Population and Economics

Population and Economics 8(4): 37–63
DOI 10.3897/popecon8.e134348

RESEARCH ARTICLE

Complementarity of Required Skills and their Mastering Impact in Vacancies without Work Experience Requirement

Anna N. Litvinova [1], Ianina A. Roshchina [2]

1 *Yandex LLC, Lomonosov Moscow State University, Moscow, 119991, Russia*

2 *Lomonosov Moscow State University, Moscow, 119991, Russia*

Received 9 August 2023 ♦ **Accepted** 27 November 2024 ♦ **Published** 19 December 2024

Citation: Litvinova AN, Roshchina IA (2024) Complementarity of Required Skills and their Mastering Impact in Vacancies without Work Experience Requirement. Population and Economics 8(4):37-63. https://doi.org/10.3897/popecon.8.e134348

Abstract

The paper identifies the factors impacting the entry-level salary offered in Moscow, Russia, to job seekers with no work experience. To identify the factors potentially impacting the entry-level salary, a frequency analysis of text descriptions of job vacancies posted at the online recruitment platform HeadHunter was conducted. In addition to assessing the direct impact of skills, their complementarity was identified. Hard skills have a positive impact on the entry-level salary, while soft skills have a predominantly indirect impact through enhancing the impact of hard skills. The paper fills a lack of research allowing to justify the choice of skills and their combinations to learn. It has been shown that the skills that are more rarely listed in job advertisements tend to pay off faster. Although the main findings come from the total sample, both the impact of skills and their pay-off are heterogeneous across occupations, so the authors conducted a separate analysis for a subsample of analysts. The resulting more specific findings suggest that further research by occupation is worth pursuing.

Keywords

employees with no work experience; factors of entry-level salary; skills complementarity; skills pay-off

JEL codes: C52, J23, J24

Introduction

The principles of salary structure formation, in particular the factors impacting the salary size and differentiation, are a topical area of labour market research. It is important for employees to understand the rationale behind their salary and the factors that contribute to its

Copyright *Litvinova AN, Roshchina IA*. This is an open access article distributed under the terms of the Creative Commons Attribution License (CC-BY 4.0), which permits unrestricted use, distribution, and reproduction in any medium, provided the original author and source are credited

growth and skills that need to be developed for this purpose. Skills can be viewed as a durable investment good (Becker 1993), with analysing the benefits and costs of acquiring them. It is important for employers to understand the mechanism of market salary formation to analyse whether their requirements and working conditions match the salaries they offer.

In today's Russian labour market, young people looking for their first job are one of the most vulnerable categories, as lack of experience and practical work skills along with often inflated salary expectations lead to a relatively high unemployment rate. For example, the unemployment rate among Russian graduates in 2022 was 8.2%, nearly twice as high as the nationwide rate[1]. Although such unemployment is temporary (Lyashok 2021), it is important to address this issue by narrowing the gap between the high demands of young people and the employers' ability to meet them. For this, in turn, it is necessary to enhance the transparency of salary formation for all participants of the labour market. In addition, today's schoolchildren do not fully understand what they will be doing in the future when choosing a career[2] – if they knew what skills were most in demand and better 'paid off' by employers, their career choices would be better informed.

The literature identifies three main reasons (groups of factors) that explain salary differentials (Reder 1962; Aigner and Cain 1977):

- heterogeneity of employees (differences in training, experience, skills, knowledge and abilities, socio-demographic characteristics);
- heterogeneity of workplaces (different working conditions, including office location, recruitment package, status);
- imperfect competition, generating discrimination in the labour market.

The factors that impact entry-level salary are different from those that affect the salaries of people who have work experience (Altonji and Pierret 1997). According to the educational signalling theory (Spence 1974), educational level is an observable characteristic correlating with productivity (which is unobserved before starting to work). (Ehrenberg and Smith 1996; Roshchin and Razumova 2000). For more capable people, the cost of education is lower, so, all other things being equal, they are more likely to decide to continue their education. A certain educational level and its prestige serve as a benchmark for companies to identify more productive and capable candidates for entry-level positions.

In the modern world it is possible to acquire a wide range of instrumental or 'soft' skills both face-to-face and online, in addition to basic education. Thus, a prominent issue is not only the cumulative but also the complementary effect of a variety of skills on an employee's salary (Volgin and Gimpelson 2022; Ternikov 2023), especially for employees with no work experience.

This paper will identify and assess the factors affecting the entry-level salary offered to job seekers with no work experience in the city of Moscow, Russia. The labour market of Moscow (rather than the entire Russia) was chosen for the following reasons. First, there are important regional differences that are difficult to take into account in modelling (for example, according to Rosstat data, the average monthly nominal gross wages in Russian regions in April 2024 ranged from 38.000 to 186.000 roubles, while according to the National

1 According to the 2023 Rosstat survey, for graduates of higher or secondary vocational education establishments. https://rosstat.gov.ru/labour_force (accessed on: 24.07.2024).

2 According to the results of a survey of 1,900 schoolchildren in grades 5-11 in Russia, published by RBC (Trends) on June 01, 2023. https://trends.rbc.ru/trends/education/62876ace9a79474c09ba6367 (accessed on: 27.07.2024).

Research University Higher School of Economics[3], in 2021, the ratio of university students to the general population aged 17-25 years old ranged from 0 to 60%). Models that are based on such a heterogeneous sample are hardly interpretable. Secondly, the data source used in this paper (Russia's largest online recruitment platform HeadHunter) is specifically relevant for Moscow, while alternative ways of job search and hiring for entry-level positions (including using one's connections or going through recruitment agencies) are more widespread elsewhere in Russia.

Literature Review

In the present study, the dependent variable is the entry-level salary offered to job seekers with no work experience. Most existing studies examine the factors influencing the equilibrium salary level, which is determined by the interplay between supply and demand. However, the salary determinants outlined below are also applicable to the salary offered to job seekers on HeadHunter, as it reflects the prevailing market conditions (Volgin and Gimpelson 2022). This section provides an overview of key studies exploring the factors that impact salaries. Initially, we review how observable worker characteristics affect the salary offered. Subsequently, we consider how it is influenced by employers' requirements and the working conditions they offer.

Impact of education and other employee characteristics

The information available about a prospective employee is limited and does not provide a comprehensive characterisation of their performance. In making hiring decisions, employers must rely on observable characteristics, with the quality of education being particularly important for recent graduates. A substantial body of research exists examining the impact of education on employee earnings. Degree holders tend to earn more on average than individuals without such qualifications. Furthermore, this salary differential remains consistent throughout an individual's career (Dale and Krueger 2011). A significant focus of the existing literature is the examination of the varying effects of different levels of education on salaries. In (Rozhkova et al. 2021), the authors examine the pay-offs of bachelor's and master's degrees separately, showing that a master's degree has a positive impact on both the probability of employment and the salary size. The prestige of an educational institution also affects salary levels by indicating the prospective employee's ability (Brewer et al. 1996; Hoekstra 2009; Dale and Krueger 2011; Bordon and Braga 2020).

However, the more information about a job seeker's skills is available, the less importance is attached to the educational institution from which they graduated (MacLeod et al. 2015). Due to the limited information available on first-time job seekers, employers highly value any signals that help them make a hiring decision. As further information becomes available (through work experience and achievements), the value of such signals (e.g., holding a diploma (degree) from a prestigious institution) declines. Similar studies have been conducted about the average diploma grade point (Loury and Garman 1995; Dale and Krueger 2011).

3 Malinovskiy S.S., Shibanova E.Yu. Dostupnost' vysshego obrazovaniya v Rossii: kak prevratit' ekspansiyu v ravenstvo. – M.: HSE, 2022 (Sovremennaya analitika obrazovaniya. # 7 (67)). [Accessibility of Higher Education in Russia: How to Turn Expansion into Equality].

Furthermore, it is essential to consider the specific field and area of specialisation. In certain labour markets, the demand for particular specialisations may be greater than elsewhere, resulting in higher salaries for recent graduates with these majors. It is also important to note that in some industries (e.g. IT), work experience and knowledge of specific technologies may be more valuable than a certain level of higher education. (Zhang 2005) looks at the impact of college prestige and academic major on earnings. Their findings show that graduates of prestigious colleges have higher rates of earnings growth early in their careers, with the rate of growth varying significantly by academic major. A similar result is obtained in the Russian market (Roshchin and Rudakov 2016): graduates of leading universities receive a stable salary premium compared with graduates of lower-quality universities.

In examining the impact of individual characteristics on individuals' salaries, in addition to the influence of education, other factors such as gender, age, skin colour, ethnicity, marital status and religious affiliation also warrant consideration. Salary differentials between individuals can be explained by two distinct factors: objective differences in qualifications and discriminatory practices within the labour market (Aigner and Cain 1977). Discrimination can result in substantial pay differences between individuals with the same qualifications and experience. Such disparities may result from discriminatory attitudes held by employers towards specific employee groups, including women, racial or ethnic groups, and individuals with specific physical or psychological characteristics. Nevertheless, it is not feasible, and we do not attempt here, to analyse the impact of discriminatory factors on the salary offered, as such restrictions are considered discriminatory and are prohibited from being mentioned in recruitment advertisements under Article 3 of the Russian Federation Labour Code ('Prohibition of Discrimination in Employment') and Federal Law No. 1032-1 ('On Employment of the Population in the Russian Federation').

Impact of employer requirements and conditions offered in job advertisements

In addition to individual characteristics of job seekers, the salary offered is also affected by the skills that the employer requires. The literature identifies two categories of skills: cognitive and non-cognitive (Deming and Kahn 2018; Gimpelson et al. 2020; Volgin and Gimpelson 2022). Cognitive skills encompass analytical skills, statistical knowledge, and proficiency in programming languages, while non-cognitive skills include teamwork skills, communication skills, and personality traits. The concepts of cognitive and non-cognitive skills are quite broad. For further details about non-cognitive skills, please refer to the source cited in (Rozhkova 2019). In this study, the term 'cognitive skills' will be used to refer to hard skills, and the term 'non-cognitive skills', to social skills. This approach was selected as a means of operationalising the above concepts.

The set of skills required of prospective employees is subject to change over time. To illustrate, during the early 2000s, there was an observable increase in the demand for cognitive skills (Autor et al. 2008). Automation of numerous routine tasks resulted in an increased demand for social skills that cannot be automated, such as teamwork, communication, and negotiation skills (Deming 2017; Autor 2014). In recent decades, there was a notable increase in the number of occupations that require predominantly non-cognitive skills. The labour market is witnessing an increasing demand for qualities that are not directly related to intellectual activity, while being crucial for effective teamwork and customer interaction (Heckman et al. 2006). For example, the National Association of Colleges and Employers (NACE)

has identified teamwork skills as being among the most important for college graduates (NACE 2015). The value of social and leadership skills to companies is increasing (Kuhn and Weinberger 2002; Borghans et al. 2014). In addition to conventional qualifications such as knowledge and experience, competencies pertaining to communication, management, interpersonal relations, and leadership are becoming increasingly important (Autor 2015). It is reasonable to conclude that the possession of non-cognitive skills is associated with higher remuneration (Rozhkova 2019). Cognitive skills (such as mathematical modelling, knowledge of various software packages and programming languages, and analytical abilities) remain significant and pertinent, and the demand for these skills continues to be high on average, although it has ceased to grow in some labour markets (Beaudry et al. 2016). It is also noteworthy that good cognitive skills facilitate greater adaptability to novel environments. In industries where fast learning and adaptation are crucial, this can be a key success factor.

Today, employees need to have a combination of different skills, including cognitive and social skills, to build a successful career (Borghans et al. 2014; Weinberger 2014; Deming 2017; Suhomlin et al. 2017). The strongest employment and salary growth is observed in jobs that require high levels of both cognitive (hard) skills and flexible (soft) skills (Deming 2017). For example, foreign language skills have a positive effect on an employee's salary (Rozhkova and Roshchin 2019), while there is evidence that the value of this skill is only significant in combination with other complementary skills (Damari et al. 2017). (Ternikov 2023) showed that the demand for AI-related skills in Russia grew rapidly in recent years, along with significant salary premiums for these skills, but the effect of AI-related skills can disappear in combination with other skills. Therefore, when analysing the pay-off of skills, one should consider the impact of not only each individual skill, but also their combinations, as well as the specifics of a particular labour market and industry.

In 2022, a paper was published examining the demand for skills (Volgin and Gimpelson 2022). The authors employed data from the HeadHunter website for 2019 and 2020 for different regions of Russia to analyse the impact of different groups of skills and their combinations on the salary offered. The results showed that social skills were in high demand and that there were 'gainful' combinations of complementary skills. The study was one of the first in Russia to rely on a large data set from an aggregator website to analyse labour demand, which makes it undoubtedly significant. That said, the authors did not group job vacancies by occupation, which limits the causal interpretation of the findings. Skill grouping makes it challenging to assess the pay-off of an individual skill and the benefit-cost ratio of learning it. The method proposed in this paper addresses this issue.

Most studies conducted on the Russian market primarily focus on the analysis of labour supply (including by using the RLMS-HSE database for monitoring the health and economic welfare of the population). The growing number of users of online platforms enables the analysis of the structure of demand for skills in job vacancies (Volgin and Gimpelson 2022; Deming and Kahn 2018; Ternikov 2023).

So, the salary offered to prospective employees, according to the literature review, depends on many factors that can vary between companies and industries. The main ones include job requirements, employee qualifications and work achievements (including work experience), the geographical location of the company, the company size, industry and occupational specifics, as well as working conditions, bonuses, and benefits.

The requirements for employees listed in job advertisements encompass a range of competencies that are essential for the fulfilment of assigned tasks, including knowledge, skills,

and abilities. Qualifications serve to determine the level of training and ability to perform the job in accordance with the requisite standards, which may include educational level and professional specialisation. The achievements of prospective employees with work experience are considered when determining the remuneration to be offered. The company size and the reputation of the employer can be the reason for both higher and lower salaries on offer. On the one hand, larger and better-known companies may have a larger payroll and offer above-market salaries. Conversely, a mature brand can cause high competition among job seekers who would be willing to accept lower salaries in exchange for the experience and other opportunities that such companies offer. The appeal of a job vacancy is contingent upon a number of factors, including the security of the position, the schedule (including its flexibility), the availability of a remote work option, the opportunities for professional development and training, as well as career prospects, benefits, and bonuses. These factors impact the salary offered for the position.

The table below summarises the main groups of factors affecting entry-level salaries.

Table 1. Factors affecting salaries

	Group of factors	Examples
1	Qualification	Education, speciality, length of service, work experience.
2	Requirements for employees	Knowledge, abilities, skills (including skills in working with specialist software packages, hardware/equipment), range of tasks and responsibilities.
3	Employer characteristics	Geographic location, company size and industry, employer brand.
4	Work achievements	Excellent performance, achievement of high results, awards/commendations.
5	Working conditions	Occupational hazards (workplace safety), work schedule, physical workload, employee benefits.

Source: compiled by the authors based on the literature review.

This paper examines the impact of complementary skills on the salaries offered by employers in job advertisements that do not require previous work experience. The educational level and specialisation of the prospective employee and the employer characteristics are used as control variables. The analysis excludes both work achievements and work experience, as neither of these factors affects the entry-level salary.

The data

The data was collected from HeadHunter, Russia's largest online recruitment platform[4]. Accessing job advertisements posted on different platforms would have been impractical as employers may post job vacancies on multiple websites simultaneously so that the sample could contain many duplicates that would be difficult to identify.

4 According to the Similarweb rating: https://www.similarweb.com/ru/top-websites/russian-federation/jobs-and-career/ (accessed on: 10.12.2021, 01.09.2022, 04.07.2023, 24.07.2024).

The data were collected between 29 December 2021 and 6 April 2022 (sample #1, 156.829 observations) and between 14 September 2022 and 16 December 2022 (sample #2, 145.195 observations). These time periods included periods of external shocks that may have had an impact on the labour market. A separate analysis of the variation in labour demand during periods of such instability can be conducted later. A total of 302.024 job vacancies in Moscow were collected. Each vacancy was recorded with the following details: title, publication date, company, salary range and currency offered, address and nearest metro station, description (company information, employee responsibilities, job requirements, job benefits), work schedule, employment format, specialisation. The job vacancies had been pre-filtered, and the sample comprised only those suitable for candidates with no previous work experience (this was a mandatory field in the job advertisement). It should be noted that the data set contains some omissions in the optional fields, namely the address, nearest metro station and salary size. Employers are free to specify either both upper and lower salary limits or only one of these. Duplicates, job advertisements where salaries were not listed in roubles and advertisements where full-time salaries were below the minimum wage in the city of Moscow (as of the publication date) were removed.

It did not make sense to create binary variables to characterise a particular employer due to their number (the sample includes 24.236 unique companies, i.e. those that published over 1.500 job vacancies, see Figure 1 below).

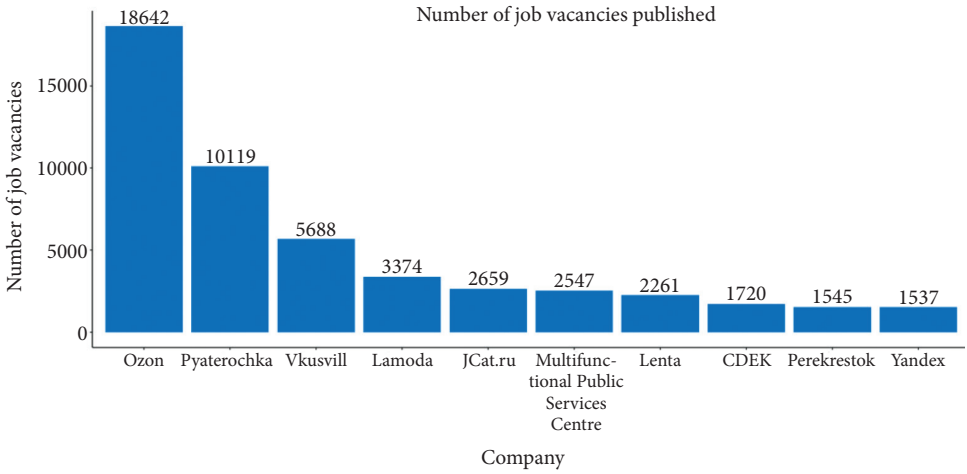

Figure 1. Companies that published over 1.500 job vacancies. *Source:* plotted by the authors according to HeadHunter data.

As a substitute variable for company attractiveness, we used the frequency of online inquiries about the company, which can indicate the company or brand awareness and the scope of services offered by the company. Yandex.Wordstat allows obtaining such information in three variants: broad match (all variants of word forms), matching an exact number of words, and morphological match. The names of some companies may coincide with popular search word combinations, and those were manually adjusted where possible. The resulting variable had a large variance, so employers were grouped based on its value, and

binary variables were created for each group. The number of groups varied between 4 and 10 to test robustness.

Additionally, the employer rating from the HeadHunter platform for 2021 was used[5] (importantly, it was calculated before the job vacancy was posted to exclude two-way association). Not all companies in the sample were included in the rating; the gaps were filled with zeros. A binary variable was created, equal to 1 for companies included in the rating and 0 for the rest. The rating variable reflects the employer's public image, which also indicates the company attractiveness.

Based on the metro station closest to the company's office, the companies were distributed by administrative district of the city of Moscow. Average salaries were calculated for each district.

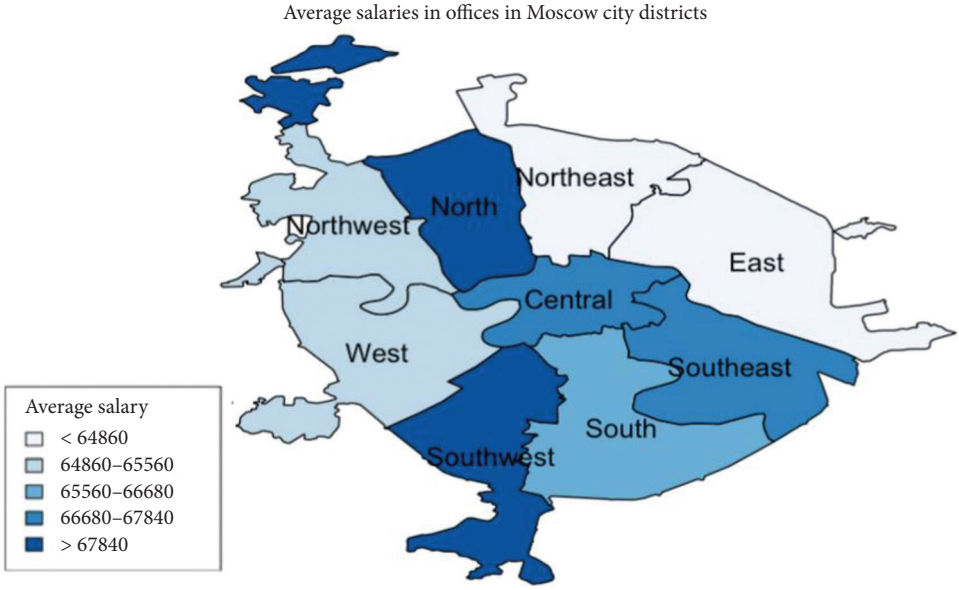

Figure 2. Average salaries offered to job seekers with no work experience. *Source:* plotted by the authors according to HeadHunter data.

Vacancies from companies with offices located in the central or northern districts of Moscow tend to offer higher salaries, but in general, salaries are about the same in all districts.

Figure 3 illustrates the processing of the original job vacancy data.

Many studies use the classification of skills proposed by Deming and Kahn (Deming and Kahn 2018; Volgin and Gimpelson 2022). In this paper, it is applied to define a group of personal and social skills (soft skills). Personal skills directly characterise a person (attentiveness, organisation, multitasking). Social skills characterise the way an employee interacts with colleagues and customers (communication skills, teamwork, etc.).

A job vacancy description is textual data that requires additional processing. A frequency analysis enables the identification of the most prevalent requirements as well as character-

5 HeadHunter Employer Rating 2021. https://rating.hh.ru/history/rating2021/ (accessed on: 15.03.2022, 24.07.2024).

Job vacancy title	Publication date	Salary (from)	Salary (to)	Company	Address	Nearest Metro station	Description	Work schedule	Specialisation
Data Analyst	10.02.2022	50000 ₽	80000 ₽	ANCOR	Moscow, Svobody street, 2	Ilyich Square	**Responsibilities:** * Automating group processes and reports; * ..... **Requirements:** * **Higher** technical **education**; * Analytical mindset; * Proficiency in **Excel** **Условия:** * Official employment in accordance with the Russian Labour Code; * Employee benefits, **private health insurance (PHI)**, ...	Full day	Analyst

✓ Frequency analysis of text
✓ Using word clouds
✓ Creating binary vectors

Job vacancy title	Publication date	Salary	...	Analyst	Engineer	...	Higher education	Excel	Python	SQL	...	PHI	...	Full day
Data Analyst	10.02.2022	65000 ₽	...	1	0	...	1	1	0	0	...	1	...	1

Figure 3. Example of data processing for the job vacancy 'Data Analyst'. *Source:* plotted by the authors based on HeadHunter data.

istics that are not directly related to remuneration. Consequently, most job vacancies require candidates to possess a higher or secondary vocational education, clear and articulate speech, commitment, communication skills, PC skills, willingness and readiness to learn. The advertisements offer a number of benefits, including official employment, a stable salary, opportunities for career growth, discounts and free services from the employer company. In addition, proximity to a metro station is often highlighted as an advantage.

The job vacancy sample contains many different occupations with different requirements. The most frequent skills will be those for the most popular occupations, so in addition to the general analysis, it is useful to analyse sub-samples by speciality/occupation. The HeadHunter platform only contains a general dictionary of occupational titles specified in the keywords. There is also a field for the job vacancy title, which could potentially identify narrower occupations. Job vacancy titles are text data that are not subject to automatic classification, i.e. the employer does not select the title from a suggested list but indicates an arbitrary title. The cluster analysis of job vacancy titles was another approach used to identify narrower occupations. This allowed to group all the unique titles, but even despite a large number of clusters, they overlapped by the keywords from the built-in common classification, so eventually the variables created based on keywords for common occupational titles (built-in common occupational classification on the HeadHunter platform) were selected as variables to characterise the occupation.

Word clouds are a good visualisation tool for a frequency analysis of text, but they allow only a limited number of skills to be identified (see Annex 2 for such a cloud for analyst vacancies). Frequency tables allow a list of common characteristics to be identified using a given threshold, a minimum number of vacancies where the characteristic is listed. Given the large number of observations, a threshold of 500 vacancies was set (an additional analysis was also conducted for sub-samples of occupations with a threshold of 200 vacancies).

Twenty-two characteristics were identified, and for each vacancy a 22-dimensional binary vector was created to characterise their presence. The most frequent skills were soft skills and PC and Excel skills (see Figure 4). Knowledge of programming languages was less frequent, but also one of the most in demand.

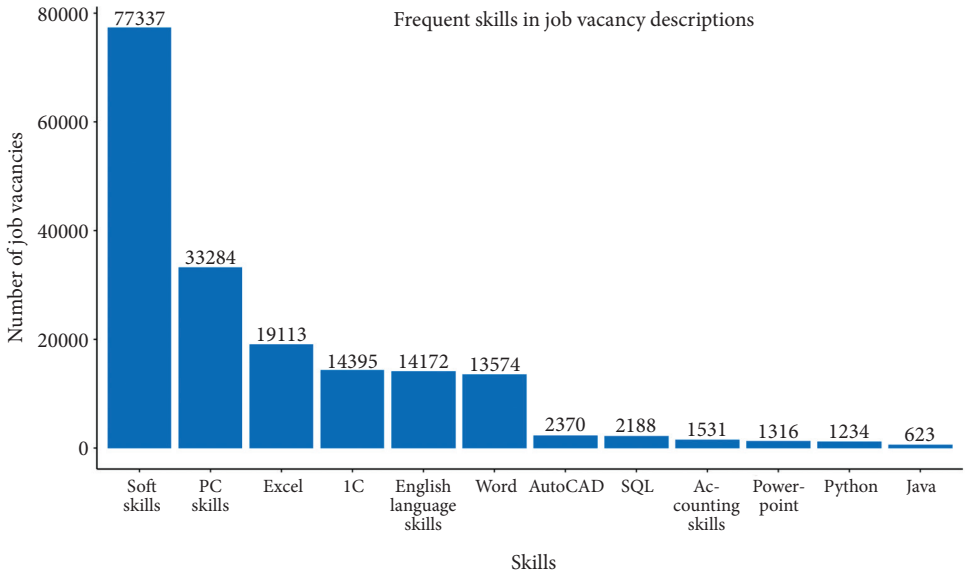

Figure 4. Frequent skills in job vacancy descriptions. *Source:* plotted by the authors based on HeadHunter data.

Frequency tables and word clouds were used to identify the skills frequently found in job vacancy descriptions. In terms of job search and career development, it is not only important to have certain skills, but also to combine them effectively. To be successful in a job interview it is important to have the combination of skills that the employer needs, so it is also important to analyse combinations of skills and the way they complement each other.

Modelling the impact of factors on the proposed entry-level salary

Complementarity of skills

To be considered for a position listed in a job advertisement, a prospective employee may need to possess all the listed skills at the same time. It is important to understand not only what skills are most required, but also what combinations of skills are most gainful.

A correlation matrix was constructed to show which of the previously highlighted skills are more likely to occur together. All correlation coefficients were above -0.15, meaning that the presence of one skill is not associated with the absence of another. The most 'popular' combination was Word and Excel skills (correlation 0.717), followed by Python and SQL

skills (0.308). The calculation of pairwise correlations is only a first step in the analysis, for it does not allow to identify 'popular' combinations comprising more than two components. In this paper, in contrast to (Volgin and Gimpelson 2022), we identify complementary skills of more than two skills that are significant in terms of salary size.

Figure 5 shows the most frequent combinations. Skills marked with shaded circles are found in advertisements and those marked with unshaded circles are not. For example, 4.341 advertisements required soft skills (both personal and social) and PC skills, while not requiring higher education, Excel, 1C, and Word skills. The histogram on the left-hand side shows the number of advertisements with a skill requirement (the more intense the colour, the more frequent the requirement). All combinations include both hard skills and soft skills (personal or social), with soft skills being the most frequent.

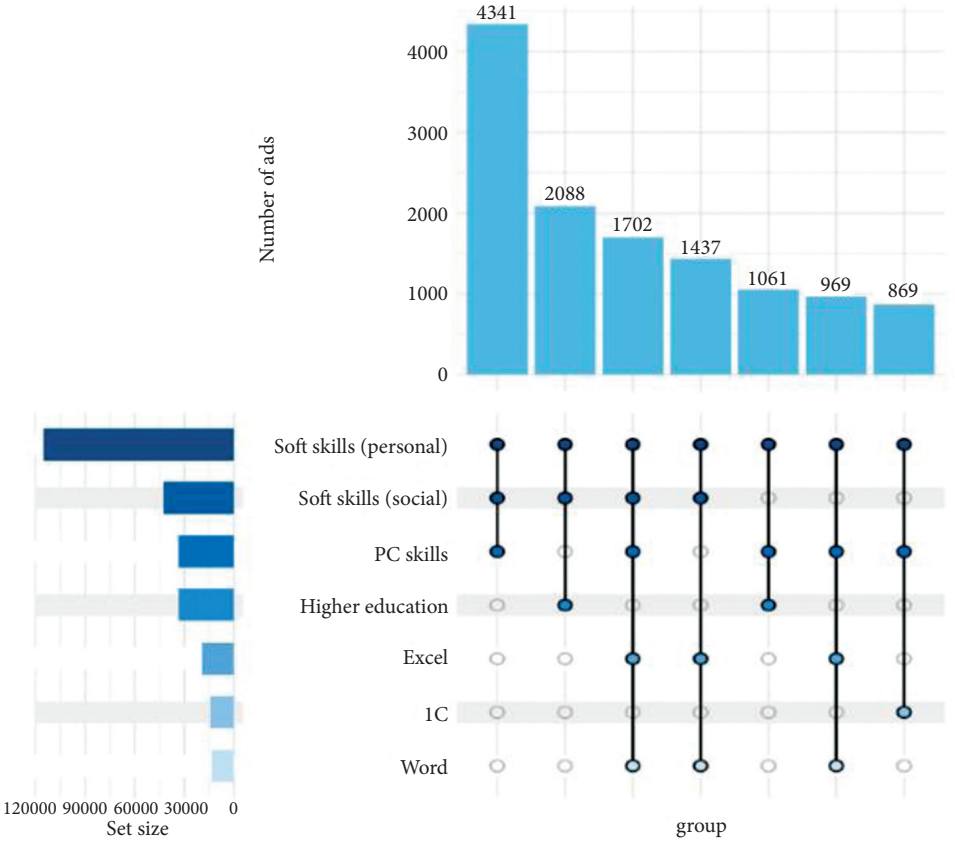

Figure 5. Combinations of required skills. *Source:* plotted by the authors according to HeadHunter data.

The association rule mining algorithm was used to identify combinations of more than two skills. The rules consist of left- and right-hand sides; if skills on the left-hand side are required, then skills on the right-hand side are also required. The algorithm enables the identification of optimal rules according to the following parameters:

- *support* – estimates the probability that all skills on the rule occur together (proportion of the number of advertisements with this combination of requirements in the total number of advertisements);
- *confidence* – estimates the conditional probability that skills on the right-hand side of the rule are present in the advertisement given that the skills on the left-hand side of the rule are present;
- *coverage* – estimates how often the left-hand side of the rule occurs in the sample (this parameter is not always constrained);
- *lift* – assesses the rule quality; it indicates the increase in the probability that the skills on the right-hand side of the rule are present in an advertisement given that the skills on the left-hand side of the rule are present. If the parameter *lift* has a high value, then those who have some of the skills on the rule should also learn the rest of the skills to be able to respond to more job vacancies (the higher the value, the more likely it is that all the skills on the rule will occur together);
- *conviction* – estimates the error rate of the identified rule (this parameter is rarely constrained).

The rules with the highest quality scores and high *support* and *coverage* values are summarised in Table 2. For these, both the *confidence* and the percentage variation in the average salary in the absence of a skill on the right-hand side of the rule were calculated. The variation was negative for all the rules. Of course, a simple comparison of the averages does not allow to conclude that the skills on the right-hand side have a positive impact on salaries, but only illustrates that higher salaries are posted by employers with a certain set of requirements. Here and below (except for Figure 7) the requirement for soft skills in a job vacancy refers to the mention of at least one of the two components, personal or social.

Table 2. Assessment of the combination of skills frequently listed by employers

Rule (combination of skills)		Number of job vacancies	Rule quality (multiplication of the probability that *R* is present given that *L* is present)	Rule confidence (proportion of job vacancies where *L* and *R* occur together among those where *L* is present)	Salary variation in the absence of skill *R*
Left-hand side (*L*)	Right-hand side (*R*)		$\frac{P(R \mid L)}{P(R)}$	$P(R \mid L) = \frac{P(R \& L)}{P(L)}$	
PC, Excel, Word	soft skills	4.150	1.8	0.77	-0.51%
PC, Word, soft skills	Excel	4.150	14	0.91	-4.34%
PC, Excel	Word	5.393	16.2	0.75	-10.88%
Excel, Word, higher education	soft skills	1.806	1.4	0.6	-1.64%

Source: compiled by the authors based on their own calculations using data from the HeadHunter platform and the analysis of the online course market.

Econometric analysis

Linear regression models were constructed to assess the impact of factors on the salary offered. Advertisements on the HeadHunter platform may indicate two salary limits, the lower and the upper, or only one of them (job vacancies that do not indicate the salary limits were excluded). For jobs with both limits indicated, the average of the two was calculated. If only one limit was indicated, this was used (when employers indicate only one limit, they usually mean exactly this salary level and there is no other way to offer an exact salary in the advertisement). To test for robustness, all the models considered were also constructed with the minimum, average (where applicable) and maximum salary as a dependent variable, and the results did not change significantly. The listed entry-level salary may not be the final salary offered, but only a proposed reference for the negotiations between the employer and the prospective employee, but this is mainly the case for experienced candidates (Volgin and Gimpelson 2022). For prospective employees with no work experience, we assume that the entry-level salary offered in the advertisement is close to the actual salary.

The regressors used were work schedule (flexible, full-time, shift, remote, rotational), occupation, publication period, company rating, required skills (SQL, soft skills, Python, etc.), non-financial incentives (benefits/bonuses, discounts on company products), and the requirement for higher education and a diploma (degree) from a prestigious university.

The functional (log-linear) form of the models was selected using the analysis of the residuals plot and the Box-Cox transformation. The Breusch-Pagan test showed heteroskedasticity in all models, so robust standard errors were used. The VIF coefficients for some occupational variables were greater than 10, so similar occupations were grouped together, e.g. chambermaid and cleaner/housekeeper, where the coefficients indicated that there was no multicollinearity. The models were tested for outliers using Cook's distance and analysing the effect of individual observations on the results of the regression analysis. A few observations were identified that had a large impact on the parameters of the models and could bias the results, and these were excluded.

Table 3 shows the results of estimating Models (1) and (2) (OLS, with and without control variables) and Model (3) (the two-stage Heckman method). In constructing Models (1) and (2), job vacancies that did not list the salary were excluded from the sample, but the omission of this variable may not be exogenous. For example, for some occupations (higher-paid and higher-skilled ones), employers may be more likely to omit the salary size in the posting, and this needs to be considered (Brencic 2012). In the literature (Volgin and Gimpelson 2022), models based on the Heckman correction are used to address this issue. In such models, at the first stage, a probit model is used to estimate an equation (selection equation) where the binary dependent variable reflects the presence or absence of the salary size offered in the advertisement, and variables characterising the occupation, work schedule, period of publication and company rating are used as regressors (to quote (Volgin and Gimpelson 2022)), "the omission of an offered salary size is more common where the salary level and its differentiation are higher and productivity is less easy to measure directly"). Based on the estimated model, the lambda parameter is determined. At the second stage, the original equation is estimated using OLS, and the lambda is included. This parameter was found to be significant, so Model (3) was selected for interpretation. As a robustness check, the model based on the Heckman correction was additionally estimated using the maximum likelihood technique, and the results were similar to Model (3).

Table 3. Multiple linear regression models

Skills pertaining to: working/learning/ graduation	Dependent variable: Logarithm of salary		
	OLS (1)	OLS (2)	Heckman 2OLS (3)
PC	-0.045***	-0.021***	-0.021***
	(0.002)	(0.002)	(0.002)
1C	-0.033***	0.006*	0.004
	(0.004)	(0.004)	(0.004)
Excel	-0.037***	-0.009**	-0.012***
	(0.004)	(0.004)	(0.004)
Word	0.004	0.031***	0.033***
	(0.005)	(0.005)	(0.005)
English language	0.021***	0.058***	0.055***
	(0.004)	(0.004)	(0.004)
Accounting	-0.038***	0.012	0.005
	(0.013)	(0.014)	(0.013)
PowerPoint	0.015	-0.007	-0.009
	(0.013)	(0.013)	(0.013)
Soft skills	-0.070***	-0.068***	-0.067***
	(0.002)	(0.002)	(0.002)
AutoCAD	0.122***	0.054***	0.047***
	(0.009)	(0.011)	(0.011)
Java	0.229***	0.154**	0.125*
	(0.073)	(0.074)	(0.071)
Python	0.249***	0.225***	0.208***
	(0.030)	(0.030)	(0.029)
SQL	0.271***	0.234***	0.225***
	(0.023)	(0.023)	(0.023)
Higher education	0.021***	0.007***	0.003
	(0.003)	(0.003)	(0.003)
Diploma (degree) from a prestigious university	-0.126***	-0.118***	-0.116***
	(0.015)	(0.016)	(0.016)
Python*Soft skills	0.186*	0.200**	0.208**
	(0.101)	(0.102)	(0.101)
Java*Soft skills	0.143	0.267*	0.301**
	(0.135)	(0.140)	(0.134)
AutoCAD*Soft skills	0.047***	0.042**	0.044***
	(0.017)	(0.017)	(0.017)

Skills pertaining to: working/learning/ graduation	Dependent variable: Logarithm of salary		
	OLS (1)	OLS (2)	Heckman 2OLS (3)
1C*Soft skills	0.059***	0.050***	0.047***
	(0.006)	(0.006)	(0.006)
SQL*Soft skills	-0.083*	-0.063	-0.059
	(0.044)	(0.046)	(0.045)
Discounts	0.119***	0.065***	0.063***
	(0.002)	(0.003)	(0.003)
Private health insurance scheme	-0.154***	-0.108***	-0.106***
	(0.002)	(0.002)	(0.002)
Benefits	0.015***	0.046***	0.048***
	(0.003)	(0.003)	(0.003)
Control variables	none	yes	yes
Constant	11.036***	10.880***	10.750***
Number of observations	263.698	263.698	293.766
Adjusted R^2	0.045	0.251	0.255

Source: compiled by the authors based on HeadHunter data.

The variables characterising the availability of a flexible schedule or remote work option significantly increase the salary compared to the rotational method in the model without the Heckman correction while being insignificant in Model (3), so that no definite conclusion can be drawn about the significance of the impact of the work schedule. It should be noted that the 'work schedule' field, to be filled in by the employer, only allows to select one of the options, so that many individuals would choose "full day", although this option does not exclude the possibility of, e.g., remote work, which is a shortcoming of the data collected and a limitation for the interpretation of the relevant coefficients.

There are skills the requirement of which has a significant negative impact on the salary offered (PC, Excel), but only within 2%. This can be explained by the fact that job vacancies listing higher salaries require narrower expertise, while the requirement to have basic software skills is implied without being listed. For example, a high-paying job advertisement may not mention Excel skills, replacing these with knowledge of SQL and/or Python. Similarly, PC skills are only listed separately for jobs that do not require any special competences.

The variable reflecting a company's top employer ranking for 2021 is significant in all the models but has a positive effect on salaries in the OLS estimation, while having a negative effect in the Heckman-corrected model. On the one hand, we can expect that companies that care about their employer brand are likely to pay higher salaries to their employees. On the other hand, large and well-known companies with well-developed internal and external HR brands can afford to offer lower salaries to employees with no work experience, as many ambitious individuals opt to embark on their careers in prestigious organisations, prioritising the acquisition of work experience there over a higher entry-level salary.

The variable characterising the requirement to hold a diploma (degree) from a prestigious university has a negative effect on the salary. This can be explained by the fact that the largest and best-known companies want to hire people with prestigious educational backgrounds and these same companies can afford to pay relatively low salaries at the entry level. It is also due to the fact that these companies often train their own employees, and this cost is also reflected in the entry-level salary. Of course, this does not mean that recent graduates from the best universities demand low salaries, but that they have the opportunity to start their careers in the largest and best-known companies and, among other things, to continue their training through practical cases and tasks.

To test the hypothesis that social skills enhance the positive impact of hard skills, the products of the soft skills variable and the variables 1C, AutoCAD, Java, Python and SQL were added to the model. In the absence of hard skill requirements, soft skills have a negative impact on the entry-level salary, which is on average 6.5% lower in such advertisements. These are usually job vacancies for simple duties and tasks, which are characterised by lower salaries, partly because the number of suitable candidates is higher than for vacancies with complex hard skills requirements. The coefficients on hard skills (Python, SQL, AutoCAD) and the products of these and soft skills are significant and positive – that is, the presence of social skills increases the (already positive) impact of hard skills on the salary. For example, the requirement for SQL (the ability to work with large amounts of information and write SQL queries to retrieve tables from databases) increases the salary offer by 25%. The listing of Python in the advertisement increases the salary by 23%. The additional soft skills requirement almost doubles this impact. A similar result is obtained for AutoCAD (design and drawing software) – the starting salary increases by 5% if there is no soft skills requirement and by 10% if there is. The variables characterising the requirement for knowledge of the Java programming language and the ability to use 1C software are not significant at the 5% level, but they have a positive impact on the entry-level salary offered given that a soft skills requirement is present.

Benefits also have a significant impact on the entry-level salary offer. Discounts and bonuses have a positive impact on it. Companies with a well-developed employee loyalty system are mindful of their reputation. It is important for them that the employees use the company's products, and they also increase the attractiveness of working for them by offering slightly higher salaries (about 5%). In contrast, private health insurance schemes have a negative impact on the salary offer, with a significant coefficient at the 1% level in all models. This can be seen as an intangible bonus that compensates for small salary differences (about 11%). It should be noted that the impacts of private health insurance schemes and bonuses/discounts have different signs, as the costs of providing private health insurance schemes are significantly higher.

Skills pay-offs

While any skill can be gainful, individuals should make their choices about which ones to learn, master and upgrade, given the finite resources, including time, available to them. For prospective employees, especially those entering the workforce for the first time, it is crucial to consider not only the potential pay-offs of acquiring new skills but also the associated costs.

Online educational platforms are actively engaging in the advancement of diverse skill sets and qualifications. The platforms offer a wide range of online courses, providing the

flexibility to learn at a comfortable pace at any time and from any location. Additionally, most platforms provide an opportunity to network with lecturers and other students, facilitating the sharing of knowledge and experience. Successful completion of studies is typically formally confirmed (e.g. by the issuance of a certificate), which can be leveraged to advance one's career and access new opportunities.

To account for both the benefits and costs associated with learning a skill, a payback period was calculated. This is defined as the amount of time that an individual needs to work using the skill in question to cover the cost of acquiring it through online courses. In some cases, skills can be acquired through Massive Open Online Courses (MOOCs), in which case the cost would be expressed solely in terms of time commitment. However, this option is often not available, and comparing payback periods can assist in selecting a skill to learn and develop. It should be noted that completion of a MOOC does not always result in the issuance of a certificate, which is a potential drawback. Furthermore, the motivation to complete training in the absence of costs and feedback is significantly lower than that associated with paid educational programmes.

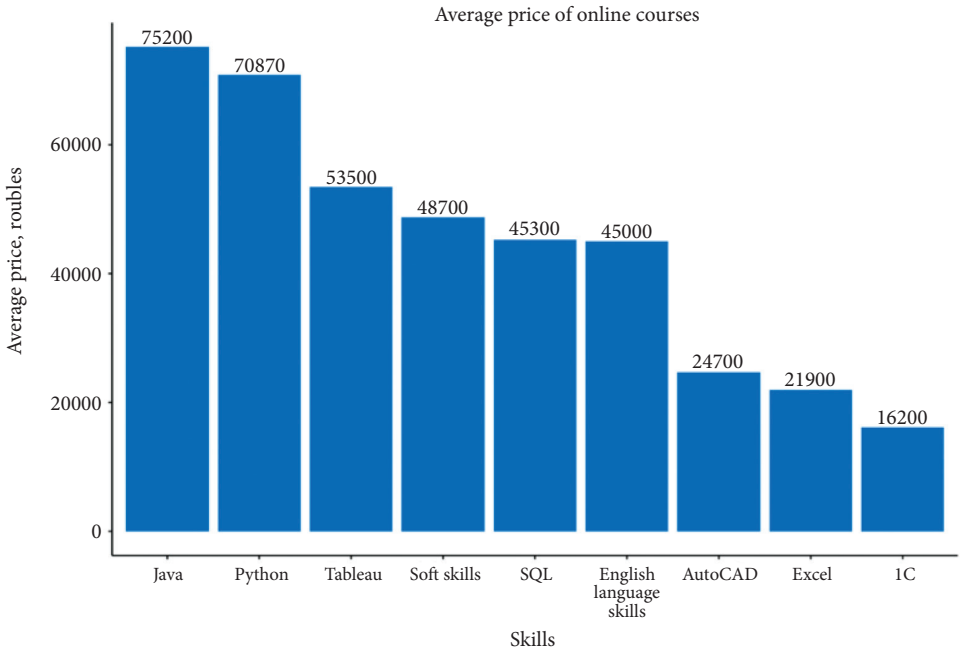

Figure 6. Average prices for online courses. *Source:* plotted by the authors in R based on their own analysis of the market of online learning programmes.

The study analysed the market for online learning programmes and calculated the average price for courses in a range of subjects, including English language, Python, SQL, Excel, 1C, AutoCAD, Java, Tableau, and soft skills. Three of the most popular educational programmes on the market were selected for each skill. The price, basic duration and training certificate provision for each programme were analysed (see Annex 1). Almost all programmes offer a discount, and this was the price used in the calculations, as the availability and size of the

discount remained consistent over time. It is widespread practice for course providers to use discounts as a marketing strategy, offering programmes at a reduced price throughout the year. It is unfortunately not possible to assess the quality of such online courses or verify that students have acquired the relevant skills. However, even the mere fact of taking such a course is a signal to the labour market.

To assess the impact of skills, models similar to (1) to (3) were constructed, with the exception of the variables representing the products of hard skills and social skills. Based on the aforementioned models and the analysis of the online course market, an estimated payback period was calculated (see Table 4). The calculations were performed solely for the skills that significantly impact salaries (in the Heckman-corrected model). As the coefficients in the log-linear model are expressed as percentages, the sample average salary was used to estimate the absolute gains. The resulting estimates should be viewed as a comparative characterisation of skills, as they were calculated subject to a number of limitations. For instance, the calculations do not consider the period of job search and the time spent on taking courses (this may vary depending on the individual, reflecting differences in the speed at which they master the course content).

Table 4. Payback periods for skills acquired through online learning programmes

Software and foreign language skills	Number of job vacancies	Impact on salary	Average price of courses	Payback period (excluding the study period)
1C	14.395	+1.8%***	16.200 roubles	16.1 months
English language	14.172	+5.5%***	45.000 roubles	14.6 months
AutoCAD	2.370	+5.9%***	24.700 roubles	7.5 months
SQL	2.188	+23.9%***	45.300 roubles	3.4 months
Python	1.234	+25%***	70.870 roubles	5.1 months
Java	623	+22.6%***	75.200 roubles	6 months

Source: compiled by the authors based on their own calculations and analysis.

The most sought-after skills are proficiency in the English language and 1C and AutoCAD software packages. SQL courses offer the fastest pay-off. In general, more in-demand skills pay back slower, although they cost less. This is because employers are willing to pay more for employees with more rare and difficult-to-master skills (or these skills are specific to higher-paying occupations).

Pay-off of analysts' skills listed in job vacancies

The impact of factors and skills pay-off may be heterogeneous depending on the occupation, so an additional analysis was conducted for a sub-sample of analysts. Additional skills highlighted were data visualisation (Tableau), business process modelling (bpmn), agile project planning and software development (jira, SAP). Figure 7 shows the most frequent combinations of required skills. Nearly every combination includes both hard skills and soft skills.

The association rule mining algorithm was used to identify the combinations of skills that employers list together in job vacancy advertisements. Table 5 illustrates the 'rules' with high values of the parameters *lift*, *confidence*, and *support*.

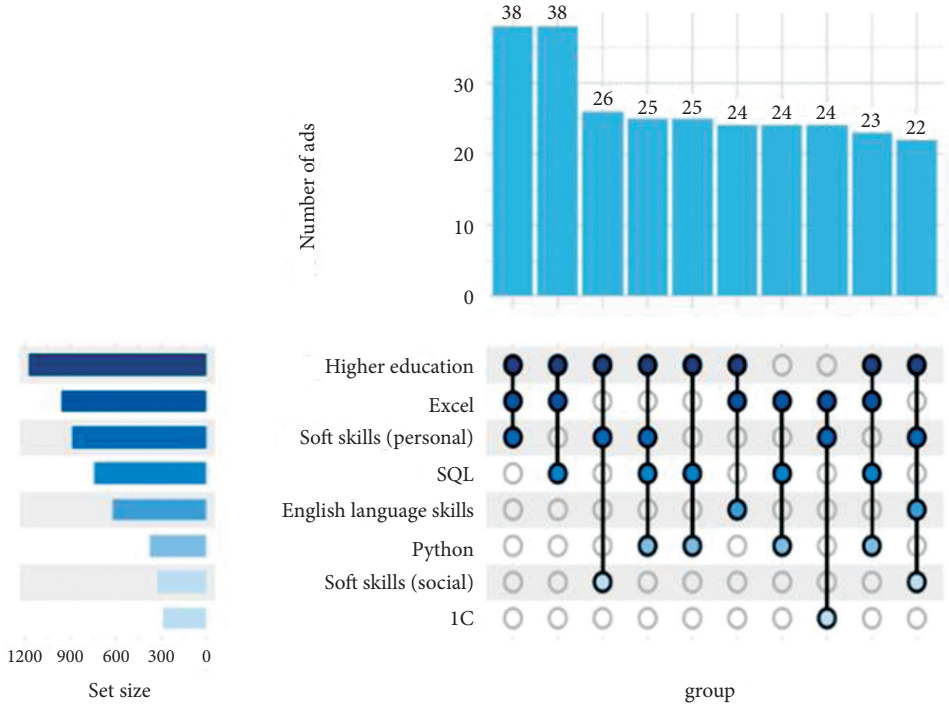

Figure 7. Frequent skill combinations listed in job vacancies for analysts. *Source:* plotted by the authors in R.

Table 5. Skill combinations frequently listed in requirements for analysts

Rule		Rule quality (multiplication of the probability that *R* is present given that *L* is present)	Rule confidence (proportion of job vacancies where *L* and *R* occur together among those where *L* is present)
Left-hand side (*L*)	Right-hand side (*R*)	$\frac{P(R \mid L)}{P(R)}$	$P(R \mid L) = \frac{P(R \& L)}{P(L)}$
Python, Tableau	SQL	3.9	0.9
English language, accounting	Excel	2.7	0.82
Excel, Word, SQL	higher education	2.5	0.9
English language, Tableau	SQL	4.1	0.95
Python, diploma (degree) from a prestigious university	Excel	3.6	0.83
Word, higher education, soft skills	Excel	3.4	1

Source: compiled by the authors.

These combinations show that analysts are sought for different tasks, e.g. data analysis (Python, SQL), product analysis (SQL, Tableau/Excel). It is worth noting that the average number of skills required in analyst vacancies exceeds two, as good mastery of only one or two skills is not sufficient for a number of job roles.

Models similar to those for the total sample were constructed for the analyst sub-sample (OLS with control variables and Heckman 2OLS). All models were tested for multicollinearity, heteroskedasticity, outliers, correct specification, and overall equation significance. Based on the constructed models and the analysis of the online courses, the payback period was estimated for those skills that were found to be significant in the Heckman-corrected model (see Table 6). The calculations were made disregarding the duration of the courses, based on the average salary offered to analysts (66.865 roubles per month).

Table 6. Skills payback periods for analysts

Skill	Impact on salary	Average course price	Payback period
SQL	+29.6%***	45.300 roubles	2.7 months
Python	+16.8%**	70.870 roubles	7.3 months
Tableau	+39%**	53.500 roubles	2.4 months

Source: compiled by the authors.

One interesting finding was that visualisation and dashboarding is the fastest paying skill. As an analyst's job involves not only analysing data, but also being able to present the results, this skill is highly valued by employers.

Conclusion

This paper identified and evaluated the factors that impact the salary offered to job seekers with no work experience in Moscow, Russia. An important result was the identified complementarity of skills. Hard skills, as expected, have a positive impact on the salary offer. However, the impact of soft skills is mostly indirect and occurs largely through enhancing the impact of hard skills. One can argue about which skills are more important, but it is clear that a successful career start requires a combination of skills.

As the impact of skills on salary and their pay-offs may be different for different occupations, a separate analysis was conducted in this study for a sub-sample of analysts. This allowed additional narrower skills (data visualisation, business process modelling, agile project planning and software development) to be identified and their complementarity analysed. The main finding is that further research by occupation is promising.

An employee's most valuable resource is their time, and the choice of skills to learn would determine their future career path. This paper fills a lack of research to inform this choice. It shows that skills that are less frequently listed in job vacancy requirements pay off the fastest.

The use of data from online platforms has a number of limitations. Job descriptions are poorly structured, so it is not possible to identify all employers' requirements and working conditions. Some companies do not carefully analyse the specific skills they need in their employees and write vacancy advertisements based on the most popular skills, and the re-

quired level of skills is not always clear. To a lesser extent, this is also the case for hard skills. For non-cognitive skills, the problem is more acute, and in order to level it out, these had to be grouped together as soft skills. In addition, the job vacancies from the online platform hh.ru are likely to be biased towards skilled and clerical jobs, which is also a limitation of the study. Nevertheless, the large amount of data collected and its representativeness allow reasonable conclusions to be drawn about the drivers of labour demand, and the use of data from online platforms seems to be a promising area for further research on the Russian labour market.

Bibliography

Volgin AD, Gimpelson VE (2022) Demand for Skills: Analysis Using Online Vacancy Data. HSE Economic Journal 26(3): 343–374. https://doi.org/10.17323/1813-8691-2022-26-3-343-374.

Gimpelson VE, Zudina AA, Kapeliushnikov RI (2020) Non-cognitive components of human capital: Evidence from Russian data. Voprosy Ekonomiki (11): 5-31. https://doi.org/10.32609/0042-8736-2020-11-5-31.

Lyashok VYu (2021) Youth Unemployment in Russia: Scope and Issues. Russian Economic Developments 28(4): 77–80. https://ssrn.com/abstract=3856322.

Malinovskiy SS, Shibanova EYu (2022) Dostupnost' vysshego obrazovaniya v Rossii: kak prevratit' ehkspansiyu v ravenstvo [Access to higher education in Russia: how to turn expansion into equality] (Sovremennaya analitika obrazovaniya № 7(67)). M.: HSE University, 78 pp. URL: https://publications.hse.ru/pubs/share/direct/810799588.pdf.

Rozhkova KV, Roshchin SY, Solntsev SA, Travkin PV (2021) The return to master's degree in the Russian labor market. Voprosy Ekonomiki (8): 69-92. https://doi.org/10.32609/0042-8736-2021-8-69-92.

Rozhkova KV (2019) The return to noncognitive characteristics in the Russian labor market. Voprosy Ekonomiki (11): 81–107. https://doi.org/10.32609/0042-8736-2019-11-81-107.

Rozhkova KV, Roshchin SYu (2019) Does knowing foreign language pay off in the Russian labor market? Voprosy Ekonomiki (6): 122–141. https://doi.org/10.32609/0042-8736-2019-6-122-141.

Roshchin SYu, Razumova TO (2000) Labor Economics (Economic Theory of Labor). INFRA-M, Moscow, 400 pp.

Roshchin SYu, Rudakov VN (2016) The effect of university quality on graduates' wages. Voprosy Ekonomiki (8): 74–95. https://doi.org/10.32609/0042-8736-2016-8-74-95.

Suhomlin VA, Zubareva EV, Yakushin AV (2017) Methodological aspects of the digital skills concept. Modern Information Technologies and IT-Education 13 (2): 146–152. https://doi.org/10.25559/SITITO.2017.2.253.

Ternikov AA (2023) Artificial intelligence and the demand for skills in Russia. Voprosy Ekonomiki (11): 65–80. https://doi.org/10.32609/0042-8736-2023-11-65-80.

Ehrenberg RD, Smith RS (1996) Modern labor Economics: theory and public policy. Moscow: Publishing House of Moscow State University, 777 pp.

Aigner DJ, Cain GG (1977) Statistical Theories of Discrimination in Labor Markets. Industrial and Labor Relations Review 30 (2): 175–187. https://doi.org/10.1177/001979397703000204.

Altonji JG, Pierret CR (1997) Employer Learning and Statistical Discrimination. NBER Working Paper No. w6279. URL: https://ssrn.com/abstract=226036.

Autor DH, Katz LF, Kearney MS (2008) Trends in US wage inequality: Revising the revisionists. The Review of Economics and Statistics 90 (2): 300–323.

Autor DH (2014) Polanyi's Paradox and the Shape of Employment Growth. NBER Working Paper No. w20485. URL: https://ssrn.com/abstract=2496241.

Autor DH (2015) Why Are There Still So Many Jobs? The History and Future of Workplace Automation. Journal of Economic Perspectives 29 (3): 3–30.

Beaudry P, Green DA, Sand BM (2016) The great reversal in the demand for skill and cognitive tasks. Journal of Labor Economics 34 (S1, Part 2): 199–247. https://doi.org/10.1086/682347.

Becker G (1993) Human capital: a theoretical and empirical analysis, with special reference to education (3rd ed.). Chicago: The University of Chicago Press, 414 pp.

Bordon P, Braga B (2020) Employer learning, statistical discrimination and university prestige. Economics of Education Review 77: 1–9. https://doi.org/10.1016/j.econedurev.2020.101995.

Borghans L, Weel B, Weinberg BA (2014) People Skills and the Labor-Market Outcomes of Underrepresented Groups. Industrial and Labor Relations Review 67(2): 287–334. https://doi.org/10.1177/001979391406700202.

Brencic V (2012) Wage posting: Evidence from job ads. Canadian Journal of Economics 45(4): 1529–1559.

Brewer DJ, Eide ER, Ehrenberg RG (1996) Does It Pay to Attend an Elite Private College? Cross-Cohort Evidence on the Effects of College Type on Earnings. Journal of Human Resources 34(1): 104–123. https://doi.org/10.2307/146304.

Dale SB, Krueger AB (2011) Estimating the Return to College Selectivity Over the Career Using Administrative Earning Data. NBER Working Paper No. w17159. URL: https://www.nber.org/system/files/working_papers/w17159/w17159.pdf.

Damari RR, Rivers WP, Brecht RD, Gardner P, Pulupa C, Robinson J (2017) The demand for multilingual human capital in the US labor market. Foreign Language Annals 50(1): 13–37. https://doi.org/10.1111/flan.12241.

Deming D (2017) The Growing Importance of Social Skills in the Labor Market. Quarterly Journal of Economics 132 (4): 1593–640.

Deming D, Kahn LB (2018) Skill Requirements across Firms and Labor Markets: Evidence from Job Postings for Professionals. Journal of Labor Economics 36 (S1): 337–369. https://doi.org/10.1086/694106.

Heckman J, Stixrud J, Urzua S (2006) The effects of cognitive and noncognitive abilities on labor market outcomes and social behavior. Journal of Labor economics 24 (3): 411–482.

Hoekstra M (2009) The Effect of Attending the Flagship State University on Earnings: A Discontinuity-Based Approach. The Review of Economics and Statistics 91 (4): 717–724.

Kuhn P, Weinberger C (2002) Leadership skills and wages. Journal of Labor Economics 23(3): 395–436. http://dx.doi.org/10.2139/ssrn.310372.

Loury LD, Garman DM (1995) College Selectivity and Earnings. Journal of Labor Economics 13(2): 289–308. https://doi.org/10.1086/298375.

MacLeod WB, Riehl E, Saavedra JE, Urquiola MS (2015) The Big Sort: College Reputation and Labor Market Outcomes. CESR-Schaeffer Working Paper No. 2015-013. http://dx.doi.org/10.2139/ssrn.2622796.

NACE (National Association of Colleges and Employers) (2015) Job Outlook Spring Update 4. URL: https://www.stjohns.edu/sites/default/files/uploads/nace_job_outlook.pdf.

Reder MW (1962) Wage Differentials: Theory and Measurement. Aspects of Labor Economics, National Bureau of Economic Research, Inc: 257–318. URL: https://EconPapers.repec.org/RePEc:nbr:nberch:0607.

Spence M (1974) Market Signaling: Informational Transfer in Hiring and Related Screening Processes. Cambridge: Harvard University Press, 221 pp.

Weinberger CJ (2014) The Increasing Complementarity between Cognitive and Social Skills. Review of Economics and Statistics 96(5): 849–861.

Zhang L (2005). Do Measures of College Quality Matter? The Effect of College Quality on Graduates' Earnings. The Review of Higher Education 28(4): 571-596. https://doi.org/10.1353/rhe.2005.0053.

Other sources of information

HeadHunter (2021) Employer Rating. URL: https://rating.hh.ru/history/rating2021/ [Accessed on 15.03.2022, 24.07.2024]

RBC (Trends) (2023) Kak sovremennye shkolniki vybirayut sebe professiyu [How modern schoolchildren choose their profession]. URL: https://trends.rbc.ru/trends/education/62876ace9a79474c09ba6367 [Accessed on 27.07.2024].

Rosstat (2023) Labor force, employment and unemployment. URL: https://rosstat.gov.ru/labour_force [Accessed on 24.07.2024].

Similarweb Rating "Most Visited Jobs and Career Websites in Russia". URL: https://www.similarweb.com/ru/top-websites/russian-federation/jobs-and-career/ [Accessed on 10.12.2021, 01.09.2022, 04.07.2023, 24.07.2024].

Information about the authors

- Anna Nikolaevna Litvinova – Developer Analyst Yandex LLC, Graduate Student of the Faculty of Economics of Lomonosov Moscow State University, Moscow, 119991, Russia. E-mail: litvinovaani@mail.ru
- Ianina Aleksandrovna Roshchina – Candidate of Economics, Associate Professor. Faculty of Economics of Lomonosov Moscow State University. Moscow, 119991, Russia. E-mail: janina-d@yandex.ru

Annex 1

Table A1. Analysing the online courses market

Skill	Company	Course Title	Price, roubles	Duration	Certificate	Link
Python	Netology	Python for data analysis	42.000 (not discounted 60.000)	4 months	yes: certificate of skill upgrading	https://netology.ru/programs/python-for-analytics#/
	SkillFactory	Python for data analysis	32.040 (not discounted 53.400)	4 months	yes: certificate of successful completion of the online course	https://skillfactory.ru/python-analytics
	Yandex Practicum	Python- developer	138.600	9 months	yes: retraining course diploma	https://practicum.yandex.ru/backend-developer/
	Yandex Practicum	Data analyst (Python and SQL) / premium version	96.000 / 168.000	6 months / 12 months	yes: retraining course diploma	https://practicum.yandex.ru/data-analyst/
SQL	Yandex Practicum	SQL for data processing and analysis	41.000	1.5 months	yes: certificate of skill upgrading	https://practicum.yandex.ru/sql-data-analyst/
	SkillFactory	SQL for data analysis	35.640 (not discounted 59.400)	3.5 months	yes: certificate of successful completion of the online course	https://skillfactory.ru/sql-dlya-analiza-dannyh
	Netology	SQL and data acquisition	24.850 (not discounted 35.500)	2 months	yes: certificate of skill upgrading	https://netology.ru/programs/sql-lessons
Excel	Skillbox	Excel from a beginner to a Pro	25.500 (not discounted 42.500)	5 months	No information available	https://skillbox.ru/course/excel-gsheets/
	Netology	Excel for data analysis	20.300 (not discounted 29.000)	2 months	yes: certificate of skill upgrading	https://netology.ru/programs/excel
	SkillFactory	Google Spreadsheet Wizard	19.800 (not discounted 33.000)	1 month	yes: certificate of successful completion of the online course	https://skillfactory.ru/google-spreadsheets-master

Skill	Company	Course Title	Price, roubles	Duration	Certificate	Link
English language	Skyeng	English language course (Intermediate)	57.500	5 months (67 lessons)	yes: certificate	https://skyeng.ru/obshchie-kursy-po-angliyskomu-yazyku/
	Skyeng	Business English course	32.000	2.5 months (35 lessons)	yes: certificate	https://skyeng.ru/programs/anglijskij-po-otraslyam/delovoy-angliyskiy-yazyk/
	Skillbox	English language course (Intermediate)	45.500	6 months (50 lessons)	yes: certificate	https://eng.skillbox.ru/
1C	Netology	1C Analyst	86.400 (not discounted 144.000)	9 months	yes: retraining course diploma	https://netology.ru/programs/1C-analyst
	Training Center FORWARD	Working with 1C software package	7.200	2 weeks	yes: FORWARD certificate	https://forward-center.ru/courses/1C
	Skillbox	1C: Accounting	25.272 (not discounted 36.103)	2 months	yes: 1C certificate	https://skillbox.ru/course/1C-work
AutoCAD	Skillbox	AutoCAD from a beginner to a Pro	23.650 (not discounted 33.786)	2 months	No information available	https://skillbox.ru/course/autocad/
	irs.academy	AutoCAD online course	30.450	22 hours	yes: certificate	https://irs.academy/kurs_po_autocad?partner=geekhacker
	Computer Training Centre 'Specialist' at the Bauman Moscow State Technical University	Autodesk AutoCAD	19.990	2 weeks (32 hours)	yes: certificate of skill upgrading / certificate of completion	https://www.specialist.ru/course/akad20101
Java	SkillFactory	Java Tester	134.000 (not discounted 206.000)	10 months	yes: training certificate, on request, in English / yes: retraining course diploma	https://skillfactory.ru/java-qa-engineer-testirovshik-po

Skill	Company	Course Title	Price, roubles	Duration	Certificate	Link
Java	Netology	Java-developer from zero	107.460 (not discounted 179.100)	14 months	yes: standard retraining course diploma	https://netology.ru/programs/java-developer
	Computer Training Centre 'Specialist' at the Bauman Moscow State Technical University	Java. Level 1. Java programming language	42.990	1 month (40 hours)	yes: certificate of skill upgrading / certificate of completion	https://www.specialist.ru/course/dzhv1-a
Soft Skills	SkillFactory	Mini-course Soft Skills for IT Beginners	4.990	7.5 hours	No information available	https://skillfactory.ru/soft-skills-it-course
	Skillbox	Soft Skills for Hard Times (format: manager)	99.000 (not discounted 152.300)	4 months	No information available	https://skillbox.ru/course/soft-skills-for-hard-times/
	Training Centre TEACHLINE	Soft Skills for the Manager	23.000 / 42.000 / 96.000 (Basic / Top / VIP)	1.5 months	yes: diploma (for Top and VIP pricing plans)	https://teachline.ru/courses/soft-skills-dlya-menedzhera
Tableau	Netology	Tableau: data visualisation	26.500 (not discounted 39.900)	2 months	yes: certificate of skill upgrading	https://netology.ru/programs/tableau
	ProductStar	Power BI and Tableau for data visualisation	39.900 (not discounted 75.000)	2 months	yes: certificate of successful completion of the online course	https://productstar.ru/analytics-mini-course-powerbi
	Yandex Practicum	Data visualisation and introduction to BI tools	63.700 (51.600 when paid upfront)	3 months	yes: certificate of skill upgrading / certificate of completion of the online course	https://practicum.yandex.ru/datavis-and-bi-tools
	Skillbox	Profession: BI analyst	83.950 (not discounted 128.350)	6 months	No information available	https://skillbox.ru/course/profession-bi-analyst

Source: Compiled by the authors based on analysis of the online course market (based on open-source data).

Annex 2

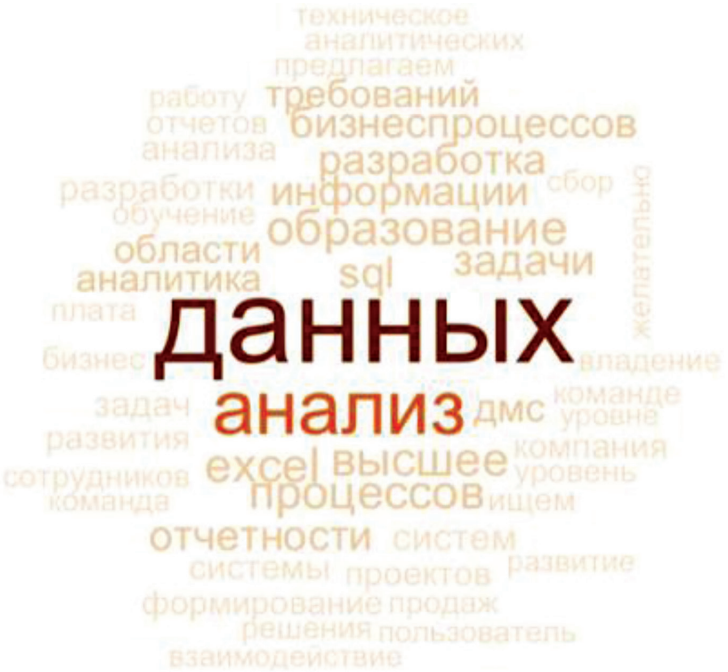

Figure A1. Word cloud for Analyst job vacancy description. *Source:* constructed by the authors in R based on HeadHunter data.