The Importance of Skills to North Carolina's Occupational Wages

Is it better to focus efforts on acquiring academic credentials or skills if you're working toward building a good-paying career? The answer, not surprisingly, is both. The following research gives evidence to the relationship between education, skills, and wages and quantifies their impacts on North Carolina occupations.

Among the most relevant findings are:

- Various professional aspects of human capital are determined by a combination (or interaction) of individual skills rather than by distinctive skills alone. Therefore, a variety of unique skills can be non-exclusively grouped into broader categories. Based on their composition of skills, we labeled these categories as General, Management, STEM, and Technical with different weights attached for each skill. "Active Learning" and "Systems Analysis" are examples of skills that are important to three different categories - General, Management, and STEM skills. Educators and workforce training specialists may find these results helpful for identifying skills which can be taught across different curriculums.
- Human capital – as proxied by various skills – significantly contributes to workers' compensation, as do education, experience, and career field. General and STEM skills have the largest explanatory power on variation in compensation; occupations that require one standard deviation higher STEM or General skills pay 14.5% and 10.8% higher wages, respectively. For Management skills, a difference of one standard deviation in the requirements between two occupations would be responsible for a 6.5% wage gap. Technical skills are found to have a relatively minor effect (2.5%) on wage determination.
- Once controlled for skills, the impact of education on wages is found to drop by more than half at each degree level. For example, compared to occupations with no formal degree required, the effect of high school education on higher wages declines from 33% to 15% when controlling for skills. For Bachelor's degrees, this effect on the wage differential diminishes from 137% to 57%. For Doctoral degrees it drops from 255% to 119%. These findings strongly indicate that individual skills are important complements to formal education in determining workers' compensation.
- The previous work experience required for entry, while being a significant contributor to wages, is also found to exert a significantly smaller influence when controlling for required skills. When no skills are included, job experience of up to 5 years is responsible for up to 31% higher wages compared to 20.7% when controlling for skills. For work experience of 5+ years it is 56% and 39% higher, respectively.
- Wage inequality between the majority of occupational clusters is reduced or eliminated once accounting for skill requirements in each field.
- When analyzing the effect of education on skill formation, our results indicate that the General skills requirement increases progressively with each additional educational attainment required. Technical Skills are more heavily related to occupations requiring fewer years of formal education (high school diploma, some college, and Associate's degree) – suggesting these skills may be acquired through high school or community college education; certification or credentialing programs; and/or other formal or informal training opportunities. Bachelor's and Master's degrees are typically the largest contributors to the strong Management skills. STEM skills are correlated

with occupations that require education at an Associate's degree or higher, but particularly at the Bachelor's and Doctoral degree levels.

- From an historical perspective, the financial return for STEM skills, in the form of wages, remained constant between 2002 and 2016. For General skills it slightly decreased. Compensation for Management skills was found to be strongly affected by the business cycle. Similar pro-cyclical effect was exhibited by General skills as well. The effect of Technical skills on occupational wages slowly increased over the past 15 years, although it still remains relatively low comparing to the rest of skills.
- For educational attainment, the return for High School and Some College remained flat for the whole period, while occupations that require Associate's or higher degrees have seen an increase in the reward for education. The wage gap between occupations with no degree and an Associate's degree requirement increased from 39% to 45%. For the Bachelor's and Master's degree this difference changed from 46% to 57% and from 62% to 75%, respectively. The largest increase in the return to their education was experienced by the doctoral and professional degree holders – from 87% in 2002 to 119% in 2016.
- The return for Doctoral, Master's, and Bachelor's education exhibited a rather unexpected countercyclical behavior. Wage compensation for these degrees was found to decline before the official start of a recession, and increase when the economy was still experiencing a downturn. This may be the result of the reduction in lower-paid, lower skilled employees during the recession; and the subsequent growth in competition for highly-productive, well-educated workers to replace them.

Introduction

Traditionally, variables such as education, years of experience, and training are seen as the main indicators of workers' human capital and, consequently, are considered to be the main determinants of wages. However, it is reasonable to assume that the level of education or even years of work experience may not fully reflect someone's true skills, knowledge, or abilities. As pointed out by Ingram and Neumann [2006], *"Using the return to a college education as a measure of the skill premium, then, obscures the differences among workers in terms of their obtained level of skill and the degree of compensation they earn as a result of that skill"*.

It is important to stress beforehand, that this research is carried out at the occupational level rather than at the level of individual workers. We merge occupational skill requirements from O*NET[1] with the Occupational Employment Statistics (OES)[2] data on wage and salary workers in nonfarm establishments. In this way we are examining the "demand side" of the labor market as the data consists of job characteristics required by employers and market wages they are willing to pay.

At the same time, it is also possible to match O*NET data with the Current Population Survey (CPS)[3] or the American Community Survey (ACS)[4], which provides information on the employment conditions of the U.S. households (i.e. the "supply side" of the labor market).

Each method has its pros and cons. While working on the demand side, we are losing a rich array of individual workers' characteristics proven to be valuable determinants of their pay - such as age, gender, race, parents'

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[1] The Occupational Information Network database (O*NET OnLine), is a program sponsored by the U.S. Department of Labor, Employment & Training Administration, and developed by the National Center for O*NET Development. https://www.onetonline.org

[2] http://www.bls.gov/oes/

[3] http://www.bls.gov/cps/ , http://www.census.gov/programs-surveys/cps.html

[4] https://www.census.gov/programs-surveys/acs/

education, etc. However, we believe that using the OES data provides a better estimate of the true return on skills as compared to the data on individuals. This is mainly because the latter requires a rather strong assumption that a close match exists between workers' skills and their job requirements. Since many workers can be either overqualified or underqualified for their jobs, their pay does not truly evaluate real skills and talents. Additionally, as mentioned by Autor and Handel [2009]: "*Given the nonrandom assignment of workers to occupations, a regression of log wages on workers' job tasks will not generally recover the average returns to those tasks. Concretely, workers with high efficiencies in given tasks will sort towards occupations that have high rewards for those tasks. The average 'return to tasks' observed in the data will therefore not correspond to the average return over all occupations*".

Skills

Data on skill requirements is obtained from the O*NET OnLine database[5] which classifies 35 various skills[6] required by more than 960 occupations. The information is based on surveys of incumbent workers, occupational experts and analysts who provide and review information on knowledge, skills, abilities, educational level, experience, and training requirements for a particular occupation. Although O*NET collects data throughout the U.S., we assume that specific job requirements would be similar for North Carolina.

For each occupation, the O*NET skills domain is evaluated across two dimensions – level and importance. While importance reflects the significance of a specific skill for a given occupation, level measures the degree to which that skill is necessary to perform essential job duties. Importance is measured on a scale from "Not Important" (1) to "Extremely Important" (5); level ranges from 0 to 7 and is assessed differently for each skill. For example, the skill "Time Management" can have the following levels[7]:

- Level 2 - Keep a monthly calendar of appointments;
- Level 4 - Allocate the time of subordinates to projects for the coming week;
- Level 6 - Allocate the time of scientists to multiple research projects.

While "Active Learning" is quantified at the following levels:

- Level 2 - Think about the implications of a newspaper article for job opportunities;
- Level 4 - Determine the impact of new menu changes on a restaurant's purchasing requirements;
- Level 6 - Identify the implications of a new scientific theory for product design.

Importance and level are both detrimental for identifying skill value, therefore we combined two measurements into a single metric. Another reason for this is to avoid collinearity - for the majority of skills level and importance appear to be highly correlated. That is, if an occupation attaches high importance to a specific skill, it is usually the case that level requirement also will be relatively high. Some researchers (Maxwell [2008], Yakusheva [2010]) use a single dimension of skill assessment (mostly importance) in their work, others average importance and level. Either alternative may result in undermining one measurement and overestimating another. Therefore, we follow the suggestion by Florida [2011] and Feser [2003] and multiply skill importance and level. To ensure the comparability of the scale, before multiplying these two dimensions, we linearly rescale the level variable to the range [1-5] in order to match that for importance. The resulting score is often referred to in the literature as "Intensity" and ranges from 1 to 25. An additional advantage of taking a product of two measurements is that skills with relatively high importance and level will get multiplicatively higher weights compared to skills with moderate requirements.

[5] Database version 21.0, released in August 2016.

[6] Appendix A. O*NET skills classification" provides detailed description of all skills.

[7] Refer to https://www.onetonline.org/help/online/scales and https://www.onetcenter.org/dictionary/20.1/excel/level_scale_anchors.html for more information about the skill ranking and scales.

Factor analysis

Having 35 various skills covered by the O*NET dataset poses a problem of potentially overlapping measurements of unique worker's talents. For example, "Science" defined as "*Using scientific rules and methods to solve problems*" potentially coincides with "Complex Problem Solving" which stands for "*Developed capacities used to solve novel, ill-defined problems …*". Or strong "Operation Monitoring" described as "*Watching gauges, dials, or other indicators to make sure a machine is working properly*" might be a necessary pre-requisite for the developed "Equipment Maintenance" and "Repairing" skills which are associated with the ability to perform maintenance and repair equipment and machinery.

On the numerical side of this potential skill homogeneity problem, 15 out of 35 computed skill intensities have a pairwise correlation with one or more other intensities in excess of 0.85. In the simple OLS regression of the log-transformed wage on all skill intensities, the variance inflation factor was found to be larger than four for 31 out of 35 of skill regressors. Also, estimated coefficients often had unexpected, and potentially incorrect, signs, pointing to the substantial multicollinearity issue. Last but not least, introducing such a large number of explanatory variables to the regression would reduce the degrees of freedom and model parsimony.

In order to reduce the dimensionality and improve model robustness, academic literature typically suggests merging similar skills into a smaller number of categories. Abraham and Spletzer [2009] create three broad job activity measures (Analytic, Interpersonal, and Physical) by averaging various O*NET skills and abilities. Maxwell [2006] also uses three categories (Basic, Physical/Mechanical and Other) to combine O*NET and BALS[8] skills, knowledge, and abilities. Florida et al. [2011] defines Analytical, Social Intelligence, and Physical skill clusters in their study of regional wage dispersion. Hirsch and Schumacher [2010] classify 168 various O*NET variables into four categories - Cognitive, Mechanical, Assisting/Caring, and Administration/Management/Sales. Bacolod and Blum [2010] identify Cognitive, Motor, People and Physical skill categories out of 44 DOT[9] skill variables.

O*NET currently groups skills into six broad categories, however some of them (such as Complex Problem Solving Skills) may include only one skill, while Basic Skills group consist of as many as ten, and includes seemingly unrelated skills such as Critical Thinking, Mathematics, and Speaking. Also, it is not clear how skill weights should be assigned if skills were aggregated based on the O*NET classification. Therefore, we employ an exploratory factor analysis (EFA) in order to collapse 35 various skills into a smaller number of orthogonal factors. While reducing the number of dimensions, factor analysis is helpful for uncovering latent dimensions that influence the observable measures, or examining which items have strong mutual association. This method was proven to be beneficial in works by Koo [2005], Ingram and Neumann [2006], Maxwell [2008], Hirsch and Schumacher [2010], and others.

Out of 35 skill vectors we extract four factors[10] which explain nearly 78% of the variation across all data. Estimated factor loadings are provided in Appendix B. Factor orthogonality helps to avoid the situation when different skills evaluate the same dimension of worker's ability. The first factor explains 24% of the common variance and places the heaviest loadings on such general skills as Listening, Speaking, Writing, Reading Comprehension, Critical Thinking, Active Learning, etc. At the same time, negative weights are attached to technical skills which describe controlling, maintaining, and fixing equipment characteristics. Therefore, for the convenience of exposition, we label this factor "General skills".

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[8] Bay Area Longitudinal Surveys

[9] The Dictionary of Occupation Titles, http://www.occupationalinfo.org/

[10] Parallel analysis and Kaiser rule suggest using five factors. However, the fifth factor adds only 2% to the explained data variation and improves R^2 in the subsequent regression by less than 0.003. None of the loadings for this factor exceeds 0.5, and only Active Listening and Speaking have coefficients larger than 0.4. Assuming these skills are well enough captured by the first factor (General skills), we decide to exclude fifth factor from the analysis.

In contrast, the second factor heavily loads Equipment Maintenance, Repairing, Equipment Selection, Troubleshooting, Operation Monitoring, Quality Control Analysis, Operation & Control, and Installation skills. It has the characteristic opposite of Speaking, Listening, Writing, Service Orientation, and other General skills. We label this factor "Technical skills", accordingly. Technical skills factor accounts for 20% of the data variation.

The largest weights for the third factor are associated with Coordination, Management of Material, Personnel, and Financial Resources, and Negotiation skills, therefore we title it as "Management skills." The last factor (labeled as "STEM skills") has the largest coefficients for Mathematics, Programming, Operations Analysis, Science, Systems Analysis, and Technology Design. Management and STEM factors explain 17% and 15% of the original skill variation, respectively.

We believe that the four factors described above provide a better classification of unique worker's abilities as compared to the O*NET skill grouping. Unlike the "hard" categorizing by O*NET, when each skill is placed into a single group, factor analysis, by construction, accounts for all interactions between skill dimensions, allowing skills to be allotted to multiple clusters. For example, Time Management, Persuasion, and Social Perceptiveness are important for the Management category, but they also play a significant role in General skills. General and Management factors also share Systems Evaluation, Systems Analysis, and Judgment skills with the STEM factor, while all three attach negative weights to many technical skills.

Original skill intensity values and factor loadings are then converted into factor scores which are used as explanatory variables in the regression analysis.

Other variables

Standard Occupational Classification (SOC) codes are used to match O*NET data on skill characteristics to the median annual wages from 2016 Occupational Employment and Wages (OES) database[11]. For several occupations O*NET classification was more detailed than the OES data; in such cases O*NET skills data was averaged.[12]

Occupational wages are log-transformed and used as a dependent variable in regression (1). The final dataset consists of 700 observations on detailed occupations. The standard test for outliers indicate that wages above $180,000 (0.7% of the total sample) lie outside the 1.5*IRQ (the interquartile range); all of them are from the healthcare field. We removed these values from the analysis since select, highly-compensated healthcare specialists lie outside the norm of occupations in the sector and can skew results.[13]

Typical education needed for entry and work experience in a related occupation are provided by the U.S. Bureau of Labor Statistics[14]. BLS data also contains information on typical on-the-job training needed to attain competency in the occupation, however, we find this data rather inconsistent[15] and therefore exclude it from our estimation.

Occupational clusters data is obtained from O*NET; all occupations are divided into 16 clusters[16] with the possibility that occupations can belong to different clusters.

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[11] Source: NC Department of Commerce, Labor and Economic Analysis Division, http://d4.nccommerce.com/

[12] For example, skill requirements for O*NET occupations 13-2011.01 "Accountants" and 13-2011.02 "Auditors" were averaged to match 13-2011 "Accountants and Auditors" from OES.

[13] As a part of a robustness check of our model, we estimate a regression with extreme observations included; there was found a subtle effect on the main conclusions.

[14] Source: http://www.bls.gov/emp/ep_table_112.htm

[15] For example, according to the BLS data, some high-skilled occupations such as Nuclear engineers or Information Security Analysts require no on-the-job training while Paperhangers and Photographers are indicated as jobs that need long-term training.

[16] These clusters are: Agriculture, Food and Natural Resources; Architecture and Construction; Arts, Audio/Video Technology and Communications; Business Management and Administration; Education and Training; Finance; Government and Public Administration; Health Science; Hospitality and Tourism; Human Services; Information Technology; Law, Public Safety, Corrections and Security;

The Model

We employ the traditional Mincer [1974] earnings model which models workers' earnings as a function of their education, experience, and other relevant characteristics:

$$\ln Wage_i = \beta_0 + \beta_1 * Skill_i + \beta_2 * Education_i + \beta_3 * Experience_i + \beta_4 * Cluster_i + \varepsilon_i \qquad (1)$$

where ln$Wage_i$ is a logarithm of the median annual wage for the occupation *i*, $Skill_i$ is a skill factor score attributed for the occupation *i*, $Education_i$ reflects educational attainment, $Experience_i$ is work experience in a related occupation, and $Cluster_i$ is an indicator variable for the occupational cluster.

Results

Return on skills

Columns 2 and 4 in Table 1 summarize the results from the OLS regression (1] without and with skill variables included, respectively. Since the wage variable was log-transformed and skill factors by construction are normalized to have a mean of zero and a standard deviation of one, regression coefficients for skill factors can be interpreted as the percentage change in the Wage when a particular factor increases by one standard deviation above its mean level across all occupations. For indicator variables such as Education, Experience, and Cluster the effect on log-transformed wage can be calculated as $(e^{\beta} - 1)$ if $\beta>0$ and as $(e^{-\beta} - 1)$ if $\beta<0$. For convenience, corresponding transformed effects are provided in the subsequent columns 3 and 4.

Coefficient estimates for General, Management, and Science skill factors are highly significant. Occupations that require one standard deviation[17] higher General skills, are expected to pay of 10.8% higher wages. For example, taking Financial Managers occupation as a reference, such a difference in skills would be associated with the occupations that require major skills from the General group[18] to have a 1.3 points higher level (on the original O*NET level scale from 0 to 7) than financial managers while holding their corresponding importance unchanged. Similarly, comparing to Dishwashers occupation, occupations with one point higher General skill requirement (and a 10.8% higher wage, correspondingly) would require approximately 2.1 points higher levels for each major general skill.

A difference of one standard deviation in the Management skill requirement between two occupations would be responsible for 6.5% different wages. For example, this approximately corresponds to the managerial skill differences between Natural Sciences Managers (standardized Management skill factor score is 1.06), Computer and Information Systems Managers (score is 2.02), and Human Resources Managers (score is 3.08).

Variation in STEM skills has the largest effect on wages – it is 14.5% difference in wages for one standard deviation difference in skills. As an illustration, approximately one standard deviation in STEM skill requirements separates Electrical and Electronic Engineering Technicians (standardized STEM factor score is 0.68), Industrial Engineers (score is 1.62), Marine Engineers and Naval Architects (score is 2.64), and Mining and Geological Engineers (score is 3.74).

Technical skills factor appears to have much smaller influence on wages, its effect of 2.5% can be accepted only at 0.1[19] level of significance.

As expected, Education and Experience play crucial roles in determining someone's wage level. All education levels are highly significant and positively correlated with wages. For example, in the regression without skill

Manufacturing; Marketing, Sales and Service; Science, Technology, Engineering and Mathematics; Transportation, Distribution and Logistics.

[17] Or one point, since factor scores are normalized to a zero mean and a standard deviation of one.

[18] Here we count only skills from the General group that have factor loadings in excess of 0.5.

[19] p-value for the Technical skills factor is 0.073

factors, occupations that require a high school degree, pay approximately 33% more than occupations with no degree requirement; while those requiring a Doctoral degree pay 255% more.

However, there is a striking change when skill variables are accounted for. When skill factors are accounted for, the general pattern essentially remains the same – advanced education levels provide higher returns. However, compared to the results with no skills included, this effect appears to be reduced nearly by half. High school education provides a 15% wage increase (compared to no formal degree) while for the doctoral or professional degree it is 119%. This can be considered as the evidence that while formal education is important, workers' skills and abilities on top of their degree matter as well. Our results support previous findings. Murnane, Willett, and Levy [1995] find that controlling for cognitive skills adding high school math scores to the regression, would reduce the estimated return to college education by nearly half for either males or females. A similar drop in the value of formal education for personal skills is reported by Ingram and Neumann [2006] when different skill variables are introduced into the model.

Previous working experience also is found to be a significant contributor to wages. We again observe a pattern similar to the education case – when various skills are taken into consideration, the impact of work experience diminishes. When no skills are included, job experience of up to 5 years will provide up to 31% higher wages versus 21% when controlling for skills. For work experience of 5+ years it is 57% and 39% higher, respectively.

Median wages also differ between some of the occupational clusters. For example, jobs in Agriculture, Arts, Education, and Hospitality pay respectively 9.7%, 9.9%, 21.3%, and 14.1% less (regression with skill factors included) than the rest of the clusters, while Architecture, Finance, and Government jobs pay 8%, 16.9%, and 14.7% more, respectively. Earlier evidence of skills being a powerful wage determinant is also supported for the case of occupational clusters. The effect of higher than average compensation in the Manufacturing, STEM, and Transportation clusters disappears when skills are controlled for. Similarly, including skills eliminates the evidence of disproportionately low wages in the Human Services sector.

Observed compensation inequality is found to be smaller for Architecture & Construction, Arts, Audio/Video Technology & Communications, Education & Training, Government & Public Administration, Hospitality & Tourism, Human Services, and Information Technology when human skills are included. Only for two sectors - Agriculture, Food & Natural Resources and Finance – introducing skill variables significantly increases the estimated pay disparity with the rest of occupations.

However, one should be very careful when interpreting these results. For example, based on Table 1 results, Architecture and Construction (A&C) occupations pay 8% higher wages and Health Science wages are not significantly different from the rest of the occupations. At the same time, the average wage in Health Science is $54,781 while it is only $42,861 for the A&C cluster. This apparent inconsistency can be explained by the education requirements for each cluster. Out of 89 occupations represented in the A&C, the majority (76%) require no formal education or only a high school diploma, and only 12% require a Bachelor's degree. For Health Care these numbers are 24% and 16% (out of 90 occupations), respectively. At the same time, 29% of occupations in Health Science require advanced degrees (Master's, Doctoral, or professional) versus only 3% in A&C. Since advanced degrees are associated with significantly higher salaries, it is not the occupational cluster that is responsible for high Health Care wages, but education. Estimates in Table 1 indicate that if we consider two jobs, one from the Health cluster and one from the Architecture/Construction cluster, that require identical education, experience, and skill levels, then the latter will pay approximately 8% in higher average wages.[20]

[20] We replicated regression results without removing wage outliers above $180,000 since these are mostly belong to the Health Care, and results remain the same – Health Care cluster pays wages insignificantly different from the rest of clusters.

Table 1. Estimation results

Explanatory variable	Regression without skills		Regression with skills	
	Coefficient	Effect, %	Coefficient	Effect, %
1	2	3	4	5
Intercept	10.1 (0.04)***		10.37 (0.04)***	
Skills				
General			0.11 (0.02)***	10.8%
Technical			0.02 (0.01)*	2.5%
Management			0.06 (0.01)***	6.5%
STEM			0.14 (0.02)***	14.5%
Education				
High school	0.28 (0.03)***	33%	0.14 (0.03)***	15%
Some college or Postsecondary non-degree award	0.40 (0.05)***	50%	0.18 (0.05)***	20%
Associate's degree	0.65 (0.05)***	92%	0.37 (0.05)***	45%
Bachelor's degree	0.85 (0.04)***	133%	0.45 (0.05)***	57%
Master's degree	1.02 (0.06)***	177%	0.56 (0.07)***	75%
Doctoral or professional degree	1.27 (0.06)***	255%	0.78 (0.08)***	119%
Experience				
Less than 5 years	0.27 (0.04)***	31%	0.19 (0.03)***	21%
More than 5 years	0.45 (0.06)***	57%	0.33 (0.05)***	39%
Occupational Cluster				
Agriculture, Food and Natural Resources	-0.05 (0.03)*	-5.6%	-0.09 (0.03)***	-9.7%
Architecture and Construction	0.1 (0.03)***	10.8%	0.08 (0.03)**	8.0%
Arts, Audio/Video Technology and Communications	-0.16 (0.04)***	-17.9%	-0.09 (0.04)***	-9.9%
Business Management and Administration	0.05 (0.03)	4.8%	0.06 (0.03)*	5.7%
Education and Training	-0.28 (0.04)***	-32.8%	-0.2 (0.04)***	-21.7%
Finance	0.15 (0.05)***	16.3%	0.16 (0.05)***	16.9%
Government and Public Administration	0.14 (0.05)***	15.0%	0.14 (0.04)***	14.7%
Health Science	0.02 (0.03)	1.6%	0.003 (0.03)	0.3%
Hospitality and Tourism	-0.16 (0.04)***	-17.8%	-0.13 (0.04)***	-14.1%
Human Services	-0.13 (0.04)***	-14.0%	-0.07 (0.04)*	-7.6%
Information Technology	0.19 (0.06)***	21.5%	0.09 (0.06)*	9.8%
Law, Public Safety, Corrections and Security	-0.06 (0.05)	-6.4%	-0.07 (0.05)	-7.7%
Manufacturing	0.06 (0.03)**	6.6%	0.02 (0.03)	1.8%
Marketing, Sales and Service	0.08 (0.04)*	8.0%	0.06 (0.04)	6.3%
Science, Technology, Engineering and Mathematics	0.15 (0.03)***	15.9%	0.03 (0.04)	2.9%
Transportation, Distribution and Logistics	0.09 (0.04)**	9.1%	0.06 (0.03)*	5.7%
Regression diagnostics				
Adj. R-sq	0.71		0.76	
F-statistic	71.02	0.00	78.71	0.00
N obs.	700		700	
Breusch-Pagan heteroscedasticity test	29.70	0.20	29.41	0.39

OLS regression coefficients from model (1) with log(Wage) as dependent variable. Standard errors are given in parentheses. Significance levels: * significant at p<0.1; ** significant at p<0.05; *** significant at p<0.01;

Skill formation

Considering such an influential effect of skills in determining wages as well as reducing the importance of other factors, it would be natural to analyze where these skills are formed. Similar to Ingram and Neumann [2006] we regress skill factors on the educational attainment indicator variable (see Table 2). While it is hard to explicitly interpret estimated coefficients, their relative size and significance reveal some important relationships.

The level of General Skills associated with an occupation is correlated with an advance in educational attainment required – implying there is a skill attainment outcome, in additional to knowledge attainment, for each level of education. Technical Skills are more heavily related to occupations requiring fewer years of formal education (high school diploma, some college, and Associate's degree) – suggesting these skills are acquired through high school, community college, certification/credentialing programs, and/or on-the-job training. At the same time, occupations that require Bachelor's and Master's degrees do not place significant importance on the employees' ability to control, maintain, or repair machinery. Bachelor's and Master's degrees are typically the largest contributors to the strong Management skills. At the same time, doctoral and professional degrees are associated with occupations that do not require developed managerial capabilities. STEM skills appear to be most associated with occupations that require education at an Associate's degree or higher, but particularly at the Bachelor's and Doctoral degree levels.

Table 2 Skills and educational attainment

Educational Attainment	General Skills	Technical Skills	Management Skills	STEM Skills
No formal education	-1.17 (0.07)***	-0.27 (0.1)***	-0.35 (0.1)***	-0.61 (0.09)***
High school	0.83 (0.08)***	0.53 (0.11)***	0.26 (0.11)**	0.27 (0.1)***
Some college or Postsec. non-degree award	1.39 (0.12)***	0.84 (0.17)***	0.15 (0.16)	0.22 (0.15)
Associate's degree	1.45 (0.12)***	0.81 (0.17)***	0.21 (0.16)	0.86 (0.15)***
Bachelor's degree	1.53 (0.09)***	-0.1 (0.12)	0.94 (0.12)***	1.33 (0.11)***
Master's degree	2.41 (0.13)***	-0.3 (0.18)	0.54 (0.18)***	1.02 (0.16)***
Doctoral or professional degree	2.86 (0.12)***	-0.33 (0.17)*	-0.29 (0.16)*	1.24 (0.15)***

Results from the OLS regression with skill factor score as dependent variable. Standard errors are given in parentheses. Significance levels: * significant at $p<0.1$; ** significant at $p<0.05$; *** significant at $p<0.01$.

Return to skills over time

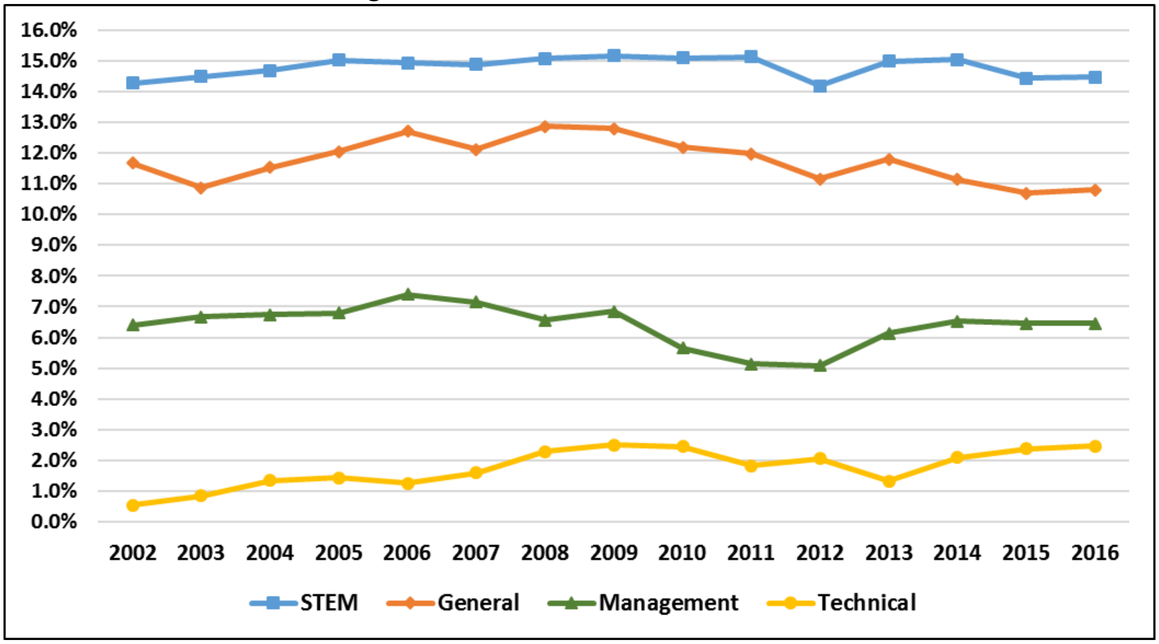
Neither OES data nor O*NET skill requirements are suitable for a time-series analysis. Nonetheless, it would be interesting to compare if our previous results hold for different time periods. Therefore, we estimated model (1) using the median wages reported by OES from 2002 to 2016; all dollar values were adjusted by the Employment Cost Index.[21] We also assume that occupational skill requirements remain unchanged over this time period, and therefore keep estimated earlier skill factors unchanged. While Knowledge or Tools & Technology requirements may change significantly over a short period of time in response to the market or technology changes, skills and abilities represent more fundamental capacities of the human capital, and are highly unlikely to experience a rapid perturbation in the short run.

Figure 1 shows estimated coefficients for the four skill groups. Return to STEM skills appears to be stable over time, minor variations can be attributed to statistical error. Compensation for General skills seems to be affected by the business cycle – it was increasing before the recession, reaching its maximum of 12.9% in 2008, and then descended by approximately 2 percentage points to its all-time minimum in 2016. Similar pro-cyclical behavior can be observed for the Management skills reward – it declined from its peak of 7.4% in 2006 to only

[21] http://www.bls.gov/ect/

5.1% in 2011,[22] however it recovered quickly to its pre-recessional level. Comparing to the rest of factors, impact of Technical skills on compensation remained relatively small for the whole period. However, it gradually increased over time rising from less than 0.5% in 2002 to the statistically significant 2.5% in 2009; it still continues to grow after the slight post-recessional decline.

Figure 1: Return to skills over time



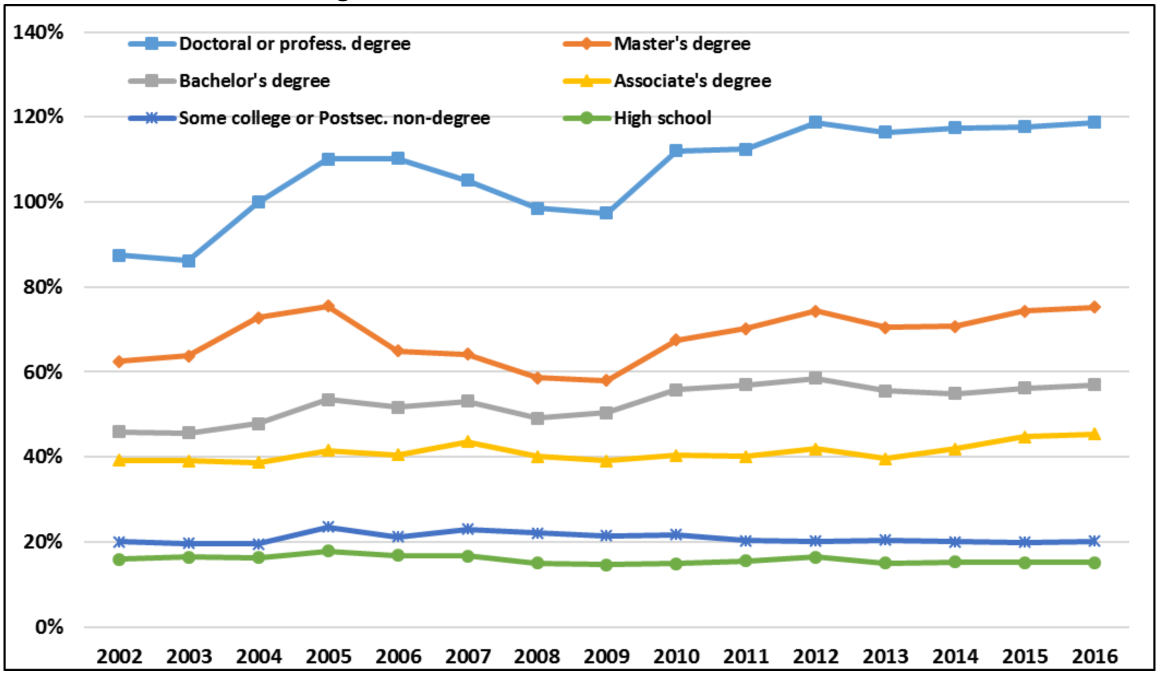
The return for education from 2002 to 2016 is shown in Figure 2. Effects of High School and Some College education remain flat for the whole period. Occupations that require Associate's, Bachelor's, or Master's degrees have seen a moderate increase in the reward for education. The wage gap between occupations with no degree and an Associate's degree requirement increased from 39% to 45%. For Bachelor's and Master's degrees, this difference changed from 46% to 57% and from 62% to 75%, respectively. The largest return was experienced by the Doctoral and Professional degree holders – from 87% in 2002 to 119% in 2016.

Historical estimates for education also allow us to capture another important fact. Returns for Doctoral, Master's, and Bachelor's degrees were clearly affected by the business cycle. However, for all three education levels, the reward for a higher degree started to deteriorate around 2004-2006[23] before the actual recession of 2007-2009 began. And all three education levels experienced an increase in a degree-related compensation beginning in 2008-2009 when the economy was still experiencing a downturn.

[22] Estimates released by BLS for a specific year are based on the six semiannual panels collected over a 3-year period; thus 2011 release would report the data collected between November 2008 and May 2011.

[23] Again, wage estimates for a specific year represent averaged values for 6 semi-annual periods preceding that year

Figure 2: Return to Education over time



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Appendix A. O*NET skills classification

Group	Skill	Description
Basic Skills	Active Learning	Understanding the implications of new information for both current and future problem-solving and decision-making.
	Active Listening	Giving full attention to what other people are saying, taking time to understand the points being made, asking questions as appropriate, and not interrupting at inappropriate times.
	Critical Thinking	Using logic and reasoning to identify the strengths and weaknesses of alternative solutions, conclusions or approaches to problems.
	Learning Strategies	Selecting and using training/instructional methods and procedures appropriate for the situation when learning or teaching new things.
	Mathematics	Using mathematics to solve problems.
	Monitoring	Monitoring/Assessing performance of yourself, other individuals, or organizations to make improvements or take corrective action.
	Reading Comprehension	Understanding written sentences and paragraphs in work related documents.
	Science	Using scientific rules and methods to solve problems.
	Speaking	Talking to others to convey information effectively
	Writing	Communicating effectively in writing as appropriate for the needs of the audience.
Complex Problem Solving Skills	Complex Problem Solving Skills	Developed capacities used to solve novel, ill-defined problems in complex, real-world settings
Resource Management Skills	Management of Financial Resources	Determining how money will be spent to get the work done, and accounting for these expenditures.
	Management of Material Resources	Obtaining and seeing to the appropriate use of equipment, facilities, and materials needed to do certain work.
	Management of Personnel Resources	Motivating, developing, and directing people as they work, identifying the best people for the job.
	Time Management	Managing one's own time and the time of others.
Social Skills	Coordination	Adjusting actions in relation to others' actions.
	Instructing	Teaching others how to do something.
	Negotiation	Bringing others together and trying to reconcile differences.
	Persuasion	Persuading others to change their minds or behavior.
	Service Orientation	Actively looking for ways to help people.
	Social Perceptiveness	Being aware of others' reactions and understanding why they react as they do.
Systems Skills	Judgment and Decision Making	Considering the relative costs and benefits of potential actions to choose the most appropriate one.
	Systems Analysis	Determining how a system should work and how changes in conditions, operations, and the environment will affect outcomes.
	Systems Evaluation	Identifying measures or indicators of system performance and the actions needed to improve or correct performance, relative to the goals of the system.
Technical Skills	Equipment Maintenance	Performing routine maintenance on equipment and determining when and what kind of maintenance is needed.
	Equipment Selection	Determining the kind of tools and equipment needed to do a job.
	Installation	Installing equipment, machines, wiring, or programs to meet specifications.
	Operation and Control	Controlling operations of equipment or systems.
	Operation Monitoring	Watching gauges, dials, or other indicators to make sure a machine is working properly.
	Operations Analysis	Analyzing needs and product requirements to create a design.
	Programming	Writing computer programs for various purposes.
	Quality Control Analysis	Conducting tests and inspections of products, services, or processes to evaluate quality or performance.
	Repairing	Repairing machines or systems using the needed tools.
	Technology Design	Generating or adapting equipment and technology to serve user needs.
	Troubleshooting	Determining causes of operating errors and deciding what to do about it.

Appendix B. Factor loadings for skills

Skills	Factor1: General	Factor2: Technical	Factor3: Management	Factor4: STEM	Communality*
Active Learning	**0.73**	-0.17	0.32	0.49	0.91
Active Listening	**0.78**	-0.39	0.31	0.24	0.92
Complex Problem Solving	**0.64**	-0.02	0.37	**0.61**	0.91
Coordination	0.39	-0.15	**0.78**	0.10	0.79
Critical Thinking	**0.73**	-0.15	0.35	0.50	0.92
Equipment Maintenance	-0.08	**0.96**	-0.15	-0.13	0.98
Equipment Selection	-0.14	**0.92**	-0.09	0.01	0.88
Installation	0.01	**0.67**	-0.08	0.00	0.45
Instructing	**0.66**	-0.15	0.37	0.28	0.67
Judgment and Decision Making	**0.63**	-0.12	0.45	**0.52**	0.90
Learning Strategies	**0.67**	-0.17	0.36	0.32	0.70
Management of Financial Resources	0.11	-0.03	**0.71**	0.31	0.61
Management of Material Resources	0.10	0.10	**0.73**	0.32	0.65
Management of Personnel Resources	0.40	-0.05	**0.76**	0.28	0.81
Mathematics	0.24	-0.02	0.21	**0.72**	0.61
Monitoring	**0.56**	-0.05	**0.54**	0.34	0.72
Negotiation	**0.50**	-0.29	**0.67**	0.04	0.79
Operation and Control	-0.34	**0.75**	-0.07	-0.04	0.68
Operation Monitoring	-0.29	**0.80**	-0.01	0.13	0.73
Operations Analysis	0.30	-0.04	0.31	**0.64**	0.60
Persuasion	**0.56**	-0.30	**0.62**	0.10	0.80
Programming	0.11	0.05	0.06	**0.68**	0.48
Quality Control Analysis	-0.24	**0.78**	0.07	0.27	0.75
Reading Comprehension	**0.77**	-0.28	0.18	0.47	0.92
Repairing	-0.06	**0.96**	-0.14	-0.12	0.96
Science	0.43	0.06	-0.02	**0.64**	0.59
Service Orientation	0.50	-0.37	0.49	-0.13	0.64
Social Perceptiveness	**0.63**	-0.36	**0.53**	-0.05	0.80
Speaking	**0.79**	-0.41	0.31	0.22	0.93
Systems Analysis	**0.52**	-0.01	0.48	**0.64**	0.91
Systems Evaluation	**0.52**	-0.02	**0.51**	**0.61**	0.91
Technology Design	0.05	0.30	0.18	**0.62**	0.51
Time Management	**0.51**	-0.12	**0.65**	0.27	0.76
Troubleshooting	-0.19	**0.92**	-0.06	0.08	0.89
Writing	**0.77**	-0.32	0.20	0.40	0.90
EFA summary					
Eigenvalues	17.86	6.48	2.24	1.66	
Proportion Var	0.243	0.201	0.174	0.154	
Cumulative Var	0.243	0.444	0.618	0.771	

Highlighted are factor loadings larger than 0.5. Extracted factors are rotated using a varimax procedure.
* For each variable communality is the part of its variance that is explained by all factors.