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RETURNS TO SKILLS IN LATVIA: WHAT CAN WE LEARN FROM JOB ADVERTS?

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Abstract

This paper examines returns to skills in the Latvian labour market using a novel dataset obtained from the job adverts. Main findings of the study suggest that most of the skills that are reported in the job adverts have a positive and statistically significant effect on wages. That is, job adverts requiring these skills (e.g. cognitive skills, project management etc.) tend to offer higher wages than those that do not. These results are robust to inclusion of other wage determinants and different methodological choices. Furthermore, the findings suggest that most of the skills exhibit a positive effect on offered wages by providing access to industries and occupations with relatively higher wages. However, certain skills, namely software skills, customer service and project management skills are rewarded even within the specific industry and occupation group. We also find that jobs adverts with a higher number of required skills tend to offer higher wages.

1. Introduction

There are numerous studies investigating labour market returns to education, particularly the relationship between the obtained level of education and wages. Since the seminal study of Mincer (1974), this topic has attracted the attention of many academics throughout the world (see Psacharopoulos & Patrinos, 2018 for a recent summary). Overall, the majority of studies present robust evidence that a higher level of education[1] is associated with higher wages. There is, however, some uncertainty whether this relationship stems from skills and knowledge acquired during studies or the diploma itself.

To solve this puzzle, various studies have tried to untangle the two effects. For example, Hanushek et al. (2015) showed that the positive effect which education exerts on wages can be largely captured by a combination of 3 categories of cognitive skills - literacy, numeracy and problem-solving. Nevertheless, education still exhibits a statistically significant impact on wages even when these skills are controlled for, hence suggesting that education offers other traits than cognitive skills (e.g. social skills).

One caveat of the vast majority of previous studies that have investigated returns to skills is the reliance on standardized test scores to measure certain skills. Firstly, this approach is limited to only those skills that can be directly measured. Secondly, it does not take into account if these skills are actually required in the workplace. To overcome these issues, some studies have relied on datasets from job adverts. For example, Deming and Kahn (2017) used information on 40000 online job adverts in the USA and showed that variance in demanded skills explains a large part of variance in offered wages. Despite these advantages, only few studies have thus far used the job adverts to account for skills that are actually required. Furthermore, these studies mainly focus on the US and Western Europe. In the case of Eastern Europe, prior studies primarily rely on standardized test scores as proxies for cognitive skills. (Hanushek et al., 2015)

To the best of our knowledge, job adverts have not been previously used to investigate returns to skills in Eastern Europe. Furthermore, there are no studies that have assessed returns to skills in Latvia. We intend to fill these gaps in literature by compiling a novel database of information obtained from online job adverts which identify the key characteristics of the position, including the required skills and offered wages. Our dataset consists of 1100 observations (job adverts) posted online during the period from October

[1] Or higher number of years spent in formal education.

2019 to January 2020 and covers 100 different occupations in Latvia. Subsequently, using econometric analysis we seek to answer the following research question: **How skills required in job adverts affect wages in Latvian labour market?** In other words, what are the labour market returns to skills in Latvia?

The novelty of this study is twofold. First, it aims at reducing the generality of present literature of skill premiums in Eastern Europe. Since the skill profiles are created from actual job adverts, our approach allows for a better understanding of the actually demanded skills in the workplace (be they measurable or not). Second, to the best of our knowledge, this is the first research investigating the skill premium in Latvia. Hence, the results will potentially elucidate a new set of wage determinants.

The main findings of this study suggest that most of the skills that are reported in the job adverts have a positive and statistically significant effect on wages. That is, job adverts requiring these skills (e.g. cognitive skills, project management among others) tend to offer higher wages than those that do not. These results are robust to inclusion of other wage determinants and different methodological choices. Furthermore, our findings suggest that most of the skills exhibit a positive effect on offered wages by providing access to industries and occupations with relatively higher wages. However, certain skills, namely software skills, customer service and project management skills, are rewarded even within the specific industry and occupation group. We also find that jobs adverts with a higher number of required skills tend to also offer higher wages.

The study is structured as follows. Section 2 reviews previous studies that have investigated returns to education and returns to skills. Furthermore, it discusses other studies that have employed job adverts to shed light on employee skill profiles. Section 3 introduces our novel dataset, briefs on the method of skill categorization and describes the secondary dataset used for further analysis and robustness checks. In Section 4, we explain our econometric methodology and elaborate on methods of robustness checks. Section 5 presents the main findings of our study, whereas Section 6 discusses them. In Section 7, we provide our conclusions and outline avenues for future research.

2. Literature review

Relationship between education and income has received a lot of attention in academic literature. Most of the previous empirical studies have relied on the methodological framework established in the seminal studies by Mincer (1974) and Becker (1964, 1994), which shows how each additional year of schooling affects income.

Over the past five decades, the majority of studies using this framework have found a statistically significant positive relationship between education and income (Badescu, D'Hombres, & Villalba, 2011; Bhuller, Mogstad & Salvanes, 2017; Furno, 2014; Trostel, Walker & Woolley, 2002). Using a compilation of past studies, Psacharopoulos and Patrinos (2004, 2018) show that in a period from 1950 to 2014, the average return (in terms of wages) to an additional year of schooling was approximately 9.7% (9.5% using only the latest data for each of the 139 countries observed). Their compilation shows a higher return to education in countries with lower income per capita and a lower return to education in countries with high income per capita. For instance, each additional year of schooling in high-income countries[2] yielded an 8.2% average return, whereas in low-income countries[3] the respective figure is approximately 9.3% (Psacharopoulos & Patrinos, 2018).

Psacharopoulos and Patrinos (2004, 2018) also compile a dataset of studies that have employed the wage differential model which shows how individual's income is affected by the highest obtained level of education (an extension of the Mincer (1974) model that uses dummy variables for each education level). On average, the returns to primary education are the highest (18.9%), followed by secondary education (13.1%) and higher education (10.8%). Also, in this case returns to education is lower in higher-income countries and higher in lower-income countries. Some studies go even further and show returns to education differ in different fields of education (see, for example, Bockerman, Haapanen & Jepsen, 2018; Vilerts & Krasnopjorovs, 2017).

Although education is a significant determinant of income, it remains unclear how much of this relationship is attributed to knowledge and skills, and how much relates to

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[2] A country is considered to be in high income group if the GDP per capita is higher than USD 12736 (in 2015)

[3] A country is considered to be in low income group if the GDP per capita is lower than USD 1045 (in 2015)

signalling effect of one's ability (Hause, 1972). Hence, a related branch of literature tries to investigate returns to skills (Borghans & Weel, 2011; Bowles, Gintis, & Osborne, 2001; Hause, 1972; Hanushek & Woessmann,2008, Hanushek et al., 2015; Heckman et al., 2006; Murnane et al., 2000).

A vast majority of previous studies find evidence that cognitive skills are important predictors of income. In some case skills provide a higher explanatory power than a simple measure of years of education. These studies have mostly relied on standardized test scores to obtain proxies for individual's cognitive skills. Overall, they find that general cognitive skills can explain 15% to 35% of wage variance. For example, Murnane et al. (2000), using math test scores as proxies for cognitive skills for 8518 people in the US, find that the test scores explain as much as 25% of annual earning variation.

Most of the studies focused on cognitive skills, however, some studies go further and investigate the attributes accounting for income differences for people with similar cognitive performance and schooling. For example, Bowles et al. (2001) using longitudinal surveys in the US find that much of the income variance still remains unexplained even after controlling for cognitive skills and education, therefore suggesting that other skills might be of importance. A 1998 survey conducted by the US Census Bureau in collaboration with the Department of Education (as cited in Bowles et al., 2001) revealed that employers regard communication skills as a more important trait than years of schooling (or industry-based skill credentials) when making hiring decisions. Furthermore, in this survey, a trait of "positive attitude" was ranked as the most important one. This supports the argument of Bowles et al. (2001) who showed that part of the unexplained variance in the standard earnings function might be due to multiple skills and traits that are not observable in standardized test scores (which are frequently used as proxies for skill measurement). Hence, in order to draw clearer and more precise conclusions on skill premiums, one must consider a relatively broad set of skills.

Although the majority of previous studies have investigated the returns in terms of income, some studies have highlighted other benefits of higher skills. For example, Heckman et al. (2006) examine how cognitive skills and personality traits affect outcomes in terms of propensity to engage in criminal activities, teenage pregnancy and longevity on a US population sample. Throughout the research, they distinguish between cognitive and noncognitive skills. They find that having stronger noncognitive skills reduces the probability of engaging in illegal activities, incarceration, illegal drug usage. This also applies, but to a smaller extent, to cognitive skills. Additionally, under the same cognitive abilities, the noncognitive factors are the dominant ones in terms of wage determination. (Heckman et al., 2006)

The existing studies investigating skill premium have obtained information on cognitive skills from test scores, therefore not necessarily reflecting the actual skills used (and paid for) at the workplace (Hanushek & Woessmann, 2008). Noncognitive skills have been measured using tests and surveys with narrow samples that cannot be easily reproduced. Furthermore, most of the studies observe salaries just after graduation and do not follow the individuals throughout their careers, capturing the natural growth levels of income and their relation to one's skills. It might be the case that some skills, such as people management become more useful at later stages in the career.

Only few studies have tried to address these problems. For example, Deming and Kahn (2017) studied variation in skill demands for employees across firms and labour markets using information posted in online job adverts. They argue that job adverts explicitly show what types of requirements are necessaryin a particular position, and hence are remunerated accordingly. By focusing on 10 general skill categories (cognitive, social, character, writing, customer service, project management, people management, financial, computer (general), software (specific)), they find that these skills account for 5% to 12% of the variation in firm productivity in their sample of data in the United States between 2010 and 2015. They categorize these skills according to predetermined keywords in the job adverts that reflect the particular category of a skill[4]. Albeit considering all ten skill groups, the authors analyse cognitive and social skill effects on wages more in-depth. They find that social skills are associated with 42.9% higher wages while cognitive skills yield 11.3% higher wages. After controlling for demographic, firm and industry effects, the estimated coefficients decrease to 7.9% and 5.2% for social and cognitive skills, respectively.

Job adverts have also been used as primary data source for other type of problems. For example, Lee and Han (2008) identified the skill requirements for entry-level programmer/analyst positions in Fortune 500 corporations.[5] Afterwards, they compared the

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[4] For example, keywords, such as, "customer", "sales", "client", "patient" reflect the skill of customer service, while "budgeting", "accounting", "finance", "cost" are all keywords representing financial skills

[5] The authors referred to the most popular commercial job boards in the United States in order to identify the required skills for each vacant position. However, as Fortune 500 companies mostly

search results with a standardized curriculum in order to map the identified skill requirements with the topics for suggested courses in the curriculum. By doing so, they attempted to point out to the gap of the skill set requirements in the job market and the skill set which higher education institutions tend to offer.

Gallavin, Truex and Kvasny (2004) reviewed required skill trends in the United States for IT professionals between 1988 – 2003. Having a dataset of 2297 decoded job adverts over 6 different years from the largest online job advert websites allowed the authors to conclude that employers are seeking employees with an increasing number and variety of skills.[6] Nonetheless, they also identify a gap between the implied *soft skill*[7] requirements and the actually required soft skills in job adverts – although employers seek various different skills, the job adverts they post tend to contain only specific *hard skills*[8].

To the best of our knowledge, there are no studies that have investigated returns to skills in Latvia. There are, however, various studies that have investigated the returns to education. Vilerts and Saksonova (2015) measured returns to education in Latvia while comparing the results with findings in other countries. They found that the returns to higher education in Latvia (based on 2011 labour market survey data) are similar to those in the European Union average but are lower than in some emerging markets. They also found that returns to education significantly differ depending on a person's gender, ethnicity, field of employment and location. Vilerts and Krasnopjorovs (2016) also conclude that higher education is associated with higher wages but argue that it differs between various fields of education. They conclude that social sciences yield the highest returns - 58% - while humanitarian sciences and pedagogy yield only a 41% premium above the wages of individuals with primary education. Romele and Purgailis (2013) conducted similar research, comparing the returns to education before and after the financial crisis of 2008, which

rely on job adverts in their own websites, Lee and Han (2008) also referred to the specific websites of these companies.

[6] The job adverts were decoded in 1988 (686 adverts), 1995 (899 adverts), 2001 (341 advert), 2002 (182 adverts) and twice in 2003 (56 and 133 adverts).

[7] Competencies that employees possess associated with activities such as customer handling, communication, problem-solving, and teamworking (Oxford University Press, 2017)

[8] Competencies that employees possess such as numeracy, literacy, fluency in a foreign language, and specific job-related technical abilities (Oxford University Press, 2008)

severely affected the labour market in Latvia. Their results suggest that the rate of return for an additional year of schooling in 2006 was 16.8%, while it decreased to 12.8% in 2008; in 2010 the rate of return increased to 13.9%. None of these studies, however, have addressed the returns to particular skills.

Hence, we intend to fill the gap in the literature and investigate the returns of skills in Latvia. We do this by developing a novel database of required skills in the Latvian labour market based on online job adverts. Our results supplement the literature on factors affecting wages.

3. Data description

3.1 Job Adverts Dataset

We compile a novel dataset from one of the largest online job advert websites in Latvia – CV online (www.cv.lv). Our dataset is comprised of 1100 job advert observations (posted between October 2019 and January 2020), covering approximately 100 occupations and 20 different industries. Each job advert observation contains information on the job title, skill requirements, the required level of education[9], prior experience required (in years), language requirements, the name and registration number of the company, as well as the industry and region.[10] We find and include a respective ISCO-08[11] 2-digit code occupation variable (see Appendix A for each job advert and a NACE Rev. 2[12] code (see Appendix B) for the industry of the company that had posted the job advert.

Furthermore, since late 2018, Latvian law requires the job adverts to include the wage or wage interval for the offered position (Labour Law, 2018). These values generally portray the monthly gross amount offered for the position.[13] In cases when wage intervals are

[9] We use binary values for each ISCED 2011 level of education (see Appendix C).

[10] For reference purposes, we also record each advert's ID number from CV online website, as well as the date the advert was posted and its expiry date.

[11] International Standard Classification of Occupations

[12] European Classification of Economic Activities

[13] In case the shown wage rate is in different form, we adjust its monthly rate accordingly. In cases when a net-of-tax wages are reported in job adverts, the amount is adjusted to reflect gross (before-tax) wages. Overall, the average wage indicated in the job adverts is notably higher than the figures obtained from the LFS dataset. There are numerous reasons why one would expect such a difference. First, job adverts gross vs LFS net. Second, vacancies reflected in the online job adverts are predominantly located in Riga. Since wages in the capital city are notably higher than in other regions, higher average wage in the job adverts dataset should not come as a surprise. Second, online job adverts are rarely posted for manual labour vacancies that offer relatively lower wages.

reported, the average figures are obtained and used in our baseline scenarios.[14] Hence, the job adverts dataset allows us to investigate how certain skills affect the offered wages.

After excluding observations for jobs located outside of Latvia, internships, or observations with missing information on the wages, our final sample is composed of 887 observations. It covers observations from 17 different industries and 34 different occupations[15]. The most popular occupations of this dataset were Business and Administration Associate Professionals, Information and Communications Technicians and Sales Workers, contributing to 114, 115 and 127 observations, respectively. Whereas Manufacturing, Wholesale and retail trade; repair of motor vehicles and motorcycles, and Information and Communications were the most frequent industries of the job adverts, constituting to 115, 225 and 151 observation, respectively.

[14] If no wage range is provided, and either only the minimum or maximum wage was provided, we use the only wage number available

[15] Decoded by 2-digit ISCO-08 code (Appendix A)

3.2 Skill categorization

We look for keywords in the skill requirements section and categorize similar skills into narrower categories following the methodology of Deming and Kahn (2017). Overall, we obtain information on 11 skills (skills and respective keywords are shown in Table 1)

Table 1: Skills and the respective keywords representing the skills in job adverts[16]

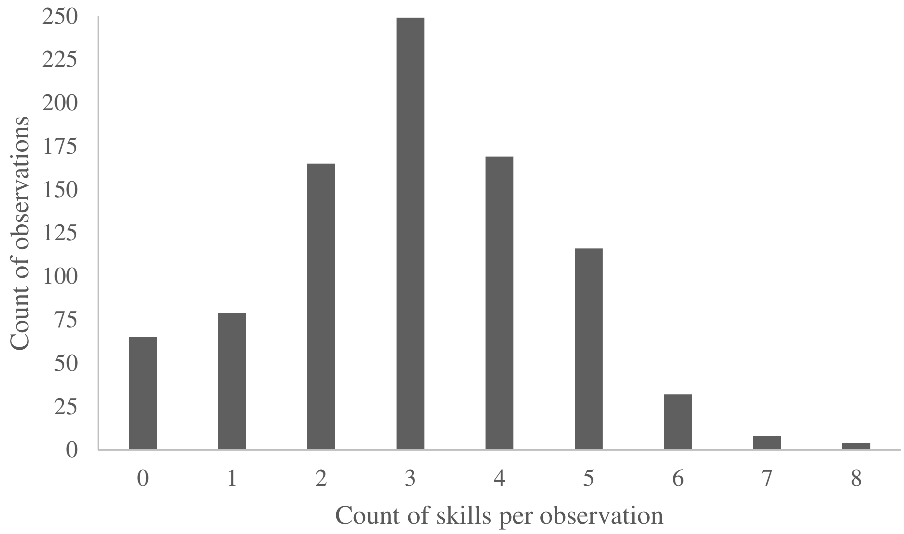
Job skills	Keywords and Phrases
Cognitive	Problem-solving, research, analytical, critical thinking, math, statistics, fast learning, adaptive
Social	Communication, teamwork, collaboration, negotiation, presentation, marketing, network
Character	Organized, detail-oriented, ethical, multitasking, time management, meeting deadlines, energetic, initiative, independence, positive attitude, goal-oriented, responsibility, stress resistance
Writing	Writing, fast typing
Customer service	Customer, sales, client, patience
Project management	Project management
People management	Supervisory, leadership, management (not project), mentoring, staff
Special knowledge	Budgeting, accounting, finance, cost, financial knowledge, AML, legal, technical, procurement
Computer (general)	Computer, spreadsheets, common software (e.g., Microsoft Excel, PowerPoint, Internet Explorer, etc.)
Software (specific)	Programming language or specialized software (e.g., Java, SQL, Python, AutoCAD, etc.)
Creativity	Creative thinking, design

Source: Authors classification of skills by keywords based on Deming & Kahn (2017)

[16] This table represents only the most commonly used keywords and phrases. Full database is available upon request.

On average, the majority of job adverts (approximately 28%) require 3 different skills, with the maximum being 8 skills in a job advert (Figure 1). Only 7% of job adverts did not have any skill requirements at all, while approximately 9% required only one skill.

Figure 1: Distribution of required count of skills



Source: Figure created by the authors using the job adverts dataset.

Table 2 presents the summary statistics for the frequency of each skill's occurrence in the job adverts dataset per each major ISCO-08 group and in total. The most commonly required skill in our dataset is *character skill*, being listed in 75.8% of job adverts. *Social* and *cognitive* skills are the second and third most dominant required skills, being required in 58.1% and 41% of the job adverts. In turn, *Writing* and *creativity* skills occur the least, in 3.2% and 4.7% of job adverts, respectively.

Table 3 provides an overview of correlation coefficients between the skills. Overall, it suggests that correlations between the different skills are rather low (not exceeding 0.25), hence justifying our skill categorization.[17] Furthermore, correlations provide information which skills are more likely to be required together. For example, cognitive skills tend to be required, along with character skills. Whereas character skills will also often be required along with social skills. Interestingly, job adverts requiring specific software skills almost never contain general computer skill requirements. Similarly, specific software skill requirements are rarely found, along with people management or social skills.

[17] It is therefore unlikely that the final results of this paper will suffer from multicollinearity issues.

Table 2: Frequency of each skill in job adverts dataset

	Cognitive	Social	Character	Writing	Cust. service	Project manag.	People manag.	Special knowl.	Computer (general)	Software (specific)	Creativity
1 – Managers	40.9%	59.1%	50.0%	13.6%	9.1%	18.2%	36.4%	36.4%	40.9%	36.4%	4.5%
2 – Professionals	56.0%	72.0%	74.9%	4.6%	19.4%	11.4%	18.9%	33.7%	31.4%	32.6%	9.1%
3 - Technicians and Associate Professionals	47.6%	59.7%	75.5%	3.9%	9.7%	5.2%	5.2%	29.1%	38.5%	47.0%	5.8%
4 - Clerical Support Workers	40.0%	71.8%	88.2%	1.8%	31.8%	2.7%	2.7%	9.1%	48.2%	14.5%	2.7%
5 - Services and Sales Workers	22.0%	47.5%	72.3%	0.0%	36.9%	0.7%	8.5%	4.3%	22.7%	2.1%	1.4%
7 - Craft and Related Trade Workers	20.0%	28.6%	74.3%	0.0%	5.7%	5.7%	8.6%	25.7%	17.1%	17.1%	2.9%
8 - Plant and Machine Operators and Assemblers	29.2%	25.0%	79.2%	0.0%	0.0%	0.0%	0.0%	8.3%	16.7%	0.0%	0.0%
9 - Elementary Occupations	15.4%	23.1%	79.5%	0.0%	7.7%	0.0%	2.6%	2.6%	17.9%	2.6%	0.0%
% of all job adverts	41.0%	58.1%	75.8%	3.2%	18.2%	5.3%	8.8%	22.0%	33.3%	28.3%	4.7%
Count	364	515	672	28	161	47	78	195	295	251	42

Source: Figure created by the authors using the job adverts dataset.

Table 3: Correlation coefficients for skills

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
(1) Cognitive	1.000										
(2) Social	0.189	1.000									
(3) Character	0.247	0.255	1.000								
(4) Writing	0.059	0.075	0.027	1.000							
(5) Customer service	0.065	0.187	0.116	-0.052	1.000						
(6) Project management	0.079	0.160	0.016	-0.014	-0.007	1.000					
(7) People management	0.081	0.175	0.083	0.035	0.029	0.140	1.000				
(8) Special knowledge	0.133	-0.001	-0.075	-0.034	-0.109	0.020	-0.021	1.000			
(9) Computer (general)	0.039	0.193	0.170	0.064	0.015	-0.007	0.085	0.012	1.000		
(10) Software (specific)	0.142	0.022	-0.071	0.116	-0.146	0.019	-0.009	0.192	-0.008	1.000	
(11) Creativity	0.095	0.082	0.027	0.081	0.005	0.137	0.024	-0.054	-0.045	0.119	1.000

Source: Table created by the authors using job adverts dataset.

In order to verify the reliability of the compiled dataset and to account for other unobserved wage determinants, we refer to the Labour Force Survey of Latvia.

3.3 Labour Force Survey

We complement our dataset with microdata obtained from Latvian Labour Force Survey 2018 (hereinafter referred to as - LFS), gathered and compiled by the Central Statistical Bureau (hereinafter referred to as – CSB) of Latvia, for two main purposes: (i) to obtain additional control variables not available in job adverts dataset; (ii) to test the robustness of findings using the job adverts dataset (using alternative measures of wage variables).

The LFS provides a broad and representative set of data on characteristics of households and individuals. These include demographics (gender, age, nationality), education attainment, employment status, monthly wage, region of residence, etc. Due to the comprehensiveness and representativeness of LFS, it has often been used in previous studies to investigate wage determinants in Latvia (Zepa et al., 2006).

We exclude the observations with missing information on wages, hours worked, nationality, education, marital status, region, occupation and industry. Furthermore, we limit our sample to full-time employees[18] with written contracts, aged 18–65, and working in Latvia. Our final LFS sample consists of 7633 observations.

LFS provides information on net wages which are reported as continuous numbers. One caveat of the LFS dataset is that net wages that are higher than EUR 2000 are censored for confidentiality reasons. We adjust these values by inputting a value of EUR 2200 for each of the 82 censored values for robustness purposes. However, this shouldn't affect our results as these observations account for less than 1.07% of the final sample.

In order for the LFS data to be compatible with the job adverts dataset, occupation and industry profiles were created indicating average values of each LFS variable used in the study. The final sample of the LFS represents 39 different occupations over 21 different industries.[19] The most commonly occurring industries in the LFS dataset were Manufacturing and Wholesale and retail trade; repair of motor vehicles and motorcycles, constituting to 1205 and 1111 observations, respectively. The most common occupations are Business and Administration Associate Professionals, Sales Workers, Drivers and Mobile Plant Operators and Labourers in Mining, Construction, Manufacturing, contributing to 540, 550, 712 and

[18] Moreover, we limit the final sample to those individuals that have on average worked between 30 to 50 hours per week.

[19] Refer to Appendix D for summary statistics of the LFS data sample used.

510 observations, respectively. Summary statistics of other occupations are provided in Appendix E, while information on other industries are displayed in Appendix F.

4. Methodology

4.1 Returns to skills

In our baseline specification (Equation 1) we draw on seminal Mincer (1974) model that investigates returns to education and adjust it to fit the needs of our study.

$$lnY_i = C + \beta_j S_{j,i} + \alpha_k Z_{k,i} + \tau_m X_{m,p,o} + u_i \ , \qquad (1)$$

where Y_i is the wage reported in the job advert i; S_{ji} is a binary skill variable that takes the value 1 if the skill j is required in the respective job advert (0 otherwise); $Z_{k,i}$ is a vector of control variables obtained from the job adverts and include the lowest required education level, necessary experience (number of years), as well as job location, and language requirements. We also include the squared variable of necessary experience following Mincer (1974), to account for the non-linear effect of an additional year of experience. α_k are the respective regression coefficients. $X_{m,p,o}$ is a vector of control variables for each industry p and occupation o combination obtained from the LFS dataset, where all the variables are continuous from 0 to 1. The vector includes: average gender proportion, where, for example, the maximum value of 1 shows that from the LFS sample only men work within the respective industry-occupation combination; marital status, showing whether the respondent is married (1, if all the respondents within the respective industry-occupation combination are married); nationality (1, if all the respondents within the respective industry-occupation combination are Latvian); and citizenship (1, if all the respondents within the respective industry-occupation combination are Latvian citizens); τ_m are the respective regression coefficients; u_i is the error, and C is the intercept.

Coefficients of interest are β_j which reveal if (and how) certain skills affect the wages posted in the job adverts, controlling for education, experience, demographics and other wage determinants.

In the industry and occupation controls specification (equation 2) we add the industry and occupation controls by including the NACE code dummy variables (I_i) and ISCO 1-digit code dummy variables (O_i) respectively into the regression.

$$lnY_i = C + \beta_j S_{j,i} + \alpha_k Z_{k,i} + \tau_m X_{m,p,o} + I_i + O_i + u_i \ , \qquad (2)$$

The results from this regression reflect the remaining skill wage effects within the same industry and/or occupation.

4.2 Skill count

In the next step, in order to see whether the number of skills listed in job adverts affects the offered wage, we replace skill dummies with the sum of skills (equation 3):

$$lnY_i = C + \partial \sum_{j=1}^{j} S_{j,i} + \alpha_k Z_{k,i} + \tau_m X_{m,p,o} + I_i + O_i + u_i, \qquad (3)$$

where ∂ is the coefficient of interest. It reflects how offered wages change with each additional skill required in the job adverts.

4.3 Robustness

To test the robustness of our baseline regression and regressions with occupation and industry controls, we employ a number of robustness checks. First, one might argue that the offered wages reflected in the job adverts do not reflect the actual situation in some industries or occupations where informal wages are relatively common.

In order to test the sensitivity of our results subject to the choice of the dependent variable, we use the minimum and maximum wages from the wage range provided in the job adverts. If only one wage is listed in the job advert, we treat it as both minimum and maximum wage for the specific advert.

Additionally, we obtain an alternative wage variable from the LFS dataset.[20] This is achieved by allocating the average wage of occupation/industry profile obtained from the LFS to the respective job advert.

[20] LFS dataset reflects both self-reported wages and imputed wages and hence is more likely to reflect also the informal part of wages.

5. Results

5.1 Baseline specification

The main results of our baseline specification are reported in Table 4. We show step-by-step results of adding each component to regression (1) in this sub-chapter[21].

Column (1) shows the estimated coefficients when only the 11 skills listed in Table 1 are included as explanatory variables. The estimates show a positive and statistically significant effect of cognitive skills on the offered wage. The coefficient for cognitive shows that having such skills increases the offered wage by 14.8%. Similarly, the effect of having social skills increases the offered wage by 7.7%. Having project management and people management skills yield somewhat higher returns, increasing the offered wages by 31.3% and 23.1%, respectively. Having special knowledge skills, increases the offered wage by 21.6%, whereas skills associated with creativity and writing increases the offered wage by 13.4% and 17.5%. Estimated coefficients show that the highest returns are associated with having software skills (38.3%). Interestingly, some skills have a negative and statistically significant effect on wages. For example, skills associated with character - like having a positive attitude, being organized, showing initiative, and having a sense of responsibility - affect wages negatively (-13.8%). Similarly, job adverts requiring general computer skills tend to offer lower wages. Negative coefficients might, however, reflect that these skills are required for more simplistic occupations that, for example, generally require a lower level of education, and have lower remuneration.

To untangle these effects, column (2) in Table 4 adds education variables, job location variable, and experience variables to the regression. Overall, the coefficient estimates do not change notably, and most of the skills remain statistically significant determinants of wages (apart from the social skills, writing skills and creativity). Also, the negative coefficients remain significant, suggesting that these skills affect wages negatively even when education and job location are accounted for. The coefficients for education variables indicate the wage effects of having a certain education level compared to having a secondary school diploma. For example, job adverts requiring only primary education offer on average 67.3% lower wage compared to those requiring secondary education, all else held constant. In turn, job adverts that require higher education on average offer 5.2% higher wage than those requiring secondary education.

[21] Intercept values of our regressions cannot be interpreted, and thus are not displayed in results tables.

Table 4: OLS regression baseline results

	(1)	(2)	(3)	(4)
Variables obtained from job adverts				
Cognitive	0.148***	0.103***	0.079***	0.072***
	(0.030)	(0.027)	(0.027)	(0.028)
Social	0.077**	0.025	-0.003	0.022
	(0.030)	(0.027)	(0.027)	(0.027)
Character	-0.138***	-0.131***	-0.124***	-0.104***
	(0.038)	(0.034)	(0.034)	(0.033)
Writing	0.175**	0.109	0.082	0.039
	(0.068)	(0.069)	(0.073)	(0.076)
Customer service	0.036	0.024	0.028	0.044
	(0.039)	(0.035)	(0.034)	(0.034)
Project management	0.313***	0.208***	0.185***	0.161**
	(0.065)	(0.061)	(0.061)	(0.067)
People management	0.231***	0.089**	0.116***	0.129***
	(0.054)	(0.044)	(0.043)	(0.046)
Special knowledge	0.216***	0.094***	0.082***	0.092***
	(0.034)	(0.031)	(0.031)	(0.031)
Computer (general)	-0.055*	-0.066**	-0.067**	-0.045*
	(0.029)	(0.026)	(0.026)	(0.026)
Software (specific)	0.383***	0.272***	0.245***	0.126***
	(0.033)	(0.032)	(0.032)	(0.034)
Creativity	0.134**	0.084	0.085	0.096
	(0.064)	(0.057)	(0.056)	(0.066)
Job location – Riga		0.046	0.029	0.079***
		(0.032)	(0.031)	(0.031)
Primary education		-0.673***	-0.651***	-0.604***
		(0.129)	(0.130)	(0.112)
Technical education		-0.088*	-0.081	-0.082
		(0.053)	(0.052)	(0.050)
Higher education		0.052*	0.029	0.071**
		(0.028)	(0.027)	(0.029)
Years of experience		0.187***	0.173***	0.146***
		(0.021)	(0.020)	(0.021)
Years of experience^2		-0.009***	-0.008**	-0.005
		(0.003)	(0.003)	(0.003)
Russian language			-0.047*	-0.036
			(0.025)	(0.026)
English language			0.171***	0.168***
			(0.030)	(0.030)
LFS variables				
Male				0.353***
				(0.043)
Married				-0.103
				(0.066)
Latvian				-0.124
				(0.083)
Latvian citizen				0.423***
				(0.125)
Obs.	887	887	887	803
R-squared	0.311	0.462	0.483	0.526

Notes: The dependent variable is the natural logarithm of the mean wage calculated from the wage interval shown in the job adverts. Robust standard errors are in parentheses. *** p-value<0.01, ** p-value<0.05, * p-value<0.1.
Source: Table created by the authors using job adverts dataset and LFS 2018 data.

The effect of the job location on the offered wage is small and statistically insignificant. The regression results also show that one year of experience increases the offered wage by 18.7%. However, the marginal effect of years of experience on wage decreases with each additional year of experience, showing that the effect of experience on offered wage is non-linear.

Next, we complement explanatory variables with the language requirements (column 3). Overall, the relationship between skill variables and offered wages do not change notably. Additionally, the regression shows that job adverts requiring knowledge of English language tend to offer, on average, 17.1% higher wages. Knowledge of Russian language has a negative 4.7% effect on the offered wage.

Finally, we add the controls from the LFS database – gender, marital status, nationality and citizenship. The introduction of the other control variables does not alter the previous findings regarding the relationship between the skills and offered wages. Hence, although the coefficient estimates are somewhat lower than in (1) column, we conclude that vast majority of skills (7 out of 11) remain as significant determinants of offered wages even after the inclusion of standard wage determinants. Additionally, we learn that job adverts in occupations and industries with higher proportion of men tend to offer higher wages. Same is true for job adverts in occupations and industries with higher proportion of Latvian citizens. Estimated coefficients for nationality and marital status are statistically insignificant.

5.2 Industry/Occupation controls

In the next step of our empirical analysis, we add industry and occupation controls to the regression. Hence the coefficient estimates reveal how skills affect offered wages within the industry and occupation group (see Table 5 for the results).

First, we add only the industry controls (column 1). The results show that the introduction of industry controls decreases the estimated coefficients and their statistical significance for nearly all skills. Project management and people management skills still exhibit a positive, and statistically significant, effect on the offered wages, 16.1% and 13.3%, respectively. Software skills also have a positive and statistically significant, albeit somewhat lower effect on wages (9.9%). Similarly, also cognitive and special knowledge skills retain a positive effect on the offered wage of 4.6% and 6% respectively.

Table 5: OLS regression results with occupation/industry controls

	(1)	(2)	(3)
Cognitive	0.046*	0.023	0.014
	(0.027)	(0.026)	(0.025)
Social	0.012	0.013	0.005
	(0.027)	(0.025)	(0.025)
Character	-0.079**	-0.023	-0.011
	(0.033)	(0.031)	(0.032)
Writing	-0.031	-0.038	-0.077
	(0.081)	(0.068)	(0.070)
Customer service	0.058*	0.101***	0.110***
	(0.034)	(0.033)	(0.033)
Project management	0.161**	0.102*	0.116**
	(0.066)	(0.057)	(0.056)
People management	0.133***	0.060	0.059
	(0.044)	(0.043)	(0.041)
Special knowledge	0.060*	0.020	0.007
	(0.031)	(0.028)	(0.028)
Computer (general)	-0.012	-0.035	-0.006
	(0.026)	(0.024)	(0.024)
Software (specific)	0.099***	0.073**	0.069**
	(0.033)	(0.031)	(0.031)
Creativity	0.077	-0.016	-0.018
	(0.063)	(0.056)	(0.054)
Job location – Riga	0.035	0.017	0.001
	(0.034)	(0.029)	(0.030)
Primary education	-0.569***	-0.531***	-0.521***
	(0.096)	(0.071)	(0.071)
Technical education	-0.043	-0.076	-0.060
	(0.050)	(0.048)	(0.048)
Higher education	0.079***	-0.024	-0.032
	(0.030)	(0.031)	(0.031)
Years of experience	0.143***	0.095***	0.097***
	(0.020)	(0.019)	(0.019)
Years of experience^2	-0.005	-0.002	-0.003
	(0.003)	(0.003)	(0.003)
Russian language	-0.030	-0.027	-0.030
	(0.027)	(0.024)	(0.024)
English language	0.131***	0.106***	0.092***
	(0.030)	(0.028)	(0.027)
Male	0.308***	0.052	0.050
	(0.049)	(0.059)	(0.063)
Married	0.054	-0.084	-0.020
	(0.070)	(0.057)	(0.056)
Latvian	-0.032	-0.082	-0.018
	(0.088)	(0.079)	(0.087)
Latvian citizen	0.256**	0.183	0.054
	(0.116)	(0.111)	(0.106)
Industry controls	Included		Included
Occupation controls		Included	Included
Obs.	803	803	803
R-squared	0.569	0.663	0.688

Notes: The dependent variable is the natural logarithm of the mean wage calculated from the wage interval shown in the job advert. Robust standard errors are in parentheses. *** p-value<0.01, ** p-value<0.05, * p-value<0.1.
Source: Table created by the authors using job adverts dataset and LFS 2018 data.

The negative effect of skills related to *character* has somewhat decreased. Interestingly, customer service skills have become statistically significant at 10% level of significance, while previously being insignificant. Overall, these findings suggest that returns to certain skills are twofold: (1) they allow individuals to access industries with relatively higher wage; (2) provide higher wage within a specific industry.

Next in column (2) we add 2-digit ISCO-08 occupation group controls (without industry controls). This specification shows the skill effects on wage in the same occupation group. In this case majority of estimated coefficients become insignificant. This includes people and project management skills that are likely to be required in all industries, but only for certain occupations. The previously insignificant customer service skills have become statistically significant and have a positive effect on wages. This suggests that customer service skills might not be a significant factor to obtain a job in a better-paid occupation, however, it increases the offered wage between people in the same occupation.

Finally, in (column 3) we include both the industry and occupation controls. This regression shows the skill effects on wage for people who work in the same occupation and industry. The results show that within the same industry and occupation, only 3 of the 11 skills hold statistical significance: customer service skills, project management skills and software skills.

Overall, our findings suggest that most of the skills exhibit a positive effect on offered wages by providing access to industries and occupations with relatively high wages. However, certain skills, namely software skills, customer service and project management skills, are rewarded even within the specific industry and occupation group.

5.3 Skill count

In the next step, in order to see whether the number of skills listed in job adverts affects the offered wage, we replace skill dummies with the sum of skills (Table 6). Overall, the obtained results suggest that the number of skills required in the job advert is positively associated with the offered wage. Coefficient estimates indicate that each additional skill required in the job advert increases the offered wage by approximately 1.8-2.3%. These findings are statistically significant with and without occupation and industry controls.

Table 6: Skill count OLS regression results.

	(1)	(2)	(3)	(4)
Skill count	0.023**	0.021**	0.018**	0.020**
	(0.010)	(0.009)	(0.008)	(0.008)
Job adverts dataset controls	Included	Included	Included	Included
LFS dataset controls	Included	Included	Included	Included
Industry controls		Included		Included
Occupation controls			Included	Included
Obs.	803	803	803	803
R-squared	0.491	0.547	0.618	0.662

Notes: The dependent variable is the natural logarithm of the respective wage calculated from the wage interval shown in the job adverts. Robust standard errors are in parentheses. *** p-value<0.01, ** p-value<0.05, * p-value<0.1.
Source: Table created by the authors using job adverts dataset and LFS 2018 data.

The positive coefficient for variable *Skill count* shows that increasing the skills set does, in fact, increase the offered wage.

5.4 Robustness

Finally, we employ several robustness checks to test the validity of the results obtained using the job adverts dataset (see Table 7).

First, we test the sensitivity of our baseline results to different measurements of wages. Column (2) presents the estimated coefficients when the maximum of wage interval posted in the job advert is used as the dependent variable instead of the average. Overall, the estimated coefficients for skill variables remain practically unchanged. Moreover, coefficients for some skills (namely creativity and customer service) that were statistically insignificant in the baseline are now significant and exhibit positive impact on wages.

Next, in column (3) we report the results when the minimum of wage interval posted in the job adverts is used as the dependent variable. Also, in this case, the estimated relationship between different skills and offered wages remains robust.

Table 7: Robustness OLS regression results using various dependent variables.

	(1) ln (Wage)	(2) ln (Max Wage)	(3) ln (Min Wage)	(4) ln (Wage LFS)
Cognitive	0.072***	0.078**	0.062**	0.058***
	(0.028)	(0.032)	(0.026)	(0.018)
Social	0.022	0.021	0.023	0.057***
	(0.027)	(0.032)	(0.026)	(0.019)
Character	-0.104***	-0.108***	-0.097***	-0.065***
	(0.033)	(0.038)	(0.032)	(0.021)
Writing	0.039	0.044	0.042	0.045
	(0.076)	(0.073)	(0.088)	(0.047)
Customer service	0.044	0.068*	-0.007	-0.045*
	(0.034)	(0.041)	(0.030)	(0.023)
Project management	0.161**	0.142*	0.195***	0.031
	(0.067)	(0.073)	(0.068)	(0.049)
People management	0.129***	0.139***	0.108**	0.016
	(0.046)	(0.053)	(0.046)	(0.039)
Special knowledge	0.092***	0.101***	0.071**	0.109***
	(0.031)	(0.036)	(0.030)	(0.024)
Computer (general)	-0.045*	-0.077**	0.005	-0.012
	(0.026)	(0.030)	(0.026)	(0.020)
Software (specific)	0.126***	0.148***	0.089***	0.101***
	(0.034)	(0.039)	(0.032)	(0.023)
Creativity	0.096	0.116*	0.085	0.068
	(0.066)	(0.063)	(0.076)	(0.056)
Primary education	-0.604***	-0.713***	-0.457***	-0.170***
	(0.112)	(0.111)	(0.113)	(0.052)
Technical education	-0.082	-0.121**	-0.019	-0.051
	(0.050)	(0.058)	(0.045)	(0.036)
Higher education	0.071**	0.061*	0.098***	0.067***
	(0.029)	(0.033)	(0.029)	(0.022)
Years of experience	0.146***	0.143***	0.146***	0.034**
	(0.021)	(0.024)	(0.020)	(0.015)
Years of experience^2	-0.005	-0.004	-0.006*	0.000
	(0.003)	(0.004)	(0.003)	(0.002)
Job location – Riga	0.079***	0.069*	0.093***	0.111***
	(0.031)	(0.035)	(0.028)	(0.020)
Russian language	-0.036	-0.041	-0.023	-0.009
	(0.026)	(0.030)	(0.025)	(0.018)
English language	0.168***	0.186***	0.134***	0.070***
	(0.030)	(0.033)	(0.029)	(0.021)
Male	0.353***	0.372***	0.327***	0.350***
	(0.043)	(0.049)	(0.041)	(0.031)
Married	-0.103	-0.138*	-0.069	0.086
	(0.066)	(0.072)	(0.066)	(0.055)
Latvian	-0.124	-0.151	-0.072	0.075
	(0.083)	(0.094)	(0.086)	(0.089)
Latvian citizen	0.423***	0.438***	0.388***	0.291**
	(0.125)	(0.145)	(0.118)	(0.132)
Obs.	803	803	803	803
R-squared	0.526	0.488	0.501	0.475

Notes: The dependent variable is the natural logarithm of the respective wage calculated from the wage interval shown in the job adverts. Robust standard errors are in parentheses. *** p-value<0.01, ** p-value<0.05, * p-value<0.1.
Source: Table created by the authors using job adverts dataset and LFS 2018 data.

Since wages posted in the job adverts might not reflect actual wages paid, in column (4) the average wage of the respective industry/occupation combination (retrieved from the LFS dataset) is used as the dependent variable. The estimated coefficients suggest that majority of previous findings hold true also in this specification. Those industries and occupations that require cognitive skills, specific software skills and special knowledge on average tend to pay also higher wages. Interestingly, social skills become a statistically significant determinant of wages in this specification. This might suggest that social skills might be remunerated on-top of the offered wage indicated in the job advert (results in line with Gallavin et al., 2004).

Next, we add industry and occupation controls to the regressions and compare the results (see Table 8) using the different wages as in Table 7. The results obtained using industry and occupation controls are mostly similar irrespective of the wage proxy used.

Overall, estimates suggest that the findings are robust to the choice of the dependent variable.[22] Most of the skills exhibit a positive effect on offered wages by providing access to industries and occupations with relatively high wages. However, certain skills, namely software skills, customer service and project management skills, are rewarded even within the specific industry and occupation group.

[22] One exception is the specification in which LFS wages are used as dependent variable. In this case, skills do not appear to be significant wage determinant within a specific occupation and industry. This might be due to different skill set required of new employees if compared to the existing ones.

Table 8: Robustness OLS regression results with industry/occupation controls

	(1) ln (Wage)	(2) ln (Max Wage)	(3) ln (Min Wage)	(4) ln (Wage LFS)
Cognitive	0.014	0.010	0.016	0.002
	(0.025)	(0.029)	(0.026)	(0.010)
Social	0.005	0.005	0.005	0.007
	(0.025)	(0.029)	(0.025)	(0.010)
Character	-0.011	-0.006	-0.017	0.006
	(0.032)	(0.036)	(0.031)	(0.010)
Writing	-0.077	-0.092	-0.046	-0.001
	(0.070)	(0.069)	(0.083)	(0.026)
Customer service	0.110***	0.139***	0.049*	0.002
	(0.033)	(0.040)	(0.030)	(0.012)
Project management	0.116**	0.096	0.153***	0.001
	(0.056)	(0.063)	(0.057)	(0.032)
People management	0.059	0.061	0.048	-0.033
	(0.041)	(0.047)	(0.045)	(0.026)
Special knowledge	0.007	0.000	0.011	0.028***
	(0.028)	(0.033)	(0.028)	(0.011)
Computer (general)	-0.006	-0.024	0.022	-0.013
	(0.024)	(0.027)	(0.025)	(0.010)
Software (specific)	0.069**	0.083**	0.043	0.009
	(0.031)	(0.036)	(0.029)	(0.013)
Creativity	-0.018	-0.011	-0.012	-0.017
	(0.054)	(0.059)	(0.059)	(0.031)
Primary education	0.001	-0.020	0.030	0.007
	(0.030)	(0.035)	(0.029)	(0.011)
Technical education	-0.521***	-0.616***	-0.384***	-0.076***
	(0.071)	(0.078)	(0.066)	(0.027)
Higher education	-0.060	-0.080	-0.023	-0.038**
	(0.048)	(0.057)	(0.045)	(0.016)
Years of experience	-0.032	-0.045	0.001	-0.030**
	(0.031)	(0.035)	(0.032)	(0.015)
Years of experience^2	0.097***	0.091***	0.101***	0.004
	(0.019)	(0.022)	(0.019)	(0.007)
Job location – Riga	-0.003	-0.002	-0.004	-0.000
	(0.003)	(0.004)	(0.003)	(0.001)
Russian language	-0.030	-0.039	-0.012	-0.005
	(0.024)	(0.028)	(0.025)	(0.010)
English language	0.092***	0.098***	0.074***	-0.013
	(0.027)	(0.030)	(0.028)	(0.012)
Male	0.050	0.062	0.033	0.194***
	(0.063)	(0.068)	(0.072)	(0.051)
Married	-0.020	-0.028	-0.027	0.135***
	(0.056)	(0.061)	(0.064)	(0.049)
Latvian	-0.018	-0.043	0.034	0.204***
	(0.087)	(0.097)	(0.096)	(0.078)
Latvian citizen	0.054	0.045	0.052	-0.197***
	(0.106)	(0.124)	(0.116)	(0.072)
Industry and occupation controls - Included				
Obs.	803	803	803	803
R-squared	0.688	0.653	0.640	0.865

Notes: The dependent variable is the natural logarithm of the mean wage calculated from the wage interval shown in the job advert. Robust standard errors are in parentheses. *** p-value<0.01, ** p-value<0.05, * p-value<0.1.
Source: Table created by the authors using job adverts dataset and LFS 2018 data.

6. Discussion

Using a novel dataset obtained from online job adverts, this paper examines returns to skills in the Latvian labour market. We decode information from online job adverts, including the offered wage interval and required skills for each position. Additionally, we supplement job adverts dataset with the variables obtained from the LFS of Latvia, which allows us to control for additional demographic factors. Our sample consists of 1100 observations ranging between 100 different occupations in Latvia covering the period from October 2019 to January 2020. Subsequently, using quantitative cross-sectional econometric analysis, we seek to find an answer to the following question: How skills required in job adverts affect wages in the Latvian labour market?

Our main findings suggest that most of the skills that are required in the job adverts have a positive and statistically significant effect on wages. The results are robust to the inclusion of other wage determinants, such as job location, education, experience, language, gender ethnicity and citizenship. Project management and people management, as well as software skills, yield the highest returns in terms of wages. Job adverts requiring these skills offer on average 12.6%-16.1% higher wages than those adverts that do not. Interestingly, some skills (such as character or general computer skills) have negative returns, i.e. those job adverts that require these skills on average offer lower wage than those that do not. Overall, our findings for Latvia (which to best of our knowledge are first) are in line with previous studies for other countries which show positive returns to skills (Deming & Kahn, 2017; Hanushek & Woessmann, 2008; Heckman et al., 2006;).

Furthermore, using information obtained from job adverts, we overcome issues that are present when skills are measured with standardized test scores, i.e. sample is limited to only those skills that can be directly measured and not taking into account if skills are actually required in the workplace. For example, we find that people management and project management skills yield one of the highest returns in terms of wages. Hence, we provide a new angle to a vast body of research that has investigated returns to skills (Borghans & Weel, 2011; Bowles et al., 2001; Hanushek et al., 2015; Hanushek & Woessmann, 2008; Hause, 1972; Heckman et al., 2006; Murnane et al., 2000;).

Furthermore, our findings suggest that most of the skills exhibit a positive effect on offered wages by providing access to industries and occupations with relatively higher wages. Nonetheless, certain skills, namely customer service, project management and software skills, are rewarded even within the specific industry and occupation group. Hence, the effect of skills (at least for some) on wages is twofold: (a) access to better-paid occupations and industry; (b) higher wages within occupations and industries. Vilerts, Krasnopjorovs and Brekis (2017) suggest this is true also in the case of education.

We also find that skill count affects wages positively. This relationship holds irrespective of the different wage types used as dependent variables. Industry and occupation controls also do not affect the significance and effect of these results. These findings are in line with Gallavin et al., 2004) who show employers are looking for employees with a more diversified skill set.

We employ several robustness tests to verify the validity of our findings. We compare the returns to skills using various available proxies for wages, namely, minimum and maximum wages from the job adverts[23], and the average wages for the respective industry/occupation combination obtained from the LFS dataset. Overall, estimated coefficients suggest that the main findings remain the same.

Therefore, findings of this study provide clear and statistically significant evidence that most of the skills that are reported in the job adverts have a positive and statistically significant effect on wages.

There are, however, several limitations to our study. First, two datasets used in the empirical analysis do not cover the same time period. The LFS contains information obtained during 2018 (most recent available at the time of writing), whereas the job adverts cover information from October 2019 to January 2020. This would cause issues if the industry/occupation profiles had significantly changed over the course of 2019. That is, control variables obtained from LFS (gender profiles, marital status profiles, etc.) and used in regressions would not reflect the situation as in 2019. It, however, seems unlikely that such characteristics of industries and occupations change so quickly.

Another potential caveat could be the reliability of the assumption that the portrayed requirements for each occupation actually represent the skills possessed by actual employees of such occupations. In other words, whether employees actually do possess the skills that employers list as requirements for these occupations. In turn, one might also argue that some job adverts may not include all the required skills for a particular position similarly to the findings of Gallavin et al. (2004). Hence, verifying the validity of this assumption provides an avenue for further research.

[23] Baseline results are based on averages from these two values.

7. Conclusions

The findings of this study provide clear and statistically significant evidence that most of the skills that are reported in the job adverts have a positive and statistically significant effect on wages. That is, job adverts requiring these skills (e.g. cognitive skills, project management etc.) tend to offer higher wages than those that do not. These results are robust to the inclusion of other wage determinants and different methodological choices. Furthermore, our findings suggest that most of the skills exhibit a positive effect on offered wages by providing access to industries and occupations with relatively higher wages. However, certain skills, namely software skills, customer service and project management skills, are rewarded even within the specific industry and occupation group. Hence our results provide not only new evidence on factors determining wages in Latvia but also reveals various channels through which that happens.

Furthermore, using information obtained from job adverts, we overcome issues that are present when skills are measured with standardized test scores, i.e. sample is limited to only those skills that can be directly measured and not taking into account if skills are actually required in the workplace. Hence, we provide a new angle to a vast body of evidence investigating returns to skills (Borghans & Weel, 2011; Bowles et al., 2001; Hanushek et al., 2015; Hanushek & Woessmann, 2008; Hause, 1972; Heckman et al., 2006; Murnane et al., 2000).

Although the research implements datasets from two different time periods, the effect on its findings is marginal. Nonetheless, the omission of required skills in job adverts due to employer fear of redundancy limits the potential effect of particular skills. This effect, however, is somewhat mitigated through occupation and industry controls.

For further research, we suggest automating the data retrieval from job adverts and to include a significantly larger sample of job adverts in order to boost the significance of various skills. Nowadays, the value of skills is constantly changing, therefore updating the skill categorization method could be valuable for future findings. (Bughin et al., 2018)

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9. Appendices

Appendix A: ISCO-08 extract

Sub-major group code	Sub-major group name
	1st Major group - Managers
11	Chief Executives, Senior Officials and Legislators
12	Administrative and Commercial Managers
13	Production and Specialized Services Managers
14	Hospitality, Retail and Other Services Managers
	2nd Major group - Professionals
21	Science and Engineering Professionals
22	Health Professionals
23	Teaching Professionals
24	Business and Administration Professionals
25	Information and Communications Technology Professionals
26	Legal, Social and Cultural
	3rd Major group - Technicians and Associate Professionals
31	Science and Engineering Associate Professionals
32	Health Associate Professionals
33	Business and Administration Associate Professionals
34	Legal, Social, Cultural and Related Associate Professionals
35	Information and Communications Technicians
	4th Major group – Clerical Support Workers
41	General and Keyboard Clerks
42	Customer Service Clerks
43	Numerical and Material Recording Clerks
44	Other Clerical Support Workers
	5th Major group – Services and Sales Workers
51	Personal Services Workers
52	Sales Workers
53	Personal Care Workers
54	Protective Services Workers
	6th Major group – Skilled Agricultural, Forestry and Fishery Workers
61	Market-oriented Skilled Agricultural Workers
62	Market-oriented Skilled Forestry, Fishery and Hunting Workers
63	Subsistence Farmers, Fishers, Hunters and Gatherers

Appendix A continued: ISCO-08 extract

Sub-major group code	Sub-major group name
7th Major group – Craft and Related Trade Workers	
71	Building and Related Trades Workers (excluding Electricians)
72	Metal, Machinery and Related Trades Workers
73	Handcraft and Printing Workers
74	Electrical and Electronic Trades Workers
75	Food Processing, Woodworking, Garment and Other Craft and Related Trades Workers
8th Major group - Plant and Machine Operators and Assemblers	
81	Stationary Plant and Machine Operators
82	Assemblers
83	Drivers and Mobile Plant Operators
9th Major group - Elementary Occupations	
91	Cleaners and Helpers
92	Agricultural, Forestry and Fishery Labourers
93	Labourers in Mining, Construction, Manufacturing
94	Food Preparation Assistants
95	Street and Related Sales and Services Workers
96	Refuse Workers and Other Elementary Workers

Source: Created by the authors using data from ILO 2012.

Appendix B: NACE Rev. 2 classification.

Section	Description
A	Agriculture, forestry and fishing
B	Mining and quarrying
C	Manufacturing
D	Electricity, gas, steam and air conditioning supply
E	Water supply, sewerage, waste management and remediation activities
F	Construction
G	Wholesale and retail trade; repair of motor vehicles and motorcycles
H	Transportation and storage
I	Accommodation and food service activities
J	Information and communication
K	Financial and insurance activities
L	Real estate activities
M	Professional, scientific and technical activities
N	Administrative and support service activities
O	Public administration and defence; compulsory social security
P	Education
Q	Human health and social work activities
R	Arts, entertainment and recreation
S	Other service activities
T	Activities of households as employers; undifferentiated goods- and services-producing activities of households for own use
U	Activities of extraterritorial organizations and bodies

Source: Created by the authors using data from Eurostat 2008.

Appendix C: ISCED 2011 classification.

ISCED level	ISCED Attainment/Program	Author classification*
0	Less than primary education	No education
1	Primary education	Primary education
2	Lower secondary education	
3	Upper secondary education	Secondary education
4	Post-secondary non-tertiary education	Technical education
5	Short-cycle tertiary education	
6	Bachelor’s or equivalent level	Higher education
7	Master’s or equivalent level	
8	Doctoral or equivalent level	

Source: Created (and amended*) by the authors using data from UNESCO 2012.

Appendix D: Summary statistics of data used in the study

	N	Mean	St. Dev	min	max	p25	Median	p75
Wage	887	1595.516	852.768	416	8500	1000	1350	2053
Cognitive	887	.41	.492	0	1	0	0	1
Social	887	.581	.494	0	1	0	1	1
Character	887	.758	.429	0	1	1	1	1
Writing	887	.032	.175	0	1	0	0	0
Customer service	887	.182	.386	0	1	0	0	0
Project management	887	.053	.224	0	1	0	0	0
People management	887	.088	.283	0	1	0	0	0
Special knowledge	887	.22	.414	0	1	0	0	0
Computer (general)	887	.333	.471	0	1	0	0	1
Software (specific)	887	.283	.451	0	1	0	0	1
Creativity	887	.047	.213	0	1	0	0	0
Job location – Riga	887	.799	.401	0	1	1	1	1
Primary education	887	.469	.499	0	1	0	0	1
Secondary education	887	.444	.497	0	1	0	0	1
Technical education	887	.107	.309	0	1	0	0	0
Higher education	887	.327	.469	0	1	0	0	1
Latvian language	887	.647	.478	0	1	0	1	1
Russian language	887	.458	.498	0	1	0	0	1
English language	887	.573	.495	0	1	0	1	1
Other language	887	.038	.192	0	1	0	0	0
Skill count	887	3.035	1.581	0	8	2	3	4
Male	803	.411	.329	0	1	.149	.333	.711
Married	803	.507	.207	0	1	.429	.547	.615
Latvian	803	.678	.201	0	1	.608	.643	.8
Latvian citizen	803	.915	.132	0	1	.873	.941	1
European Union citizen	803	.003	.01	0	.059	0	0	0
Other country citizen	803	.083	.132	0	1	0	.034	.127
Job loc. – Riga CSB	803	.476	.275	0	1	.248	.481	.679
Wage CSB	803	744.313	268.181	325.786	1994	540.75	706	898.389

Source: Table created by the authors using the author's dataset (top) and weighted average values for all available industry and occupation combinations in Latvian CSB's LFS 2018 (bottom).

Appendix E: Count of observations per each ISCO-08 code

ISCO-08	Count of observations in job advert dataset	Count of observations in LFS	ISCO-08	Count of observations in job advert dataset	Count of observations in LFS
11	0	99	51	10	308
12	18	215	52	127	550
13	4	190	53	2	221
14	0	67	54	2	156
21	15	137	61	0	47
22	7	185	62	0	37
23	3	424	63	0	3
24	92	312	71	4	264
25	36	65	72	22	311
26	22	140	73	4	22
31	44	189	74	4	136
32	14	94	75	1	314
33	114	540	81	16	220
34	43	86	82	4	40
35	115	33	83	4	712
41	20	58	91	2	251
42	53	103	92	0	94
43	31	216	93	29	510
44	6	30	94	2	68
0	11	0	96	6	186

Source: Created by the authors using the job advert dataset and the LFS.

Appendix F: Count of observations per each NACE Rev. 2 code

NACE Rev. 2	Count of observations in job advert dataset	Count of observations in LFS	NACE Rev. 2	Count of observations in job advert dataset	Count of observations in LFS
A	9	391	L	17	173
B	0	49	M	83	169
C	115	1205	N	52	202
D	2	135	O	1	634
E	7	99	P	11	909
F	19	569	Q	37	589
G	225	1111	R	5	164
H	35	680	S	0	63
I	26	228	T	0	1
J	151	138	U	0	2
K	92	122			

Source: Created by the authors using the job advert dataset and the LFS.