispanic (omitted)					
White			0.235*	0.239*	0.220*
			(0.101)	(0.101)	(0.100)
Black			0.136	0.142	0.092
			(0.098)	(0.101)	(0.109)

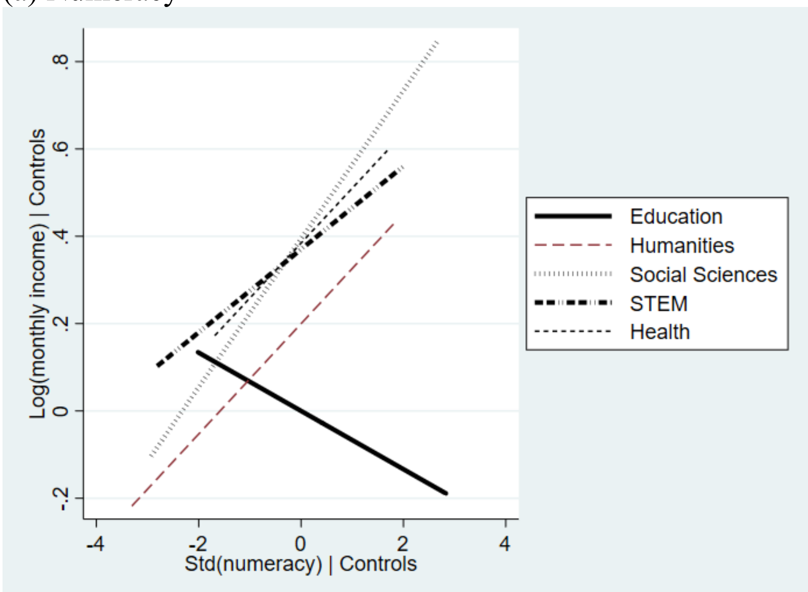
Other			0.141	0.147	0.126
			(0.111)	(0.108)	(0.102)
Major * Literacy					
Education * Literacy (omitted)					
Humanities * Literacy				0.136*	0.066
				(0.069)	(0.057)
Social Science * Literacy				0.160**	0.129*
				(0.056)	(0.055)
STEM * Literacy				0.114*	0.099*
				(0.052)	(0.050)
Health * Literacy				0.183	0.137
				(0.109)	(0.119)
Observations	974	974	974	974	956
R-squared	0.045	0.108	0.233	0.24	0.241

Notes: Least squares regression weighted by sampling weights.
Standard errors in parentheses. *** p<0.001, ** p<0.01, * p<0.05
Source: PIAAC 2012/2014, authors' calculations.

Figure 3 provides a visual representation of the relationship between log earnings and cognitive skills for each major, predicted through Equation 1 with the full set of controls. While education majors display a negative slope, the coefficient estimate is not statistically significant. There are statistically significant returns to numeracy for graduates of humanities, social sciences and STEM majors, and statistically significant returns to literacy for humanities, social sciences, and health majors. In other words, among graduates with the same major, people with higher literacy and numeracy skills tended to have higher earnings. In addition, it is evident that although there are mean differences in earnings across majors, high-skilled individuals of relatively low-earning majors (e.g., humanities), earn more than low-skilled individuals of relatively high-earning majors (STEM).

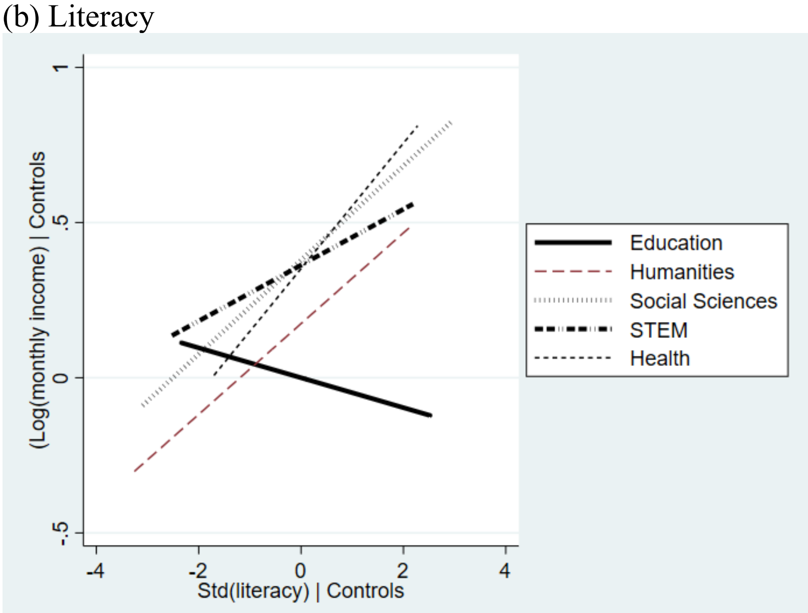
Figure 3. Added variable plots - Monthly income and cognitive skills

(a) Numeracy



Note: Plots based on regressions weighted by sampling weights. Humanities, Social Sciences and STEM majors have slopes that are statistically significant at the p <. 05 level. The first plausible value of numeracy was used.
Source: PIAAC 2012/2014, authors' calculations.

(b) Literacy



Note: Plots based on regressions weighted by sampling weights. Humanities, Social Sciences, and Health majors have slopes that are statistically significant at the $p < 0.05$ level. The first plausible value of literacy was used.
Source: PIAAC 2012, authors' calculations.

Discussion

Variation in earnings of college graduates across different majors has been well documented through research, with consistent patterns being found over time. In general, science, engineering, and health majors have obtained a significant earnings premium compared to graduates of other fields of study. Human capital theory would posit that such variation in earnings is stems from differences in the degree to which the knowledge and skills conferred by different majors contribute to economic productivity. Within the human capital framework, it is also possible to differentiate between general human capital, or skills and knowledge that have relevance across fields, and human capital that is very specific to a certain field or occupation (Kinsler & Pavan, 2015). While media and public policy discussion on college majors and earnings have tended to only consider the human capital that is specific to certain majors, general human capital, which can be obtained regardless of one's college major, can also contribute significantly to earnings.

The findings of our study indicate the plausibility of the hypothetical scenarios among majors, cognitive skill, and earnings illustrated in Figure 2, for example, that highly skilled education majors could out-earn lower-skilled engineering majors. This suggests that a nuanced definition of human capital, one that includes cognitive skills from general learning, should be considered in concert with majors as a force driving labor market earnings. Focusing on higher education reforms that cultivate generalizable literacy and numeracy skills development on campus -- across all majors -- would best serve students to thrive in their economic futures.

In light of these findings, parents, advisors and policymakers may be encouraged to focus on the cognitive skills that students cultivate on campus, not just the major field that is printed on their diplomas when they graduate. A relevant initiative to this end is the adoption of a common, skill-based curriculum that cuts across all majors. This has most often been advocated for by liberal arts colleges. An example for this line of reasoning and this type of problem-based interdisciplinary curriculum has been proposed by the American Association of University Professors (Sternberg, 2008). Additionally, the Lumina Foundation, one of the largest donors of higher education research and innovation, been recently advocating for "high quality credentials," rather than just "credentials." High quality credentials refer to certificates and degrees that lead directly to employment and/or further education, both in the short- and long-run (Lumina Foundation, 2017). The new, added emphasis on not just credentials, but "high quality" credentials, is in line with the findings of this study. Credentials that certify the learning of high level math and literacy skills (no matter the major) are indeed high quality and garner returns for the degree holder.

Degrees that certify high levels of generalizable skills match a shifting labor market. First, this is because projections suggest that the nature of work has changed, millennials, on average, have four jobs by the time they are 32 and are expected to change careers five times during their working years. Therefore, it is unlikely that the content knowledge that they learn through their majors alone will ensure their economic future; a combination of strong job-specific knowledge and general skills appear to be a more promising route for economic success. Secondly, our findings suggest that cognitive skills play a role in determining within-major earnings differences. For example, while STEM majors on average earn high incomes, low-skilled STEM graduates earn less than their highly skilled STEM peers.

We find that it was a college graduate's cognitive skills in conjunction with their major, that was predictive of their income (see Figure 3). The group of students most at risk for low labor market returns are those who graduated with both low math and verbal skills, these students within each major, reaped the lowest labor market returns. While we show that there is generally a positive association between cognitive skills and earnings within different majors, future research in this area could look more closely into the differential associations between skill type and college major.

Conclusion

The analyses in this study demonstrate that college majors are not the end all be all when thinking about labor market outcomes. Our findings indicate that considering cognitive skills is useful when estimating the relationships between majors and earnings. That is, within each major, earnings varied by levels of cognitive skills. We understand this finding to support a human capital framing of labor market returns: skills and competencies, rather than credential alone, proved to be important in determining labor market returns. As previously mentioned, the findings do not establish a causal relationship between skills and earnings. The skill measures we use are a culmination of learning that takes place in various environments throughout the life course, including before, during, and after one's college years. While much effort goes into encouraging students to pursue specific majors that are perceived to be lucrative, our assessment is that more attention may need to be given to development of general literacy and numeracy skills, as they have the potential go the distance in garnering labor market rewards. In other words, investments in developing students' writing, critical thinking and numeracy skills *across and within majors* would be a strong step toward ensuring that universities are best serving students.

Our findings provide hints on the potential positive labor market outcomes associated with developing curriculum that allows students to develop and practice math and literacy skills, regardless of major. Recent work has demonstrated that many students in higher education do not make measurable gains in critical thinking over the course of four years (Arum & Roksa, 2011). Most students reported that (across majors) they were not assigned forty pages of reading a week or twenty pages of writing a semester (Arum & Roksa, 2011). If universities do not ask students to practice these cognitive skills it is unlikely that they will develop them further.

Building on the findings of the study, a future research topic is examining the degree to which working in fields that have direct ties to one's major affects the skills-earnings relationship. Not all graduates of a given major work in a field that is directly relevant to what is taught in that major. It would be interesting to examine how the role of job-specific and general skills changes depending on how well-matched the field of work is to the field of study.

Another topic of future research is an internationally comparative study about the relationship between cognitive skill, majors and earnings. The relationship between skills, majors and earnings may vary across educational systems because due to factors such as differences in way college admission is done (e.g., admission to a major versus admission to a college) and differences in social perception (e.g., the value put on the prestige of an institution). The PIAAC data from other countries can be used to explore these patterns beyond the United States.

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Appendix A

Table A1. Variables of interest

Variable	Description & Coding	Mean	SD	N
Dependent Variable				
Monthly income	Monthly income, excluding bonuses, for wage/salary workers (self-employed excluded)	6122.41	3573.19	970
Covariates				
Numeracy	Respondent's level of numeracy	299.07	43.04	970
Literacy	Respondent's level of literacy	307.28	38.02	970
Education	1 if respondent's academic major for highest education level is "Teacher training and education science"	0.14	0.35	130
Humanities	1 if respondent's academic major for highest education level is "Humanities, language and arts"	0.14	0.34	130
Social sciences	1 if respondent's academic major for highest education level is "Social sciences, business and law," "General studies," or "Services"	0.36	0.48	360
STEM	1 if respondent's academic major for highest education level is "Science, mathematics and computing," "Engineering, manufacturing and construction," or "Agricultural and veterinary"	0.25	0.44	230

Health	1 if respondent's academic major for highest education level is "Health and welfare"	0.11	0.32	110
Graduate school	1 if respondent completed graduate school	0.41	0.49	390
Female	1 if respondent is a female	0.51	0.50	540
Work experience	Years of paid work during lifetime	21.61	11.57	970
Immigrant	1 if respondent is an immigrant	0.19	0.39	180
Parent below high school	1 if highest of mother's or father's education level is below high school	0.06	0.23	50
Parent high school	1 if highest of mother's or father's education level is high school	0.36	0.48	340
Parent above high school	1 if highest of mother's or father's education level is above high school	0.58	0.49	580
Hispanic	1 if respondent is Hispanic	0.05	0.22	50
White	1 if respondent is White	0.75	0.43	710
Black	1 if respondent is Black	0.08	0.28	100
Other	1 if respondent is Other race	0.11	0.32	110

Notes: Sampling weights applied in calculations of mean and standard deviation values.
Source: PIAAC 2012/2014, authors' calculations.

Table A2. Comparison of analytical sample and census data

	Current Population Survey	Analytical sample
Graduate	35.12%	40.80%
Female	47.20%	50.92%
Hispanic	5.72%	5.32%
White	77.52%	75.21%
Black	7.42%	8.26%
Other	9.03%	11.21%

Source: CPS data (Census Bureau); PIAAC 2012/2014, authors' calculations.