Wage premium for soft skills in IT sector

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Abstract

Purpose – This study aims to investigate the relationship between the demand on "soft" skills and suggested salaries for IT specializations in Russia.

Design/methodology/approach – Based on the database of vacancies, econometric modeling and cluster analysis of job occupations are implemented.

Findings – The results show positive association between demand for "soft" skills and wage if the model is controlled for the working experience and narrow professional occupations. Findings provide evidence that there is significant wage premium for "soft" skills in cases when job positions either imply no experience or require specialists with at least three years of tenure.

Originality/value – This research provides new evidence on the relationship between "soft" skills and wage using job postings data from Russia. This paper identifies the presence of wage premium for "soft" skills among IT specialists if controlling for sub-specializations, year, region and working experience. The robustness checks indicate no significant changes in the obtained results.

Keywords Skill identification, Wage premium, Cognitive skills, Job advertisements, Vacancy clustering

Paper type Research paper

Introduction

Academic research in job occupations provides evidence of skill mismatch and its impact on wages of workers. The skill mismatch is created by different representations of an ideal candidate (Brunello and Wruuck, 2021). For example, companies hiring specialists demand not only relevant education degree and working experience but also different combinations of two main types of skills, namely, "soft" (cognitive abilities, teamwork, communication, etc.) and "hard" (technical) skills (Samek *et al.*, 2021). Recent studies analyzing job postings and curriculum vitae data argue that both types of skills are important determinants of wage returns (Balcar, 2014; Deming and Kahn, 2018; Deming and Noray, 2020). Some authors suggest paying more attention to "soft" skills in educational curriculum in order to satisfy labor demand (Balcar, 2016; Deming, 2021; Loyalka *et al.*, 2021). Although competencies declared in educational programmes might not be supported with real personal abilities, a candidate's education is one of important signals which provides the potential employer with information about their knowledge and proficiency (Heckman and Rubinstein, 2001). Thus, the demand for skills is aimed to cover the information gap between employers' vision of the working tasks and employees' perceptions of particular job positions. The suggested salary is therefore affected by the skills demanded.

Many authors highlight the role of digital transformation in terms of penetration of IT skills in many professions (Alekseeva *et al.*, 2021; Li *et al.*, 2021; Özkiziltan and Hassel, 2021). Consequently, this is reflected by the labor market (Bana, 2021; Lovaglio *et al.*, 2018; Ternikov and Aleksandrova, 2020; Vooren *et al.*, 2019; Wikle and Fagin, 2015). Extant research highlights that one of the main sources of the wage premium is the inclusion of

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both modern IT skills and "soft" skills in a job description. For example, when analyzing job advertisements in the UK (Calanca *et al.*, 2019) found that such "soft" skills related to supervision as leadership and team building are associated with higher wages but subordination skills (e.g. punctuality, willingness to learn) are attributed to wage penalties. At the same time, not all "soft" skills are significant in different job occupations and can cause salary penalties. Other authors have similar results using regression analysis based on job advertisements data (Deming and Kahn, 2018; Volgin and Gimpelson, 2021; Ziegler, 2020). Authors highlight that wage premium for "soft" skills can vary depending on skill combinations, narrow job occupations and demanded working experience. Studies based on survey data in different countries propose that wage premium for "soft" skills exists among graduates (Albandea and Giret, 2018; Busso *et al.*, 2020; Murnane *et al.*, 1995; Ramos *et al.*, 2013) and employees (Balcar and Dokoupilová, 2021; Neves *et al.*, 2017; Stewart *et al.*, 2020). The summary of related works applying traditional econometric analysis is presented in Table 1. Despite there are many works analyzing the connection between "soft" skills and wage, they do not account for the use of detailed skills identification based on natural language processing techniques. It allows not only to enrich the skill database if compared to the standard use of only search query keywords extraction but also aggregate jobs using information about skills. In addition, it enables the use of different classifications of job occupations for robustness checks, which is overlooked in extant research.

The aim of this study is to extend existing knowledge about the connection between wage and the demand for "soft" skills. Our findings based on job postings for IT specialists in Russia suggest that the declaration of "soft" skills in vacancies generally leads to the higher suggested salary if controlling this effect for experience level and narrow job occupations. In addition, we provide robustness checks using two approaches for job occupations detection, namely, specializations codes aggregation from the job advertisements database and skill-based clustering analysis.

Data and methodology

The analysis is divided in four parts: data collection and processing, skills identification and standardization, job occupations aggregation and econometric modeling.

We used the job advertisements from the largest online hiring platform in Russia, HeadHunter (hh.ru). IT vacancies from 2016 till 2020 were downloaded and processed. The typical structure of job advertisement includes the following fields: vacancy id, area name (city), job position title, set of key skills (unstructured text fields), vacancy publishing date, experience (categorical variable), salary (indicating lower and upper bounds, currency, type [net or gross]) and specialization codes according to HeadHunter dictionary (https://api.hh.ru/specializations).

Only vacancies with mentioned sets of skills were obtained to simplify data processing. The initial sample containing 1,116,503 observations is representative by both regional and specialization structure. For the purposes of the research, only vacancies with provided salary (in Rubles) were selected, which resulted in the final of 503,882 observations (45.1% from the initial amount). Then, the salary field was standardized using the mean number between lower and upper bounds followed by conversion to the net salary (13% tax deduction if present).

After that, raw fields with skills were processed to be standardized for the further steps of the analysis. Firstly, the threshold with Zipf's curve was used for frequent terms extraction. Secondly, natural language processing techniques were implemented for finding synonyms, reducing redundant symbols and spacing. We used term frequency – inverse document frequency approach with uni-, bi- and tri-grams. Thirdly, the obtained terms were

Reference	Key findings	Main control variables	Source of Data	Research target	Region
Volgin and Gimpelson (2021)	Positive and negative relation between specific skills combinations and wages	Education, experience, region, year	Job ads	Vacancies	Russia
Deming and Kahn (2018)	Cognitive skills are positively related to earnings in narrow occupations	Education, experience, occupations	Job ads	Vacancies	The USA
Ziegler (2020)	More skills – higher wage (different effects from skills)	Education, experience, occupation	Job ads	Vacancies	Austria
Albandea and Giret (2018)	Positive relation between specific cognitive skills and income	Education	Survey	Graduates	France
Busso *et al.* (2020)	Positive wage returns from "soft" skills	Education, experience, occupation	Survey	Graduates	Colombia
Murnane *et al.* (1995)	Wage returns to cognitive skills increase after graduation in two and in six years	Education, experience, year	Survey	Graduates	The USA
Ramos *et al.* (2013)	Non-linear dependence of cognitive skills and wages	Education, experience, occupation	Survey	Graduates	Chile
Buchmueller and Walker (2020)	No relation between mental skills and wages	Education, region	Survey	Graduates	England
Balcar and Dokoupilová (2021)	Need for communication skills increases the wages	Education, experience, industry, occupation	Survey	Employees	Czech Republic
Neves *et al.* (2017)	Positive wage returns to cognitive skills	Region	Survey	Employees	Brazil
Stewart *et al.* (2020)	"Soft" skills and STEM (science, technology, engineering and mathematics) competencies provide wage premium across regions	education, occupation, region	Survey	Employees	The USA
Barone and Van de Werfhorst (2011)	Cognitive skills affecting education are positively related to earnings	Education, region	Survey	Individuals	Germany, the Netherlands, the UK, the USA
Fernandez and Liu (2019)	Cognitive skills affecting education are positively related to earnings	Education, experience	Survey	Individuals	The USA
Palczyńska (2020)	Positive and negative relation between specific cognitive skills and wages	Experience	Survey	Individuals	Poland
Carbonaro (2007)	Education and cognitive skills are positively related to earnings in narrow occupations	Occupations, education, region	Survey	Individuals	The USA
Salahodjaev and Malikova (2020)	Positive relation between cognitive skills and income	Education, region	Survey	Households	Tajikistan

Table 1. Summary of related work on wage premium for "soft" skills

manually checked and separated into two groups of 1,548 "hard" skills and 41 "soft" skills based on the logic of the existing skill databases.

Next, vacancies were merged with previously processed "hard" and "soft" skills. For the research purposes, we eliminated vacancies with only soft skills to estimate the effect in combinations with "hard" skills. In total, 477,415 entries with the proposed skills and salary were obtained after matching.

The most frequent "soft" skills are teamwork (34.7% of vacancies with declared "soft" skills), negotiation skills (32.2%), business communication (25.0%), sales skills (17.8%) and presentation skills (17.0%).

Then, only Russian regions were selected. We removed outliers by salary (more than ₽8,700 and less than ₽375 000) and obtained the final sample of 473,792 vacancies. The natural logarithm of salary distribution is close to normal according to Figure 1.

The distribution of vacancies by city is concentrated in Moscow and Saint-Petersburg. Top five regions cover 52.3% of the sample, namely, Moscow – 29.37%; Saint-Petersburg – 12.72%; Novosibirsk Oblast – 3.72%; Krasnodar Kray – 3.34%; and Sverdlovsk Oblast – 3.16%. Thus, the categorical variable for controlling regional factors (*regfactor*) was created. The Figure 2 below demonstrates the distribution of log (*salary*) by the obtained regional groups.

The number of vacancies in the obtained sample indicates an average 44% yearly increase (in 2016 – 41,584 vacancies; 2017 – 56,807; 2018 – 83,782; 2019 – 115,256; 2020 – 176,363). There are no substantial fluctuations in log (*salary*) for the analyzed period (Figure 3).

The shares of vacancies according to experience in years (*exper* variable) are the following:

- between1And3 – 55.6%;
- between3And6 – 22.9%;
- moreThan6 – 2.0%; and
- noExperience – 19.5%.

Moreover, in general, the more experience demanded, the higher salary is proposed according to the boxplots (Figure 4).

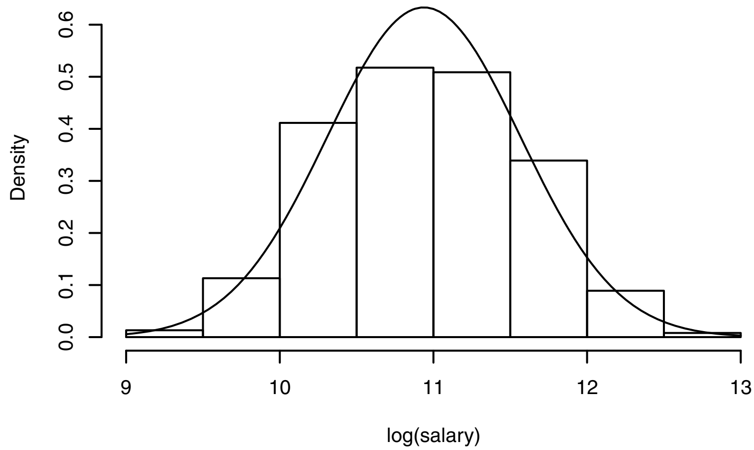

Figure 1.
Logarithm of salary distribution with normal density curve overlay

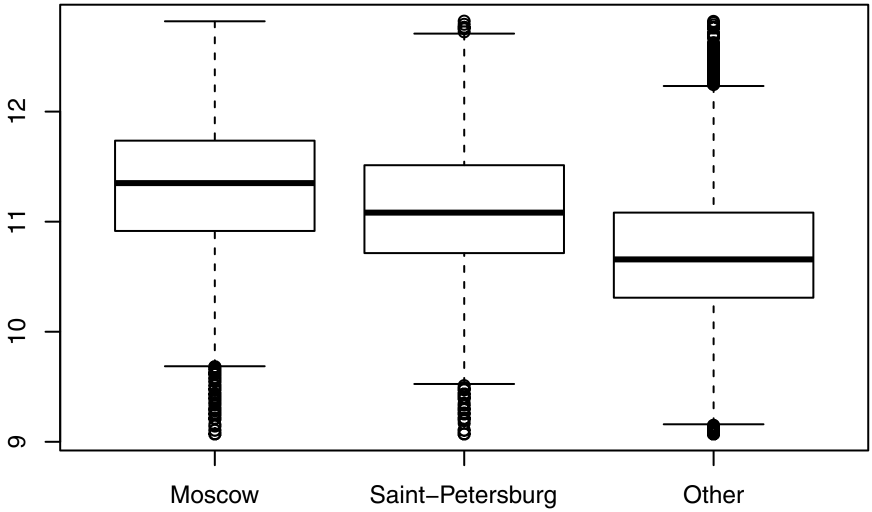

Figure 2.
Boxplots of the logarithm of salary among regions (*regfactor* variable)

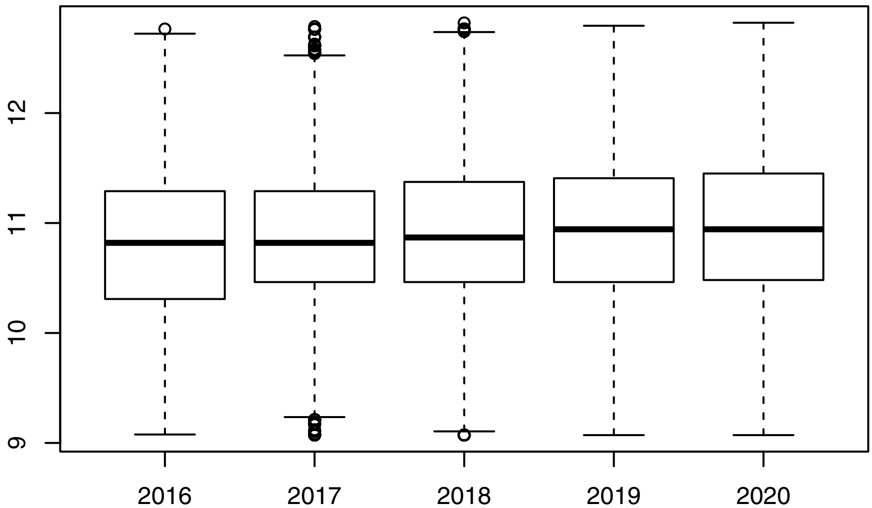

Figure 3.
Boxplots of the logarithm of salary by vacancy publishing years (*year* variable)

According to the sample structure, 34.1% of vacancies contain "soft" skills. As for the experience, the share of "soft" skills is approximately 30% ("between1And3" – 33.4%; "between3And6" – 23.9%; "moreThan6" – 27.1%; "noExperience" – 48.9%).

Finally, to control for specializations, the robustness check was conducted using two approaches:

- skill-based clustering analysis; and
- HeadHunter specializations grouping.

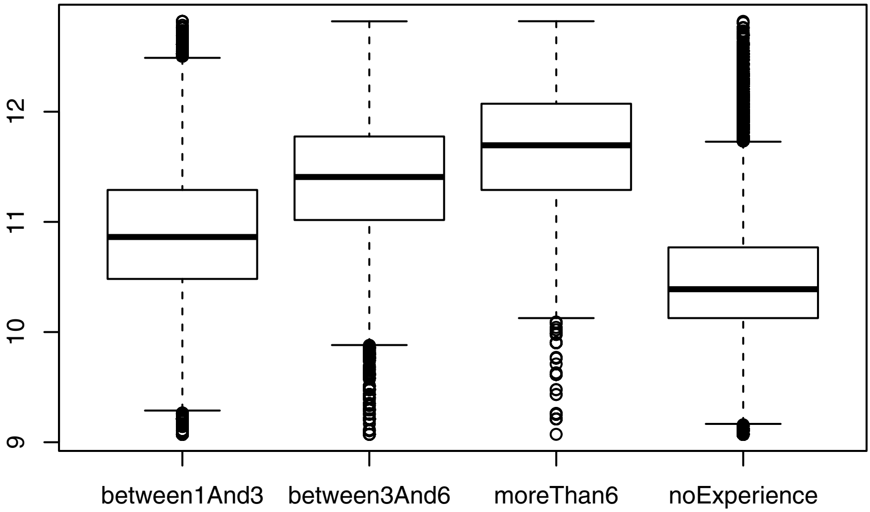

Figure 4.
Boxplots of the logarithm of salary among the experience intervals in years (*exper* variable)

The distribution of number of skills proposed in the initial sample is right-skewed (min: 1, 1st Qu.: 4, median: 6, mean: 7.2, 3rd Qu.: 9, max: 30). The processed "hard" skills (min: 1, 1st Qu.: 3, median: 5, mean: 5.3, 3rd Qu.: 7, max: 29) and the vacancies with "soft" skills (min: 1, 1st Qu.: 1, median: 2, mean: 2.1, 3rd Qu.: 3, max: 16) have approximately the same distributions.

For skill-based clustering analysis, Jaccard dissimilarity matrices among vacancy IDs were calculated using each pair of "hard" skills. Jaccard dissimilarity distance between two item-sets A and B equals $d_J(A,B) = 1 - |A \cap B|/|A \cup B|$. Next, hierarchical agglomerative clustering procedure was run with a different number of clusters. In total, 12 groups were obtained using different number of clusters and validated with internal validity measures. The top representative skills for each cluster are the following:

- Cluster 1, Administration: SAP, C, Unix, Qt, STL;
- Cluster 2, Big_Data: Python, C++, SCALA, Hadoop, Spark;
- Cluster 3, Software: HTML, JavaScript, PHP, CSS, SQL, Git, Java;
- Cluster 4, Marketing: SEO, SMM, Yandex Direct, Contextual Advertising;
- Cluster 5, Web_Design: Adobe, Bootstrap, UI, UX, Graphic Design;
- Cluster 6, Security: Information Security, Cisco, Juniper, SIEM, DLP, Check Point;
- Cluster 7, Hardware: Linux, Windows, Configuring DNS, IP, TCP, Active Directory;
- Cluster 8, Testing: QA, Selenium, UML, BPMN, Redmine, Test Automation;
- Cluster 9, ERP: 1C, Accounting, B2B, Business Correspondence;
- Cluster 10, Analytics: Excel, PowerPoint, Financial Analysis, VBA;
- Cluster 11, Management: Business Planning, Strategic Planning, Recruitment, Personnel Evaluation; and
- Cluster 12, Engineering: Project Documentation, AutoCAD, Visio, GOST, Circuit Design.

The second approach for aggregation of job occupations was based on classification logics used in related works (Lovaglio *et al.*, 2018; Ternikov and Aleksandrova, 2020). The resulting seven groups based on HeadHunter specialization codes are presented in Table 2.

Two approaches for vacancies categorization were used to conduct the robustness checks. The heat map diagram below presents the diversity between vacancies among several dimensions of job grouping (Figure 5). There is no exact concentration of vacancies

Name	Short name	HeadHunter specialization ID
High-level IT specialists	high	1.327, 1.272, 1.25, 1.113, 1.3
Low-level IT specialists	low	1.172, 1.296
Engineering professionals	engineers	1.82, 1.295, 1.117, 1.277
Software developers	soft	1.221
Web and multimedia developers	web	1.9, 1.89, 1.10, 1.400, 1.475, 1.161
Administrators and database designers	admin	1.211, 1.270, 1.273, 1.50, 1.536, 1.420, 1.395, 1.203, 1.110
Others	others	1.474, 1.359, 1.274

Source: Ternikov and Aleksandrova (2020)

Table 2. Distribution of IT vacancies among HeadHunter specialization codes

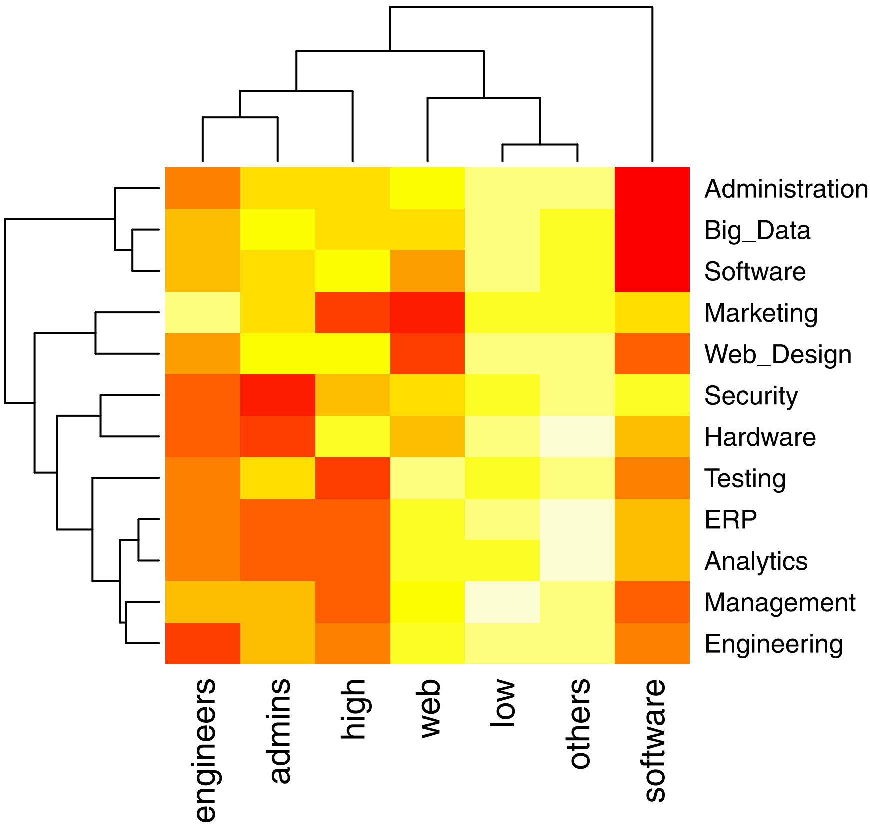

Figure 5. Heat map dendrogram between the professional groups generated by skill-based clustering algorithm (vertical axis) and aggregation of HeadHunter specializations (horizontal axis)

in one group of any dimension. This allows us to validate the results of the analysis based on non-overlapping groups of vacancies. Interestingly, the cluster names in some cross-sections include quite similar job occupations.

Finally, the prepared data sample was ready for econometric analysis. The main effect of "soft" skills demand on the dependent variable (suggested salary) was controlled by year, region (city), working experience and specializations. Moreover, the robustness checks over two approaches of job occupations separation were also implemented.

Results and discussion

We tested four regression models (OLS) with dependent variable of log (*salary*) and variable of interest *dsoft* (boolean variable indicating the presence of at least one "soft" skill in a vacancy). Estimation results are presented in Table 3. Following the descriptive analysis, each model includes control variables for publishing year (*year*), vacancy region (*regfactor*), and experience interval in years (*exper*). In the first two models, we estimated the main effect from *dsoft* and its interaction with working experience (*exper*). The models do not bring any insight about the proposed salary premium for "soft" skills demand. In other words, if the vacancy has at least one "soft" skill, the proposed salary decreases significantly (by 10.8% on average or from 3.1% till 14.5% depending on working experience).

Following the results of related works, control variables for professional areas were introduced. Model 3 is based on job occupations obtained via skill-based approach, whereas aggregation of HeadHunter specializations is used in Model 4. The results indicate that the negative effect of "soft" skills on the proposed salary is wiped out in both models. A significant negative effect of *dsoft* is only presented for the group with the demanded work experience of one to three years. All the other groups demonstrate the positive effect. Marginal effects from interaction terms in these two models are presented in Figure 6.

As a result of conducted regression analysis as well as the corresponding advanced robustness checks procedure, we can conclude that the demand for "soft" skills alongside with the demand for "hard" skills bring significant salary premium (on the stage of the vacancy posting) for the specialists with no working experience or with the experience from three years and more. According to the estimations, the premium for "soft" skills is the highest for not experienced specialists (from 4.5% to 7%). The premium for job candidates with at least three years of experience decreases according to the following splits: three to six years of experience provide about 1% increase in the declared salary, whereas six and more years of experience result in 2%–3% premium. Interestingly, the demanded "soft" skills penalize the salary by about 3%–4% for specialists with experience from one to three years.

Estimates for control variables are significant and show relative increase in average proposed salary every year. Accordingly, the higher salary is suggested if more experience is demanded. In addition, there are regional differences, for example, comparing with Moscow, the average salary in Saint-Petersburg is around 19% less, whereas the other regions, it is 50% less *ceteris paribus*.

For precisely formulated groups of specialists, quite similar conclusions are observed if comparing the results for job occupations between the two proposed classifications. For example, with all else being equal, for Software group the salary premium is 22%–37%, for high-level specialists and managers – a 7%–10% increase; for engineering specialists – a 7%–10% wage penalty.

	Dependent variable: log (salary) (1)	(2)	(3)	(4)
dsoft	–0.108*** (0.002)	–0.145*** (0.002)	–0.042*** (0.002)	–0.025*** (0.002)
exper (between3And6)	0.414*** (0.002)	0.400*** (0.002)	0.352*** (0.002)	0.328*** (0.002)
exper (moreThan6)	0.636*** (0.005)	0.614*** (0.006)	0.554*** (0.006)	0.519*** (0.006)
exper (noExperience)	–0.373*** (0.002)	–0.428*** (0.003)	–0.374*** (0.002)	–0.327*** (0.002)
dsoft*exper (between3And6)		0.045*** (0.004)	0.052*** (0.004)	0.026*** (0.004)
dsoft*exper (moreThan6)		0.074*** (0.011)	0.072*** (0.011)	0.041*** (0.011)
dsoft*exper (noExperience)		0.124*** (0.004)	0.087*** (0.004)	0.095*** (0.004)
year (2017)	0.023*** (0.003)	0.024*** (0.003)	0.033*** (0.003)	0.031*** (0.003)
year (2018)	0.081*** (0.003)	0.083*** (0.003)	0.094*** (0.003)	0.095*** (0.003)
year (2019)	0.138*** (0.003)	0.140*** (0.003)	0.159*** (0.003)	0.164*** (0.003)
year (2020)	0.186*** (0.003)	0.188*** (0.003)	0.212*** (0.002)	0.223*** (0.002)
regfactor (Other)	–0.499*** (0.002)	–0.499*** (0.002)	–0.488*** (0.002)	–0.498*** (0.002)
regfactor (Saint–Petersburg)	–0.183*** (0.002)	–0.183*** (0.002)	–0.189*** (0.002)	–0.187*** (0.002)
Administration			0.090*** (0.004)	
Analytics			–0.113*** (0.002)	
Big_Data			0.183*** (0.003)	
Engineering			–0.007*** (0.002)	
ERP			–0.061*** (0.002)	
Hardware			–0.140*** (0.002)	
Management			0.078*** (0.002)	
Marketing			–0.120*** (0.002)	
Security			–0.042*** (0.004)	
Software			0.221*** (0.002)	
Testing			0.143*** (0.004)	
Web_Design			–0.178*** (0.002)	
admins				–0.077*** (0.002)
engineers				–0.010*** (0.001)
high				0.101*** (0.002)
low				–0.198*** (0.002)
others				0.056*** (0.002)
software				0.371*** (0.001)
web				–0.050*** (0.002)
Constant	11.132*** (0.003)	11.143*** (0.003)	11.088*** (0.003)	10.963*** (0.003)
Observations	473,792	473,792	473,792	473,792
Adjusted R^2	0.400	0.402	0.481	0.490
Residual Std. error	0.488 (df = 473,781)	0.487 (df = 473,778)	0.454 (df = 473,766)	0.450 (df = 473,771)
F statistic	31638.910*** (df = 10; 473,781)	24477.840*** (df = 13; 473,778)	17548.910*** (df = 25; 473,766)	22792.580*** (df = 20; 473,771)

Notes: $*p < 0.1$; $**p < 0.05$; $***p < 0.01$; year base – 2016, exper base – between1And3, regfactor base – Moscow

Table 3. Regression models results

The research has the following limitations. First, the usage of data from HeadHunter can be extended by the combination with other online hiring platforms, such as "Job.ru" and "Work in Russia," for a broader coverage of job market. Second, the information provided by companies and HR-specialists may not fully cover real demands of the employers, so further research can use a follow up surveys to triangulate the demand for job skills. Third, vacancy description salary is not the same as the real wage, which can be altered after the job interview. Fourth, several skills attributed to particular vacancies (job positions and working experience) could have been omitted in job postings because of the fact that such skills are demanded by default.

Conclusion

This work provides the evidence for the existence of wage premium for demanded "soft" skills in IT vacancies on Russian labor market. The novelty of this paper lies in the adoption of new approaches for categorization of job occupations. Moreover, new findings regarding under-investigated Russian labor market are shown. The results provide insights about salary premium in attribution to demanded working experience and affiliation with a certain job occupation (specialization). The positive returns from demanded "soft" skills in IT-sector relate to non-experienced candidates and people with at least three years of employment. Interestingly, the specialists with working experience from one to three years are given wage penalties, which may be the cause of a large variety of these positions and different demands mostly related to technical skills (e.g. junior and middle positions without strong evidence of demanded "soft" skills). On the contrary, the candidates with no experience are expected to have particular "soft" skills such as teamwork and communication. Moreover, more experienced candidates are required to possess "soft" skills for such higher managerial positions as senior specialists and team-leads.

In terms of research contribution, this article introduces the clustering procedure for job advertisement skills identification. It allows separating different vacancies among professional groups for further use in econometric analysis. Moreover, the positive effect from the introduction of "soft" skills in job postings is validated within different approaches for job grouping and within working experience interaction. It extends related research regarding the significance of cognitive abilities of IT specialists and brings new insights into under-investigated Russian labor market.

In terms of practical significance, the results and approaches used in this article could be useful for educational organizations, businesses and HR specialists. The results of this paper can help to improve educational programmes connected with the IT-sphere in terms of introducing sets of learning courses related to the development of cognitive skills. Moreover, the interaction between new graduates and employers can be more focused with the introduction of specific cognitive skills in job advertisements for specific professional areas.

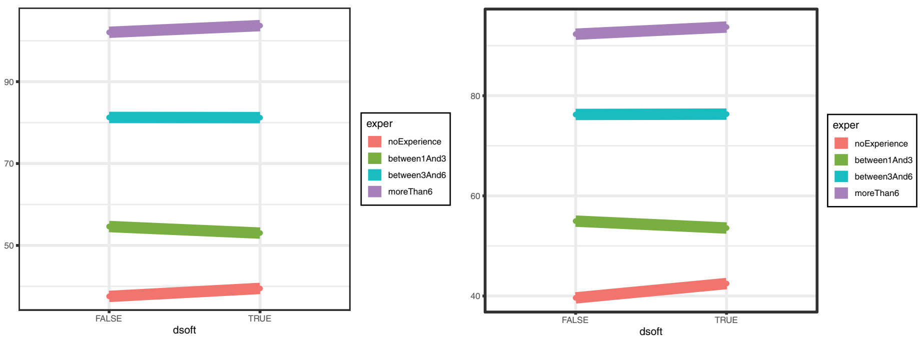

Figure 6.
Marginal effects of soft skills demand (*dsoft* boolean variable) on salary (in thousands of Rubles) by experience intervals in years (*exper* categorical variable) in models (3) – (a) and (4) – (b)

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