Identifying the effects on wages of the multiple skills in the skill biased technological change. Evidence from Switzerland

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Abstract

This thesis uses Swiss individual data matched with the Dictionary of Occupational Titles to investigate the relationship between wages and occupational skills. I use the factor model to aggregate the multi-dimensional skills dataset. The empirical results indicate that occupations that require planning intelligence pay higher wages while there are lower returns for skills that require physical skills regardless of the type of manual tasks required. Verbal and perception intelligence do not show any relation to wages while precision skills have higher return than the mean and the effect has increased with time. For occupations where computer use is at high level, occupations skills have lower effect on real wages. The empirical results also show that 2/3 of the occupations require at least 2 skills in top quartile.

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1. Introduction

The structure of the wages is in constant dynamics. In the light of a three facts (1) the stagnant median wages with significant variations within the groups; (2) the rapid technology advance on productivity, wages and employment; (3) the increasing importance of the outside-formal-education and the on-the-job trainings, occupational skills become more relevant in explaining the skill influence in the wages rather than the individual formal education.

Over the past decades, research related to US data shows that real wages have been stagnant (Cowen, 2011). In the same time there is great variance across the groups. Workers with college degree have increased their salaries while individuals with no college degree have experienced lower wages (Autor, 2011). Neumann et al. (2006) show that wages have not increased uniformly when using formal education as the indicator to measure the skills, implying that education alone is not a complete measure of skill. This is in line with the increasing role of the outside-formal-education and on the job trainings (Daron Acemoglu, 2003). Moreover, within the same formal educational group there is great variance of wages. They find that the occupational skills do have explanation power over the wage variance.

Another important trend is the rapid technological change that has effected productivity and employment. Previously, augmented technology would result in augmented productivity driving wages upwards. However, after a certain moment, about the time the computers moved from internal corporate automation to information and collaborative activities, technology has become a substitute for some of the skills (David, 2003). This leads to some of the occupations to cease to exist. For example, there were fewer bank tellers in US in 2014 than in 2006 and those that remain earned less wages. In the same time employment and wages of physician assistants have increased significantly. Technology has also changed the skill demand on an intensive margin by changing the skill content of the occupations.

There were fewer secretaries in 2014 than in 2006 and the remaining ones require more cognitive and interpersonal skills than before (Frank MacCrory, 2015).

In the same time European countries have shown similar pattern of development. Occupations high paid jobs like professionals and managers as well as low paid jobs like personal service, truck drivers and sales workers are among the fastest growing ones. The European data is in line with the pervasiveness job polarization that in advanced economies technology is becoming more intense in use of non-routine tasks concentrated in high paid and low paid jobs at the expense of routine tasks concentrated in manufacturing and clerical work. (Goos Maarten, 2009).

Gaining knowledge about the relation between occupational skills and wages may help understand the changes of the wage inequality as well as what skills are more relevant to develop from the educational point of view.

The above mentioned literature is performed only on US data. There are a few sources, to the best of my knowledge, that perform similar research on European data. The approach of the latter is to use aggregated data at the level of occupation or trends of the countries. For the aggregation of the occupational skill the previous literature uses the linear combination of subjectively assigned by the authors skills into categories describing the type of occupations. For example, the skill variables are categorized into: abstract, routine or service (Goos, Manning, & Salomons, 2014); (Adermon & Gustavsson, 2015).

Motivated by the above related facts and the existing literature caveats, I aim in my thesis to explain the role of occupational skills on earnings and how they have changed with skill biased technological change. Following the methodology use by Neumann (2005) and McCrory (2015), using Occupational Information Network Dataset (O'NET) I identify eight dimensions of skills across 338 occupations in the reference year 2000, and then I extend the analysis using the Swiss Household Panel Survey (SHP) data. I analyse the returns to various components of skill and how they have changed over the period 1999-2013. I then add the Computer and Electronics skill and estimate how technological change has influenced the effect of skills on wages.

The main aim of the research is to convey that the occupational skills do explain the dynamics of the wages better than the formal education. The explicit differences of the present research in comparison to the previous one is that I use the factor model to aggregate the multidimensional occupational skills. To the best of my knowledge, no previous study has made a formal statistical investigation of the relation between the occupational skills and the wage profile in Switzerland.

In examining the returns to various components of skills I find that the return to planning skills and precision skills increase over time. Computer technologies for these skills are complements rather than substitutes. Occupations that require any forms of physical skills relate negatively to wages. Verbal and perception skills are mainly determined by education while constructive intelligence seem to have the potential to be substituted more and more by technology. In the same time, it is not enough to have the expertise of the top quartile in one skill. The results show that the market offers higher reward for the occupations that require at least two skills in the top quartile.

The contributions of the research are the insight regarding the skills that matter the most for different occupations. From an individual perspective this research provides data evidence of the skills that individuals should focus in developing when going on the labour market. In the same time the findings offer a guidance of the labour market demands for skills. This aims to contribute to educational policies that will make the formal schooling responding to the needs of the employers.

The rest of this paper is organized as follows. In the next section I present the literature review, following with the description of the data set and the model that I use for the estimations. The following sections shows that regression results and the effect interpretation.

The final section presents the concluding remarks.

2. Literature Review

There is a significant amount of literature explaining the relation between wages and the skills using different proxies. Having the formal education granularly refined, US data shows empirical developments. Changes in the return to college, expanding economies and dynamic markets have incentivised a great deal of research to be focussed on identifying the factors that drive the wage variations within the same education group and how these drivers are rewarded on the market (Autor, 2011).

The effects of the skilled biased technical change are widely spread. Berman (2000) finds that pervasiveness of the skilled biased technological change is the main driver of job polarization across OECD countries, the increase is concentrated in the same manufacturing industries across the analysed countries and the employment increased despite the rising or stable relative earnings.

Skill biased technology change (SBTC) has been identified as driving the increase in the wage variance for the high skilled labour and has been identified to have an impact on the employment distribution, wages and type of tasks of different occupations (Autor, 2011). According to Buera et. al. (2015) skill biased structural change is the one that accounts for roughly 30% of the overall increase of the skill premium due to technical change.

In contrast, Card et. al (2002) emphasize that SBTC fails to explain the decrease in the wage gender gap, young versus old education wage gap after 1990s when the wage inequality stabilizes while computer technology continues to advance. Further, Deming (2015) argues that technology is not yet as advanced for the tasks where there is no “rule” and the work requires additional skills that are not developed while in formal education.

While there is literature that focusses on technological change, Neumann and Ingram (2005) provide evidence that in order to fully comprehend the variance of earnings there is need for additional dimension for measuring the skills. Testing for various dimensions of skill, they argue that some skills account for a significant proportion of the variation in wages among the individuals with a college degree and some of the increase in wage dispersion among the ones that do not have a college education.

Autor, Katz, Kearney (2008) find that the skills and the changing demand for skills that are driven by technological change succeeds to explain the growth of the upper tail wage distributions and the contraction of the lower tail wage distribution observed in US data. Autor et al. (2003) take a step forward in differentiating the tasks of the job. They find that jobs that involve cognitive routine task can be easily replaced by computers while the technical capital acts as a complement to the non-routine, problem solving and interactive job tasks. The shifts in the demand can be mostly explained by the changes in the task content induced by computerization.

Other sources show that there is evidence of job polarization and offshoring that originates from the skill automation towards replacing the routine tasks (called routine biased technology change). According to Goos and al. (2014) these two factors have a negative influence of the middle relative to high skilled occupations.

In a growing economy the factors that contribute the most to the earnings variance are persistent increase in the base wage, rising return to human capital and a high sector wage premium (Suqin Ge, 2012). The mentioned research shows that, in developing economies, on the example of China, factors like changes in the worker characteristics, the gender composition of the labour force and reallocation of workers across industries and regions have little or no impact on the earnings growth. The authors provide evidence that the driving force of the wage increase are the skill biased technology change, exports, and capital accumulation.

The employment shares have also suffered considerable changes along the last decade. Manning and al. (2014) show that the employment structure shows evidence of job polarization for high-paid professionals and managers and for low paid service workers.

One of the features of the job polarization is the non U shaped employment. Polarization results from the combination between consumer preferences which favours variety over specialization and the decreasing costs of automating of codifiable job tasks. Author and Dorn (2013) find that markets that reallocated low skilled labour into service occupations earnings growth at the tails of the distributions and received inflow of skilled labour.

When assessing the polarization pattern of the labour markets, Autor and Katz (2006) find that the US market has experienced, over the last decades, inequality increase in earnings in the upper tail of the wage distributions. In the same time the lower tail of the wage distributions has seen expansion and then compression. The standard institution facts do not succeed to explain these facts. The authors argue, however, that the changing job tasks demands combined with information technology and the indirect impact on international outsourcing do.

Other sources provide evidence that information and communication technology drives the polarization of the market and the lag is one quarter. (Michaels, 2014). MacCrory et. al. (2015) find that technology improvements out-crowed not only the cognitive manual tasks but occupations like lawyers and journalists are threatened as well. The effect of the technology is affecting at least five distinct dimensions of skills. Moreover, according to MacCrory et al. (2015) having the high level of one skill is not enough to succeed on the labour market. It pays off higher when individual rate above the 75th percentile in two or more skills are the ones eligible for high paid jobs in the economy. This shows that even if diversity is preferred the specialization is the one paying higher earnings.

Furthermore, Deming (2016) finds that jobs that require both high level of social and cognitive skills have an increased employment and wage. The relative growing importance of the social skills has also played a role in narrowing down the gender gap. Moreover, the recent literature aims to explain the impact of soft skills on wages and the role that communication, cooperation and leadership skills play on the labour market. Even though there is not extensive data that would allow measuring this trend Bacolod and Blum (2008) found that wage returns for occupations requiring soft skills have doubled between 1968 and 1990. Also they provide evidence that soft skills don't present any value by themselves but only as a complement to other skills (Balcar, 2014).

3. Data and Methodology

3.1 Dataset description

For the purpose of the research I use the data from Swiss Household Panel (SHP) and the Occupational Information Network Dataset (O’NET).

The SHP survey collects data on social change and the changing living conditions in Switzerland. SHP data, up to date, comprises three samples drawn by the Swiss Statistical Office: SHP_I (the sample of households and individuals selected in 1999 and interviewed for the first time in that year), SHP_II (a sample of households and individuals interviewed for the first time in 2004) and SHP_III (a sample of households and individuals interviewed for the first time in 2013).

The three waves of the survey are stratified by major geographic regions (NUTS II). Within one major region, each household or individual had the same inclusion probability, independent of the size of the household. The proportions of distributions of the addresses are presented in the Appendix Table 1. The number of individuals interviewed in the three waves is presented in the Appendix Table 2. The general rule of the follow-up is to interview all households that completed at least the grid during the last wave.

The samples are designed by major geographic regions (NUTS II) in proportion to the number of households per stratum. Within the stratum the sampling design reflects the proportional number of individuals ensuring that small regions are not overrepresented. Within one region each individual had the same inclusion probability.

The employment status of the individual is described by a group of variables. For the purpose of the research I focus on the ones that use the ISCO-08 (International Standard Classification of Occupations) nomenclature, administered by International Organisation of Labour (ILO).

ISCO-08 is a four-level hierarchically structured classification that allows all jobs in the world to be classified into 390 unit groups. These groups form the most detailed level of the classification structure and are aggregated into 116 minor groups, 28 sub-major groups and 10 major groups, based on their similarity in terms of the skill level and the skill specialization required for the jobs. ISCO database focuses on the skills required to carry out the tasks and duties of an occupation - and not on whether a worker in a particular occupation is more or less skilled than another worker in the same or other occupations.

Based on the structure of the ISCO classification described in the previous paragraph the 2-digit or the 3-digit codification is adequate to characterize the occupations. When analysing the 2-digit classification I find that the list of occupations is similar to that used in other research (Sabirianova, 2002).

When inspecting the Swiss dataset, I find that some of the occupations are aggregated in one group and some that are additionally included to the existing ISCO-08 occupation nomenclature. Some example of the aggregation Appendices Table 3 presents.

3.2 Occupational Skill data from Dictionary of Occupational Titles.

The source of the data for occupational skills is O'NET 19.0 (Occupational Information Network).[1] (version release July 2014). This is a database of occupational descriptions that was elaborated and is maintained by US Department of Labour. Information like work characteristics, work requirements, skills and occupation specific information can be found in this data source. O'NET database is constructed having as the starting point the SOC 2010 (Standard occupational classification system) occupations.

The original version of SOC has 6 digit codes for every occupation. The O'NET SOC classification has 8 digit codes, where the first six are the same as in SOC. The last two digits

[1] version release July 2014. Source: https://www.onetcenter.org/db_releases.html

indicate if the occupation is more detailed than the SOC classification. If it is more detailed then the last two digits are 01, 02 etc. depending on how much detailed occupation are for SOC occupations. For the purpose of the research I use the six-digit codification for O'NET SOC and I average the indexes in cases when the occupations are more detailed in O'NET SOC in comparison to SOC nomenclature. The O'NET 19.0 version use for the purpose of this research contains information about 770 occupations.

For each occupation the skills have an importance value index ranging from 0 to 5, in ascending order. The index is an average of the importance that a group of specialized analysts have given to each skill for each occupation. The dataset is revised on a yearly basis. The dataset also provides a version of the mapping to ISCO version of the occupation classification.

The O'NET dataset contains 52 skills. It is highly unlikely that all the 52 skills represent a separate dimension of the occupational skills. For example, "number facility" and "mathematical reasoning" both attempt to measure mathematical skills, "oral comprehension" and "oral expression" measure communication skills. Using the skills in their separate form will not be informative. I use the factor model to aggregate the occupational skill into groups by similarities.

Factor analysis searches for such joint variations in response to unobserved latent variables. The observed variables are modelled as linear combinations of the potential factors, plus an error term. The information gained about the interdependencies between observed variables can be used later to reduce the set of variables in a dataset to the relevant number of latent variables. Factor model is a two stage process. By construction factors are with mean zero and variance one, as they are latent variables composed of pieces of varying scales. For more technical details and explanations of using the factor model in this case see Neumann et al. (Beth Ingram, George Neumann, 2006).

To run the factor model I include all the 52 skills. The first stage aims to find the common patterns between the variables that are being factored. The second stage estimates the factor loadings – data that can be used for further analysis. Previous literature uses a baseline year to define the factors and their loadings (Frank MacCrory, 2015). To estimate the factors loading I take the year 2000 in the SHP dataset as a baseline. In such circumstance the best option would be to have the weights of the occupations in the Swiss economy for each year to weight the importance of the factors accordingly. However, since this data is not available I take the year 2000 data as the best alternative.

Table 4 in Appendices shows the coefficient estimates and they describe how relevant is the skill for the factor. The columns define the factors and the relevant characteristics for each factor. Following Neumann and Ingram (2006) I divide the skills between factors using the relevancy coefficient described by factor loadings and conventionally name them. The factors are the one that have the eigenvalue greater than 1.0. The skills that loaded with any factor with a value greater or equal to 0.6 are the skills that describe the factor. The eight factors explain 87% of the variance in the data. There are 8 skills that do not show any pattern to be similar to other skills and be part of the factors. The maximum value of the uniqueness is 0.33 meaning that only 33% of the variance of this skill is not shared by other skills in the factor model. The greater is the value of the uniqueness the lower the relevance of the skill in the factor model.

The eight factors are described below in the following order:

Physical (factor 1): gross body coordination, static strength, stamina, trunk strength, dynamic strength, extent flexibility, gross body equilibrium. Occupations typically are labourers in mining and construction.

Spatial (factor 2): glare sensitivity, peripheral vision, spatial orientation, sound localization. These are specific to occupations like drivers and mobile plant operators, skilled agricultural and fishery worker.

Verbal intelligence (factor 3): written expression, written comprehension, oral expression, speech clarity, oral comprehension, speech recognition, time sharing. These skills are related to occupations like life science and health professionals, office clerks, teaching professionals, models, salespersons and demonstrators.

Precision (factor 4): mathematic reasoning, number facility, perceptual speed. This factor is related to mathematical and engineering occupations.

Perception (factor 5): selective attention, etc. The occupations that fall under this factor are designers, architects.

Motoric (factor 6): near vision. The occupations that have a high score for these skills are those that require working with high precisions tools and instruments.

Constructive intelligence (factor 7): visualization, originality, fluency of ideas. The occupations that are included in this factor are managers of small enterprises, life science and health professionals.

Planning Intelligence (factor 8): deductive reasoning, problem sensitivity. The occupations related to these skills are professionals and associate professionals.

Factor one, two and six are related to manual and repetitive work. Factor three and five and seven require ability to deal with people, active communication skills, ability to lead negotiations and control. These occupations require a degree level education. Factor four and eight are strongly related to occupations that require post graduate activity and solid knowledge of the occupational technical information.

Table 5 provides a data description of the factor means. Motorical and physical factors have decreased their weighted mean between 2000 and 2013 meaning these group of skills are considered less and less important in the occupations. In the same time constructive and planning intelligence have increased. In the same time verbal intelligence, the one reflecting the first representative of soft skills, has increased in weighted mean. This is in line with previous literature regarding the growing importance of cognitive analytical and interactive abilities. Considering the survey data framework, the detected polarization can be driven by two factors. The qualitative part of the change is that the importance of the major skills in the factors has decreased. This topic is analysed in the following chapter. The quantitative part is that there are less individuals in the dataset in 2013 that have occupations related to physical and motorical factor and more individuals that have occupations that are connected to constructive and planning intelligence. Analysing this issue is not feasible considering the existing dataset. Mapping the Swiss occupational nomenclature with the ISCO one lacks partly the one-to-one matching of the equivalent occupations.

Table 5 Means of dictionary of occupational titles occupational task measure overall, 2000-2013

Variable	2000	2013	Variance
Physical	1.9454	1.8985	(0.05)
Spatial	1.3166	1.3117	(0.00)
Verbal intelligence	3.5405	3.5595	0.02
Precision	2.6918	2.6857	(0.01)
Perception	3.0952	3.0943	(0.00)
Motoric	3.6244	3.6057	(0.02)
Constructive intelligence	2.8360	2.8502	0.01
Planning intelligence	3.6315	3.6648	0.03

For the factor regression I excluded "Computer and Electronics" skill. This variable is used separately for the purposes of measuring the skill biased technology change on the skills and earnings. The occupations for which the computer and electronic skill have a high importance are application programmers, database and network professionals, software developers, telecommunications engineers. By construction factors are orthogonal to each other with mean zero and standard variation one. After further analysis there is significant negative correlation between factor 1 and Computer and Electronics. This is partially expected since occupations that require programming skills and software development do not require any physical skills. However, (David, 2003) occupations that require physical skills with non-routine tasks and technology might be complements rather than substitutes.

3.3 Measuring earnings

To adjust the sample measurements to the population of Switzerland I use the longitudinal individual weights. The size of the dataset is 33240 observations and the first year of observation is 2000.

I convert the individual earnings to real values using the Swiss CPI data extracted from Federal Reserve Economic Data (FRED) seasonally adjusted with year 2010 as the baseline[2].

All the summary statistics are estimated using the weight variable that adjusts the sample estimates to the Swiss population.

The table below shows a raw description of the wage data. The quartiles are defined based on reference year 2000. It shows that the individuals that experience the highest wage also see a higher wage growth over time. Real wage has different growth patterns among the quartiles. This is in line with the previous literature (Adermon & Gustavsson, 2015).

Table 6 Mean of the real wage, by quartiles

	Percentile				
	10%	25%	50%	75%	90%
2000	11,867	29,007	57,136	80, 980	109,878
2005	10,236	25,671	55,620	82,335	112,632
2013	10,005	27,213	55,927	82,842	114,457
Overall	10,000	26,390	55,456	81,040	111,256
Growth rate 2013/2000	-16%	-6%	-2%	2%	4%

The wage distribution follows a skewed pattern with 1868 observations having more than five hundred thousand annual wage. It has a heavy tail displaying a kurtosis of 445.

[2] https://research.stlouisfed.org/fred2/tags/series?t=cpi%3Bswitzerland

The occupations that are paid the most are doctors and judges, pilots, finance and industrial managers. The least paid occupations are retail sales persons and clerks, currier and childcare workers. Table 7 in Appendix present more details.

To have a better understanding of the distribution of the wages I calculate the mean wages for the occupations that are in the highest 25% of the distribution of each factor. The descriptive statistics in table shows that there are significant differences in the distribution of the wages between factors.

Table 8 Top quartile real wage descriptive statistics

Variable	Observations	Mean	Std. Dev.
Physical	10,054	41,441	29,843
Spatial	9,512	55,488	87,376
Verbal intelligence	10,312	57,474	38,040
Precision	10,893	71,439	53,387
Perception	10,176	75,798	89,312
Motoric	9723	57,954	47,249
Constructive intelligence	8,228	57,976	45,361
Planning intelligence	11,434	70,805	56,689

The data regarding wages spread are in line with the official data about the average wage in Switzerland[3]. The highest paid wages are the one that relate to factor planning and intelligence and the precision. These are the jobs that require analytics interactive cognitive skill – professional and associate professionals.

Computer and Electronics has a high negative correlation with factor 1, as expected. Occupations that require physical strength do not require ability to work with the computer or skills of software development.

[3] Medium level position in R&D is paid on average with 10000 CHF monthly. Bank industry average is 17000 CHF, tabacco industry-22000 CHF, heath industry – 9000 CHF and building industry – 8000 CHF. All values are approximated to thousands. Also there is 10% of the full time workers that receive less than 4000 CHF monthly. The numbers relate to year 2010.

3.4 Descriptive analysis of the control variables

The gender representation in the sample is approximately even for the time frame analysed of 49% male and 51% female.

When analysing the Swiss educational system, it is important to emphasize that there are five sublevels of vocational trainings and that they can be done at any level after the secondary school completion. This fact emphasis that the education is highly connected with the labour demand and the employer requirements. In table 9 I present the descriptive statistics in the aggregated groups, however for the purpose of the regression I use the years of schooling according to the level of education declared.

Table 9 Mean return on formal education, 2000 and 2013

Highest level of education achieved,	2000	2013
Primary	28 463	18 783
Vocational	57 074	56 449
Secondary	57 479	49 818
Tertiary	99 187	87 259
N	2,426	2,661

Average age of individuals in the sample is 42 years old. The youngest person is 15 and the oldest is 89. These might seem doubtful since the answer to the occupation might have been regarding expected earnings in total rather than achieved ones. However, after further investigation of the data and of the online resources regarding the trend in the Swiss society to extend the period of work until the official retirement date I keep these observations in the sample.

3.5 Methodology

To measure the wage impact of the skilled biased technological change I use the hedonic regression model. This model uses the observed prices, in this case the real wages, as the dependant variable and skill factors as explanatory variables. The factors estimated are orthogonal to each other, by construction, and have the same scale (mean zero and variance one). This allows to directly quantify the aggregate marginal willingness to pay for these skills.

$$\text{Real Wages} = \beta_0 + (\sum_{k=1}^{n} \beta_f \ Score^{n-k}) * \varepsilon_{i;t}$$

There are a variety of other variables that can influence wages in an occupation. One of them is the level of education. Using an OLS estimation results in the education coefficient to be biased independent of schooling being endogenously determined or some of the factors are influenced by school variable. As mentioned by Neumann et al. (2005) and Card (2000) the average return to an additional year of schooling does not significantly differ from the OLS estimates. Thus the focus of the regression is to analyse the relation between the skills factors and wages within the same educations group. Conversely, the claim is not that we can rely on the magnitude of the schooling coefficient. To solve the identification problem, there is need for a richer dataset.

The next section presents the estimation results.

4. Results

4.1 Empirical findings

The baseline model regression output is presented in Table 10.

Table 10 Regression output, full sample

	coefficient	st. dev.	coefficient	st dev	coefficient	st dev	coefficient	st dev
Physical	-0,2609***	0,0233	0,1395***	0,0154				
Spatial	0.0063	0,0193	0,0868***	0,0120	-0,0029	0,0150	0,06178***	0,0149
Verbal intelligence	0,0855***	0,0118	-0,0394***	0,0096	0,0866***	0,0099	-0,0308**	0,0125
Precision	0,2096***	0,0198	0,0870***	0,0125	0,1493***	0,0148	0,0664***	0,0139
Perception	0,0699***	0,0148	-0,007	0,0119	0,0675***	0,0131	-0,014	0,0135
Motoric	0,0110	0,0212	0,0426***	0,013	-0,0410	0,0151	0,0339	0,0130
Constructive intelligence	-0,0561**	0,0210	-0,0144	0,0127	-0,0333**	0,0146	-0,0185*	0,0122
Planning intelligence	0,1557***	0,0196	0,1065***	0,0122	0,1421***	0,0131	0,0997***	0,0128
Computer and Electronics	-0,0811**	0,0356	-0,0112	0,0204	0,1256***	0,0279	0,0965***	0,0180
Constant	10,9380***	0,0638	10,3167***	0,1514	10,3840***	0,0536	9.7228***	0,1422
Controls	No	No	Yes	Yes	No	No	Yes	Yes

*** represent the significance level at 1%, ** significance level at 5%, * significance level at 10%.

Since by construction the factors have zero mean and standard deviation one, the regression coefficient is interpreted as the impact of one standard deviation change of the factor on real wages. Occupation that require physical skills that are described by factor 1, pay less by 13% than the average real wage. Skills that require precision, described by factor 4 payoff higher wages by 6%. Occupations with near-vision described by motorical factor, as the main skill in occupations like dentist will receive a real wage that is between 1% and 4% higher than the mean earnings. An occupation with one standard deviation above the mean in deductive reasoning and problem sensitivity is paid 8% higher real wage than the mean wage. Occupations related to spatial skills are paid 6% more real wages than the average. Computer use is associated with cognitive skills, processing and working with information as well planning. This is in line with previous literature saying that computer skills on its own do not provide a wage premium (David, 2003). Moreover, based on the negative correlation between the physical factor and the computer skills, when excluding physical factor, the estimates for the computer use become significant showing that occupations that do require computer knowledge tend to pay more by 7% than average real wage. Verbal intelligence appears to be driven by the additional controls and by itself does not contribute to the real wages. The same pattern follows perception skill factor.

The above analysis does answer the question whether the skills have an impact on wages. However, it is informative to consider that some skills may have different impact on the real earnings depending on the occupation level. Occupations that pay higher wages might price some skills higher than occupations with lower wages. The quartile regression allows analysing how some skills impact the real wages for some segments of the populations differently than for others. Table 11 presents the estimated coefficients for specified quartiles with and without controls. The full table of the estimation is presented in the Appendix.

Table 11 Estimated coefficients, by wage quartile

	Q25	Q50	Q75	Q25	Q50	Q75
Physical	-0,3241***	-0,2282***	-0,1996***	-0,2011***	-0,1533***	-0,1475***
Spatial	0,0679***	-0,0019	0,0109***	0,08614***	0,0466***	0,0540***
Verbal intelligence	0,1286***	0,0913***	0,0453***	-0,0278***	-0,0197***	-0,0323***
Precision	0,2669***	0,1577***	0,0114***	0,1135***	0,0721***	0,0673***
Perception	0,07441***	0,0827***	0,0784***	-0,0269***	0,0004**	0,0088
Motoric	-0,0444***	-0,0047	-0,0202***	-0,0194	-0,0025	0,0154
Constructive intelligence	-0,005	-0,0303***	-0,0270***	-0,0012***	-0,0168***	-0,0241***
Planning intelligence	0,2840***	0,1645***	0,1142***	0,1633***	0,0998***	0,0864***
Computer and Electronics	0,0410***	-0,0012	-0,0265***	0,0061	-0,013*	-0,0327*
Constant	10,12***	11,0241***	11,3425***	10,6047***	10,2818***	11,3384***
Controls	No	No	No	Yes	Yes	Yes

*** represent the significance level at 1%, ** significance level at 5%, * significance level at 10%.

The estimated coefficients in table 11 confirm that planning intelligence skill is the one that has the highest wage premium while occupations that require physical skill to be more developed pay less wages. The physical skill is the one that does have lower than average real earnings when looking at all the real wage quartiles. Precision intelligence focussed occupations do provide higher wages approximately by 10% while constructive intelligence skill pays slightly lower wage than the mean of the quartile. The interesting fact is that once going up the wage scale, precision and perception factors decrease in magnitude of influence on wages. This means that at high paid occupations skills factors are not the sole driver of the real wages magnitude.

A great deal of analysis emphases the importance of computer use. There is evidence to believe that skill biased technology change has led to job polarisation with the routine and the tasks that can be programmed have been delegated to computers. The impact on the job polarization or the employment is not feasible using this dataset, however performing the analysis while looking in details at occupations that require different level of computer skills is attainable. Thus considering the SBTC hypothesis, I run the regression for each computer use quartile to determine the effects of the factors on earnings considering the complementarity or the substitutability with computer use.

Figure 1 Skills Factor effect on wages, by computer and electronics use quartile

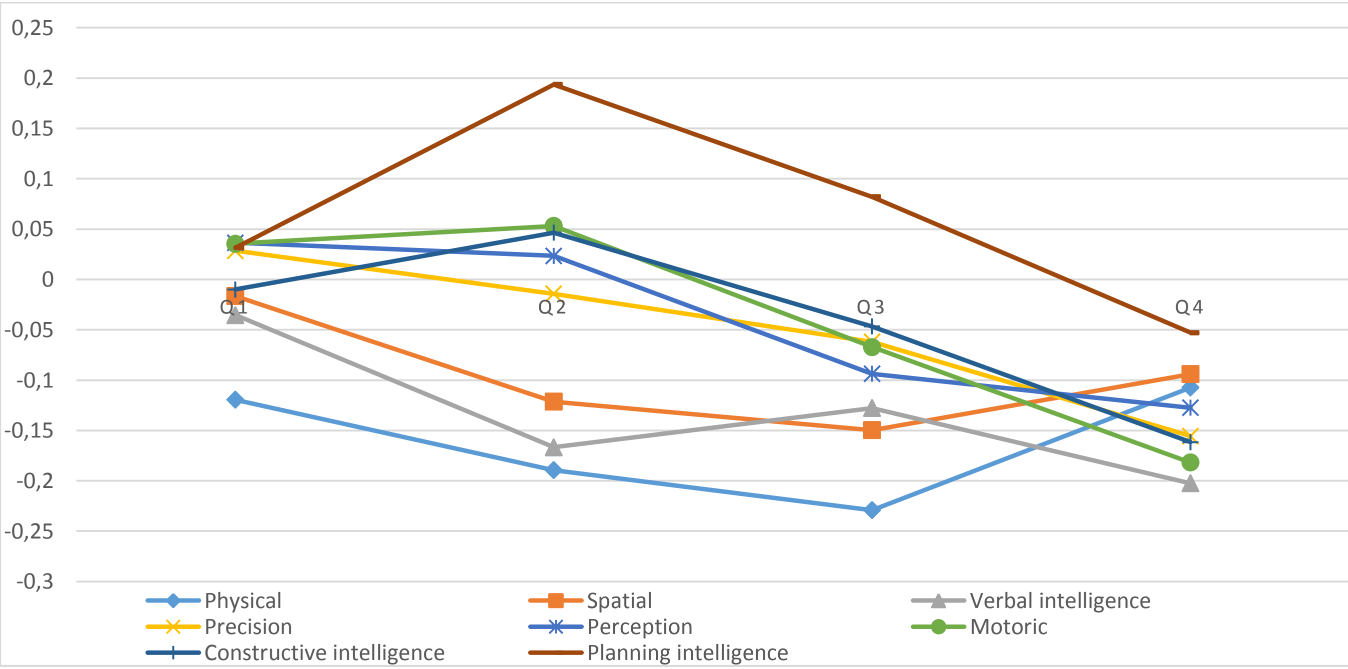

Table 13 in Appendices and figure 1 (above) reveals interesting facts about the use of computers and the effect on wages. For example, physical skill has a hump shaped across the computer use quartiles. This means that higher wages are paid by occupations that either have very little of the computer use or are in the top usage of it in comparison with the occupations where computer is a complement to the daily tasks. Computer is a complement for the occupations that require some usage of technology. In the same time, I can conclude that for planning intelligence computer usage is in all case a complement rather than a substitute. Overall figure 1 clearly states that in occupations where computers have a high usage, skills are less relevant for the wages.

Occupations that have the main skill planning, precision, constructive and spatial skills have increased in earnings over the time analysed by 4p.p., 6p.p., 3p.p. and 2p.p. respectively. Table 14 shows the estimated effect of skills in time.

Table 14 Estimated factor coefficients dynamics

	2001	2012
Physical	-0,1532***	-0,1574***
Spatial	0,0479***	0,0641**
Verbal intelligence	-0,0521	-0,0106
Precision	0,0552*	0,1151***
Perception	0,0044*	0,0079
Motoric	-0,0248	-0,0567
Constructive intelligence	-0,0324***	-0,0076**
Planning intelligence	0,1056***	0,1475***
Constant	10,0201***	10,6422***
Controls	Yes	Yes

*** represent the significance level at 1%, ** significance level at 5%, * significance level at 10%.

Considering all the above analysis, the effects of the skill factor raises the question to disentangle the pure effect of education and the individual skills. Some skill elements like mathematical ability or written expression might be developed during formal education. If so than the contribution of the skills to earnings represent part of the return to education. Conversely the skills might represent innate abilities in this case the effect on earnings is separate from the returns to education. Finally, unobserved training that happens outside the formal education might be the source of the acquired skills. Following Neumann et al. I estimate the effect of education on each of the factors holding the demographic variables constant. Table 15 shows the estimated coefficients. I report the results for two separate years to show the stability of the relation. Formal education has a negative significant effect on the physical factor while positive effect on all the other factors. An additional level of education results in increased wages ranging from 2% to 9% of a standard deviation.

Table 15 The effect of education on skills

Skills factors (independent variable)	Education (dependent variable)	
	2000	2013
Physical	-0.1387***	-0.1087***
Spatial	0.067***	0.0747***
Verbal intelligence	0.021**	0.0496***
Precision	0.038***	0.0527***
Perception	0.0764***	0.111***
Motoric	0.0383***	0.0489***
Constructive intelligence	0.001*	0.0079
Planning intelligence	0.071***	0.0429***
Computer and Electronics	0.0904***	0.0714***
N	2076	2807
R	4-17%	5-21%

*** represent the significance level at 1%, ** significance level at 5%, * significance level at 10%.

The main point at this stage is to show that education and the skill are interconnected, however there are other than formal education channels to develop the skills.

The regressions above reflect the effects of differences in skill requirements across jobs. However, they tend to hide the absolute magnitude of those differences. Do the majority of the occupations require the mean of the skills? Is there a skill that is predominant? Does the labour market prefer candidates profile with high scores for one skill or those who excel in multiple domains? In table 16 I present the proportion of occupations that require top quartile of skills. The interesting fact is that 2/3 of the occupations require at least 2 skills with top quartile and 1/3 of the occupations require 3 skills in top quartile. This is in line with previous literature. MacCrory (2015) finds based on US data that 86% of occupations require at least one top quartile. The proportion of occupations that require top quartile per each factor is not quite in line with the expectations. Lines 4 to 11 in table 16 show that there is no significance polarization towards some more skilled occupations.

Table 16 Share occupations with top quartile skill requirements

	2000	2013	Variance
At least one top quartile	96.4%	95.9%	-0.6%
At least two top quartile	68.8%	66.8%	-2.1%
At least three top quartile	34.0%	27.9%	-6.1%
Physical	26%	26%	-0.3%
Spatial	24%	22%	-1.2%
Verbal intelligence	25%	23%	-2.2%
Precision	26%	23%	-2.7%
Perception	26%	23%	-2.9%
Motoric	25%	24%	-1.6%
Constructive intelligence	26%	18%	-7.2%
Planning intelligence	29%	27%	-1.8%

As mentioned before the way the skill dataset is constructed is by having experts revise the importance of the skills for each occupation a couple of times a year. This is also a source of information how the skill demand within an occupation has changed over time. I use the two versions of the skill datasets: one from 2002 and the one from 2015. Cognitive skills have significantly changes in their importance. Skills like deductive reasoning, flexibility of closure, inductive reasoning, problem sensitivity, selective attention have increased their average importance with more than one unit over a decade period. Verbal intelligence skills have increased by slightly less, while physical and precision related skills have decreased in overall importance.

4.2 Robustness check

As mentioned earlier the used dataset contains the information in the form that can be interpreted in different ways. One of the variables is education level. To additionally specify the model, I use the degree of education instead of years of education. This is somehow cumbersome since the educational system in Switzerland is rather flexible and permeable at all stages after the compulsory schooling. This means that there is possibility to attend a vocational school right after obtaining bachelor's degree. This level of vocational level is different than the one that can be attended right after high school. However, the data does not provide a clear distinction among them. With additional research about the Swiss educational system I am able to categorize them into 5 groups, with subgroups for the vocational training. Nonetheless, the estimates do not vary significantly and are directionally similar as the ones estimated in the above section.

By the method of the factor model, we estimate as many factors as eigen values are higher than unity. However, considering the fact that previous literature finds less than eight skill occupational factors, I take into account the hypothesis that some of the factors might significantly overlap and thus do not bring added value to the model. I estimate the results with different number of predicted factors reducing up to 3 factors. The results do not change significantly. However intuitive this approach might be, the issue arises when interpreting the results. Broader specified factors combine various skills.

Various studies aggregate the individual survey data per each occupation and sector when analysing the occupational skill and wage relation. Following the same method, I estimate the regression and the results per each factor are directionally and in magnitude similar to the my main estimates.

5. Conclusions

The aim of the present thesis is to analyse the relation between occupational skills and real wages using the Occupational Information Network (O'NET) and Swiss survey data for 2000- 2013. Motivation for such research is driven by the dynamics of the labour markets specifically: the stagnant wages, the influence of the rapid technological change and the significant variance of the wages within the same educational group. Also there is little literature that studies these trends on the European countries.

The main focus of the research is based on revealing the influence of the skill that are relevant for an occupation on wages and in dynamics. I use factor model to aggregate the multiple dimensions of the skill provided by O'NET into similar groups of skills that provide more informative estimates. By construction the skill groups, called factors, are orthogonal to each other thus the estimated coefficients can be interpreted as one standard deviation change of the factor on real wages.

The empirical analysis shows that physical skills pay less real wages during the whole analysed time frame. Independent of the specification of the regression, occupations that require as main physical skills have wage that are between 10% and 20% lower than the mean. This is some in contradiction with the skill biased technological change trend since a truck driver, for example, will be paid less regardless of the fact that his tasks can or cannot be substituted with technology. Occupations that require cognitive interactive and analytic skills, like deductive reasoning and problem sensitivity pay higher wages that are around 15% higher than the mean and the upward deviation from the mean has increased during the time frame analysed. Also cognitive skills are associated with usage of the computer. This is in line with previous literature saying that computer skills are a complement rather than a substitute in such skills and they do not provide added value by themselves. Both types of skill factors are robust to different specifications of the regression and are directionally and in magnitude similar.

There is no clear evidence of the relation between verbal intelligence and perception on wages. It seems like these skills are fully developed by educations. Precision skills influence on wages are partly explained by education. The effects on wages is decreasing when going to high paid occupations. This is evidence that, for example for an audit staff, it is not enough to have the technical expertise. This is in line with previous literature regarding the soft skills growing importance (Deborah A. Cobb-Clark, Michelle Tan, 2011).

Occupations that require constructive intelligence have lower wages on average by 2%. Occupations that relate to these skills, for example subway and street car controllers and music directors, do tend to be substituted by technological advance. In the same time occupations that require spatial skills pay higher wages.

One important finding is that at high quartile of computers usage the effects of all the skills on wages decrease. This means that to some extent technological advances are substituting some of the tasks regardless of occupation type.

There are a couple of limitations of the present research. One of them is the rather small dataset. Further investigations are required to have a better mapping of the occupations across European countries. Another limitation of the research is the fact that even if there is evidence to believe that there is relation between the skills and the wages, it does not provide a causality relation. Thus observing how skills demands change on the market can describe the evolution of real wages, it is not sufficient for any educational policy improvement.

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Appendices

A. Table 1 Stratification of Gross Sample

Strata	Cantons*	SHP_I	SHP_II	SHP_III
Lake Geneva region	VD, VS, GE	18.45	18.22	18.90
Mittelland	BE, FR, SO, NE, JU	23.25	22.92	22.25
North-west Switzerland	BS, BL, AG,	13.44	13.86	13.57
Zurich	ZH	17.51	18.22	17.52
Eastern Switzerland	GL, SH, AR, AI, SG, GR, TG	15.68	13.70	13.98
Central Switzerland	LU, UR, SZ, OW, NW, ZG	7.20	8.75	9.53
Ticino	TI	4.47	4.33	4.25
Total		100	100	100

A. Table 1 Extension Table 1: Full name of the cantons

AG Aargau	NW Nidwalden
AR Appenzell Ausserrhoden	OW Obwalden
AI Appenzell Innerrrhoden	SH Schaffhausen
BS Basel-Stadt	SZ Schwyz
BL Basel-Landschaft	SO Solothurn
BE Bern	SG St. Gallen
FR Fribourg	TG Thurgau
GE Geneva	TI Ticino
GL Glarus	UR Uri
GR Graubünden	VS Valais
JU Jura	VD Vaud
LU Lucerne	ZG Zug
NE Neuchâtel	ZH Zurich

A. Table 2 Number of persons interviewed in SHP_I, SHP_II and SHP_III (1999-2013)

Year	Wave	SHP_I, n	SHP_I, %	SHP_II, n	SHP_I %	SHP_III, n	SHP_III, %	Total
1	2	3	4	5	6	7	8	9
1999	1	7799	100					7799
2000	2	7073	91					7073
2001	3	6601	85					6601
2002	4	5700	73					5700
2003	5	5220	67					5220
2004	6/1	4413	57	3654	100			8067
2005	7/2	3888	50	2649	72			6537
2006	8/3	4091	52	2568	70			6659
2007	9/4	4630	59	2350	64			6980
2008	10/5	4494	58	2410	66			6904
2009	11/6	4800	62	2309	63			7109
2010	12/7	5057	65	2489	68			7546
2011	13/8	5103	65	2481	68			7584
2012	14/9	5032	65	2414	66			7446
2013	15/10/1	4880	63	2327	64	6090	100	13297

A. Table 3 Examples of occupation aggregation in the data

ISCO-88	Data
Food preparations assistants; Street and related sales and services workers; refuse workers and other elementary workers;	Elementary occupations
Personal service workers; Personal care workers; Protective service workers;	Personal and protective services worker
-	Service workers, market sales workers
Market-oriented skilled agriculture workers; Market-oriented forestry, fishery and hunting;	Skilled agricultural and fishery worker
Electrical and electronics trades workers; Food processing, woodworking, garment and other craft related trades workers;	Other craft and related trades workers
-	Plant and machine operators assemblers

A. Table 4 Estimated factor loadings

	Factor1	Factor2	Factor3	Factor4	Factor5	Factor6	Factor7	Factor8	Uniqueness
ArmHandSteadiness	0.8607	0.0675	0.2213	0.3121	-0.1523	-0.0205	-0.0407	0.13	0.066
Auditory attention	0.6302	0.5272	0.2106	0.0602	0.1196	-0.0847	-0.2513	-0.1628	0.1658
CategoryFlexibility	-0.4612	0.6087	-0.2462	0.1326	-0.1377	0.004	0.2195	0.1787	0.2396
ControlPrecision	0.8675	0.0406	-0.0661	0.3465	0.0767	0.087	-0.0746	0.1616	0.0762
DeductiveReasoning	-0.4496	0.6743	-0.157	-0.2415	-0.0763	0.3237	-0.1808	0.1646	0.0899
DepthPerception	0.7936	0.3255	-0.3665	-0.0699	0.0543	-0.0146	-0.0693	0.1582	0.0921
DynamicFlexibility	0.6126	-0.1001	-0.1007	-0.3141	-0.1657	-0.1406	0.3189	0.1776	0.3254
DynamicStrength	0.8947	0.1368	0.2056	-0.1624	-0.1388	0.0077	0.1571	0.0591	0.0646
ExplosiveStrength	0.4249	0.2109	0.4596	-0.2061	0.1107	0.4039	-0.091	0.0158	0.3373
ExtentFlexibility	0.8895	0.0781	0.2877	-0.1096	-0.1782	-0.02	0.1306	0.0707	0.0537
FarVision	0.4058	0.6156	-0.2742	-0.2844	0.0252	-0.1227	-0.0478	-0.1132	0.2695
FingerDexterity	0.6806	0.1224	0.0414	0.5189	-0.235	-0.0385	-0.1438	0.0295	0.1726
FlexibilityofClosure	0.0932	0.8627	-0.1215	0.1213	-0.134	-0.0547	-0.0151	-0.139	0.1772
FluencyofIdeas	-0.4888	0.6905	-0.1393	-0.2275	-0.211	-0.2216	-0.0848	0.1819	0.0792
GlareSensitivity	0.7826	0.1479	-0.3845	-0.1023	0.3131	-0.0243	0.107	-0.0745	0.0918
GrossBodyCoordination	0.8423	0.1872	0.36	-0.2511	-0.0907	0.0767	0.1162	0.0045	0.0352
GrossBodyEquilibrium	0.8159	0.2308	0.3271	-0.1452	-0.0472	0.0729	0.2252	0.0385	0.0931
HearingSensitivity	0.6411	0.4773	0.0503	0.0697	0.0813	-0.0439	-0.2861	-0.2099	0.2193
InductiveReasoning	-0.4874	0.6748	-0.1349	-0.2258	-0.0673	0.2159	-0.1241	0.1988	0.1318
InformationOrdering	-0.524	0.5989	-0.0914	0.1523	0.113	0.006	0.1805	0.1991	0.2502
ManualDexterity	0.8857	-0.0152	0.1296	0.3315	-0.1019	-0.0616	0.0071	0.1132	0.0616
MathematicalReasoning	-0.4208	0.5362	-0.2467	0.1845	-0.3634	0.3121	0.2684	-0.2214	0.09
Memorization	-0.4864	0.6758	0.0384	-0.0344	0.0003	0.0714	-0.1021	-0.1978	0.2494
MultilimbCoordination	0.9251	0.185	0.1487	-0.0159	-0.0234	-0.02	0.0182	0.111	0.074
NearVision	-0.094	0.2835	0.1444	0.6982	0.3177	-0.04	0.2291	0.2855	0.166
NightVision	0.7325	0.2136	-0.4052	-0.0757	0.4223	0.0146	0.1204	-0.0554	0.0518
NumberFacility	-0.3367	0.5523	-0.1725	0.2272	-0.3624	0.3434	0.3204	-0.218	0.1007
OralComprehension	-0.7336	0.359	0.365	0.0722	0.2678	-0.0614	0.067	0.0699	0.1097
OralExpression	-0.7106	0.4538	0.3457	-0.1273	0.2416	-0.081	0.0105	0.0257	0.0877
Originality	-0.4269	0.6368	-0.2129	-0.2949	-0.2811	-0.3033	-0.1086	0.1133	0.0843
PerceptualSpeed	0.2237	0.7561	-0.065	0.3826	-0.1103	-0.0151	0.1184	-0.2333	0.1469

PeripheralVision	0.7433	0.2333	-0.3916	-0.1081	0.4034	-0.0356	0.1261	-0.0646	0.044
ProblemSensitivity	-0.2741	0.7578	-0.0788	-0.1801	0.0349	0.3043	-0.1554	0.1675	0.166
RateControl	0.8753	0.1618	-0.2118	0.082	0.1388	0.1741	-0.1364	0.0698	0.083
ReactionTime	0.8786	0.2021	-0.1664	-0.0258	0.1345	0.2081	-0.1759	0.0663	0.0621
ResponseOrientation	0.88	0.1854	-0.0687	0.0269	0.1719	0.2481	-0.1896	0.0714	0.0536
SelectiveAttention	0.0171	0.5987	0.2273	0.3705	0.1028	-0.2795	-0.0937	-0.2775	0.2779
SoundLocalization	0.7171	0.277	-0.3022	-0.0667	0.3901	-0.1286	0.0996	-0.1303	0.1176
SpatialOrientation	0.7469	0.2679	-0.3581	-0.146	0.3207	-0.0815	0.2036	-0.0369	0.0684
SpeechClarity	-0.6096	0.495	0.4221	-0.1237	0.2581	-0.0926	0.0703	0.0892	0.1019
SpeechRecognition	-0.6615	0.4217	0.4138	-0.0284	0.2861	-0.1031	0.0266	0.0382	0.1179
SpeedofClosure	-0.1043	0.8731	0.095	-0.0438	-0.0981	0.0116	-0.0758	-0.1693	0.1717
SpeedofLimbMovement	0.8745	0.1888	0.2034	-0.1383	0.0109	0.0353	0.2134	-0.0766	0.0863
Stamina	0.8494	0.1811	0.3664	-0.2261	-0.1147	0.0518	0.1079	-0.0033	0.0328
StaticStrength	0.8623	0.1713	0.3776	-0.0935	-0.0916	0.0585	0.1094	0.0261	0.0513
TimeSharing	-0.0807	0.6812	0.4585	-0.104	0.1893	-0.1795	-0.0181	-0.0121	0.2399
TrunkStrength	0.7746	0.1274	0.4023	-0.2648	-0.1678	-0.0675	-0.0075	-0.0637	0.1149
VisualColorDiscrimination	0.6141	0.5177	0.0337	0.2136	-0.2985	-0.1557	-0.0748	0.0254	0.1886
Visualization	0.3609	0.566	-0.3588	0.0102	-0.3345	-0.3609	-0.0282	0.2753	0.1019
WristFingerSpeed	0.748	-0.0113	0.0925	0.3924	0.0745	0.1098	-0.1431	0.1848	0.2056
WrittenComprehension	-0.7741	0.4277	0.1769	0.139	0.1811	0.1306	0.1339	0.0953	0.0904
WrittenExpression	-0.8084	0.3194	-0.0004	0.1128	0.3047	0.0692	0.0646	0.0938	0.121

A. Table 7 Best paid and least paid occupations

Occupations	2000	Occupations	2013
Physicians and Surgeons	237 336,50	Lawyers	430 145,80
Logisticians	227 498,10	Anesthesiologists	201 642,20
Family and General Practitioners	222 503,00	History Teachers, Postsecondary	169 027,00
Anesthesiologists	203 437,80	Family and General Practitioners	150 102,00
Physical Therapists	197 780,50	Commercial Pilots	148 947,70
Judges, Magistrate Judges, and Magistrat	191 313,60	Foresters	147 883,20
Communications Teachers, Postsecondary	190 858,10	Computer and Information Systems Manager	143 958,50
History Teachers, Postsecondary	185 693,90	Human Resources Managers	135 002,00
Lawyers	164 366,00	Industrial Engineers	133 200,20
Administrative Law Judges, Adjudicators,	164 267,70	Financial Managers	132 982,40
Childcare Workers	28 926,93	Laundry and Dry-Cleaning Workers	25 112,56
Lodging Managers	27 469,51	Barbers	25 012,51
Dietitians and Nutritionists	21 975,61	Maids and Housekeeping Cleaners	22 785,90
Tailors, Dressmakers, and Custom Sewers	21 133,60	Engineering Teachers, Postsecondary	22 011,01
Photographic Process Workers and Process	18 129,88	Childcare Workers	20 621,06
Retail Salespersons	14 284,14	Opticians, Dispensing	19 509,76
Counter and Rental Clerks	13 185,36	Couriers and Messengers	13 154,87
Instructional Coordinators	13 113,86	Pressers, Textile, Garment, and Related	12 006,00
Word Processors and Typists	6 592,68	Technical Writers	12 006,00
Barbers	5 933,41	Door-to-Door Sales Workers, News and Str	10 800,30

A. Table 12 wage quartile regression estimates (details)

	50		75		25		50		75		25	
Physical	-0,1590	0,0048	-0,1792	0,0038	-0,1544	0,0089	-0,1306	0,0041	-0,1398	0,0026	-0,1113	0,0062
Spatial	-0,0204	0,0038	0,0030	0,0033	-0,0376	0,0045	0,0355	0,0042	0,0483	0,0039	0,0277	0,0048
Verbal intelligence	0,0778	0,0025	0,0407	0,0025	0,1344	0,0036	-0,0106	0,0029	-0,0273	0,0034	-0,0052	0,0042
Precision	0,1100	0,0043	0,0892	0,0036	0,1412	0,0067	0,0537	0,0062	0,0621	0,0045	0,0565	0,0042
Perception	0,0821	0,0038	0,0764	0,0023	0,1014	0,0079	0,0107	0,0047	0,0140	0,0044	-0,0031	0,0047
Motoric	-0,0269	0,0048	-0,0207	0,0042	-0,0188	0,0073	-0,0037	0,0042	0,0076	0,0040	-0,0118	0,0050
Constructive intelligence	-0,0333	0,0041	-0,0318	0,0037	-0,0310	0,0048	-0,0204	0,0045	-0,0210	0,0037	-0,0166	0,0056
Planning intelligence	0,1116	0,0049	0,1038	0,0021	0,1625	0,0047	0,0722	0,0031	0,0779	0,0029	0,0902	0,0064
Comp_Electr	-0,0012	0,0071	-0,0212	0,0046	0,0334	0,0090	-0,0099	0,0056	-0,0287	0,0059	0,0025	0,0068
_cons	11,0241	0,0188	11,3821	0,0129	10,5144	0,0277	10,9066	0,0546	11,3384	0,0618	10,6047	0,1132
Controls	No	No	No	No	No	No	yes	yes	yes	yes	yes	yes

A.Table 13 Estimated coefficients by quartile of the computer use in the occupation

	Q1	Q2	Q3	Q4	Q1	Q2	Q3	Q4
Physical	-0,2003***	-0,2902***	-0,3249***	-0,1671***	-0,1195***	-0,1894***	-0,2291***	-0,1074***
Spatial	-0,0096	0,0726***	-0,0485**	0,0363**	0,1030***	0,0680***	0,0794***	0,0134
Verbal intelligence	0,1194***	0,0630***	0,1094***	-0,0144	-0,0189**	-0,0453***	0,0220	-0,1085***
Precision	0,2345***	0,1792***	0,1244***	0,1305***	0,0639***	0,1525***	0,0658***	0,0469***
Perception	0,0549***	0,0714***	0,0263***	0,0499***	0,0079	0,0377	-0,0318**	0,0282***
Motoric	0,1260**	0,0757***	-0,0114	-0,0799***	-0,0009	0,0296***	0,0266**	-0,0544***
Constructive intelligence	-0,0938***	-0,0323***	-0,0003	-0,0024	-0,0455**	-0,0066	0,0204	0,0202***
Planning intelligence	0,1272***	0,165554***	0,2536***	0,1870***	0,04152**	0,1471***	0,1287***	0,1088**
Constant	11,0129***	11,0051***	10,9655***	11,0833***	10,60***	9.9734***	10,26***	10,77***
Controls	No	No	No	No	yes	yes	yes	yes

*** represent the significance level at 1%, ** significance level at 5%, * significance level at 10%.

A.Table 13 Computer quartile regression estimates (details)

	Q1		Q2		Q3		Q4		Q1		Q2		Q3		Q4	
factor1	-0,1536	0,0128	-0,1712	0,0114	-0,2189	0,0150	-0,1146	0,0101	-0,0941	0,0143	-0,1680	0,0097	-0,1862	0,0194	-0,0803	0,0210
factor2	-0,0633	0,0154	0,0375	0,0052	-0,0066	0,0126	0,0089	0,0093	0,0495	0,0115	0,0635	0,0083	0,0655	0,0221	0,0592	0,0154
factor3	0,0951	0,0078	0,0797	0,0040	0,1063	0,0092	-0,0326	0,0122	-0,0165	0,0059	-0,0237	0,0074	0,0124	0,0107	-0,1062	0,0260
factor4	0,1302	0,0149	0,1608	0,0154	0,1127	0,0068	0,0845	0,0080	0,0413	0,0118	0,1228	0,0165	0,0638	0,0148	0,0374	0,0130
factor5	0,0726	0,0173	0,1656	0,0174	0,0421	0,0054	0,0870	0,0107	0,0225	0,0107	0,0473	0,0187	-0,0194	0,0089	0,0354	0,0121
factor6	0,0203	0,0241	0,0156	0,0095	-0,0490	0,0101	-0,0810	0,0049	-0,0264	0,0136	0,0237	0,0089	0,0103	0,0078	-0,0469	0,0090
factor7	-0,0969	0,0126	-0,0043	0,0118	-0,0096	0,0084	0,0329	0,0078	-0,0267	0,0106	-0,0107	0,0106	0,0128	0,0065	0,0313	0,0093
factor8	0,1263	0,0107	0,1040	0,0058	0,2327	0,0124	0,1035	0,0111	0,0276	0,0098	0,1078	0,0044	0,1397	0,0147	0,0297	0,0139
_cons	11,0129	0,0163	11,0051	0,0078	10,9655	0,0148	11,0833	0,0081	10,9251	0,0851	11,1546	0,1743	10,7493	0,1381	10,8650	0,0717
Controls	No	No	No	No	No	No	No	No	yes	yes	yes	yes	yes	yes	yes	yes