Impact of COVID-19 on skill requirements and skill returns: Evidence from job websites[1]

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This paper analyzes the requirements of employers for the professional skills of applicants. The aim of the study is to identify the determinants of skill requirements, and investigate the association between skill requirements and wages. The database of the study was constructed by the authors on the basis of vacancies posted by Russian employers on the portal "Work in Russia" of the Ministry of Labor of the Russian Federation in 2019-2021. Using the requirements in the vacancies, we identify 13 main skill groups. Our analysis of 5,412,089 vacancies indicates a significant return on cognitive and management skills. The selected period allowed us to assess changes in the requirements before and after the beginning of the COVID-19 pandemic. There has been an increase in requirements for general computer skills, while requirements for education and work experience, character skills, and professional knowledge have decreased. As a result of the pandemic, there have been significant changes in the rates of return to human capital. The return to education and work experience, management, writing and customer service skills have decreased, and the return on professional knowledge has increased.

KEYWORDS: *human capital, coronavirus pandemic, vacancies, skills, competencies.*
JEL: *J22, J23, J24*

Introduction

The results of various studies indicate that a significant gap in pay occurs not only between workers of different occupations (inter-occupational inequality), but also among employees of the same occupation (withinprofessional inequality) (Barth, 2013; Card, 2016; Helpman, 2017; Kim, Sakamoto, 2008; Xie, Killewald, Near, 2016). The wages of employees who hold the same position may vary significantly between firms. Such differences are not fully explained by the financial performance, size, and industry affiliation of firms. Knowledge, skills and abilities of employees play an important role.

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The study of the requirements for professional skills of employees is an important scientific task for several reasons. First, identifying wage differentials within a profession associated with the required skills allows us to more accurately identify the causes of wage inequality. Secondly, the study of occupations through the lens of professional competencies makes it possible to assess the degree of influence of technological progress on the work content, and therefore to make a forecast regarding the viability of the occupation in the future. Third, a comparison of the skills required by employers with the skills of applicants applying for this position helps to determine the causes of an imbalance in the labor market with simultaneous significant number of vacancies and unemployed people. Fourth, the study of skills requirements allows us to identify trends in the transformation of employers' requirements for human capital.

In the context of global instability caused by the COVID-19 pandemic, employers are forced to quickly respond to changes in the external environment, revising the labor functions of employees, and redefining "hot" skills. Changes in skill requirements lead to a devaluation of existing human capital and the need for additional investment in it. Most studies estimate human capital using the number of years of education and length of experience (Consoli et al., 2016). This approach does not take into account either the assessment of the quality of accumulated capital or the changes in skill requirements. Changes in workers' skills were particularly substantial during the COVID-19 coronavirus pandemic. According to our hypothesis, the restrictive measures taken during the pandemic affected the labor demand through the transformation of the requirements imposed by employers on job seekers. However, the pandemic has exacerbated and accelerated the processes that began before it including the digitalization of the economy, the transition of many professions to remote work, and the development of distance education. The impact of these processes on the accumulation and development of human capital has not been sufficiently studied.

This paper analyzes the requirements of employers for the professional skills of applicants. We study the content of vacancies, and also reveal the determinants of the requirements in vacancies and association between wages and requirements.

The novelty of the study is that for the first time a methodology for assessing the requirements for human capital was developed and tested based on the analysis of employers' requests for the skills and competencies of applicants. Our methodology, in comparison with existing approaches to human capital investigation, makes it possible to assess transformational changes in the demand for applicants' competencies. Our methodology allows to get rapidly information about changes in the labor market, since data on vacancies are available in real time. Traditional human capital studies are based on data from statistical agencies and microdata from labor force surveys, which become available with a certain time lag.

As a database for the study, we use a full sample of vacancies posted by employers on the portal "Work in Russia" in April and December 2019 and 2020. The Internet is very popular for job seekers in Russia. The article by S. Roshchin, S. Solntsev, and D. Vasiliev shows that in the 2010s, the Internet became one of the most popular ways to search for both jobs and personnel in Russia [Roshchin et al., 2017]. The selected periods allow for a comparative analysis of employers ' requirements before the pandemic and during different periods of imposed restrictions.

Literature review

Online vacancies in Russia have not yet become a source of large-scale research on employers 'requirements for job seekers' skills. At the same time, there are studies in foreign countries devoted to a detailed investigation of skill requirements based on extensive databases of online vacancies.

In this regard, first of all, we should mention the work of D. Deming and L. Kahn, based on the data of the US labor market (Deming and Kahn, 2018). The large-scale database used in their study included 45 million professional vacancies posted in 2010-2015 on approximately 40 thousand sites and collected by Burning Glass Technologies. Based on the study of skill requirements, they organized all skills into 10 main groups:

1) cognitive (problem solving, critical thinking, analytical and mathematical skills);
2) social skills (communication skills, teamwork);
3) character (organization, multitasking, time management);
4) writing;
5) customer service;
6) project management;
7) people management;
8) financial;
9) general computer programs (MS Office, etc.);
10) specific software (e.g., Java, SQL, Python)

For example, for accountants and auditors they provide the following results: financial skills, that are professional for this category of workers are indicated in 84 % of the vacancies, cognitive skills in 46 %, basic computer skills in 44 %, skills in 35 %, social skills in 33 %, specific software skills in 31 %, writing skills in 22 %, management skills in 15%, customer service skills in 8 %, project management skills in 5 % (Deming, Kahn, 2018).

Based on the results of the authors ' analysis of this work reveal the significant differentiation of skill requirements between firms, show that the higher requirements for education and work experience are associated with the higher requirements for skills, and find that municipalities with higher salaries have higher skill requirements. In addition, they show that skill requirements are higher in public companies and companies with higher average salaries.

As an explanation for the results, Deming and Kahn argue that more successful firms use modern technologies more effectively, which require qualified professionals, which is ultimately reflected in the growth of wages and skills requirements in vacancies.

The authors found a positive correlation between wages and the selected skill groups. It has been shown that within-occupational inequality is a consequence of differences in skill requirements, resulting in about 15 percent of total wage inequality.

A limitation of their analysis is that the data on wages are not taken from vacancies (due to the fact that in their database they were indicated in only 13% of vacancies), but are determined by calculation. For public companies, they use data on the average salary in the company, and for all other firms they use the average salary for employees of this occupation in this municipality.

In addition, the correctness of systematization of skills based on machine processing of a large number of vacancies raises some questions. Deming and Kahn share of vacancies for the position of accountant that contain requirements for the use of professional software is seemed to be very low (31 %). We conducted an analysis of 10 vacancies for the position of accountant posted on the site indeed.com that is one of the most popular job search sites in the United States-by employers in San Diego, which is given in the article as an example of a city with relatively low skill requirements. Our analysis showed that 6 out of 10 vacancies contain requirements for skills in using specialized software, which in some cases are presented only in the form of software product names, which could have been omitted in machine analysis.

The Burning Glass Technologies' extensive job database has also been used in some other studies. The article by B. Hershbein and L. Kahn, based on the analysis of vacancies placed in 2007, 2010-2015, found that in agglomerations that experienced a more significant decline during the recession, there is an increase in the requirements for the skills in vacancies (Hershbein, Kahn, 2018). The authors explain this result by saying that firms affected by the crisis were forced to restructure production.

Based on the data on vacancies from the same database for 2007, 2010-2014, the analysis of the dependence of employers ' requirements on the situation on the labor market was carried out by Modestino et al., 2016. The authors of this paper did not limit the sample to specialists only, which eventually increased the number of vacancies to 82.5 million. As in the paper by Hershbein and Kahn, they identified an increase in job requirements as a result of the recession, and explained this pattern by the fact that with increasing labor market tightness and an increase in the number of applicants per job, employers can use competition between applicants to hire more qualified employees.

The COVID-19 pandemic and the restrictive measures taken to combat it have had a large-scale impact on the economy and society, which naturally aroused an active interest of researchers in studying the consequences of this impact. Special attention was paid to the problems of the labor market in Russia and other countries. At the same time, the first studies on the impact of the pandemic on the labor market focused on its impact on such important labor market indicators as wages and employment (Gimpelson, Kapelyushnikov, 2020; Drobot, 2020; Gupta et al., 2020). These indicators reflect quantitative characteristics of labor demand, while changes in qualitative characteristics, such as employers' requirements for job seekers' skills, may not be as noticeable for statistics, but at the same time they can be also significant.

The literature review shows that online vacancies are a very promising source of data for analyzing the skills requirements of job seekers in the labor market. At the same time, studies in this area are still few, mainly based on materials from the United States and contain controversial and contradictory conclusions. In this regard, it is important to develop further research in this area, including the usage of Russian data. In particular, it is promising to use online job databases to study the transformation of requirements in the context of the 2020 coronavirus pandemic.

Data description and research methodology

The database of the study is the all-Russian database of vacancies "Work in Russia", presented on the website https://trudvsem.ru, which is supported by the Federal Service for Labor and Employment. More than 1 million vacancies are posted on this portal, reflecting its wide popularity among employers. The database of vacancies is publicly available at https://trudvsem.ru/opendata as an xml-file.

For the analysis, we used all vacancies posted by employers of Russia, as of the following dates:

- April 30, 2019;
- December 31, 2019;
- April 30, 2020;
- December 31, 2020.

There are two reasons for choosing these dates for analysis. The selected months are those in which the activity of the working-age population is high because it is not the summer vacation period or months with low activity as January. Second, April 2020 is the month when the pandemic was announced and restrictive measures were introduced.

Vacancies are active on the portal for 30 days, so the database reflects vacancies for April and December 2019-2020. The total number of vacancies for these periods is 5,412,089.

Analysis of data for April and December 2019 provides insight into the state of the labor market before the pandemic. The study of data for April 2020 provides an opportunity to assess the labor market's response to the introduction of restrictive measures, while data for December 2020 make possible to assess the functioning of the labor market under the imposed restrictions. To assess the impact of the pandemic, each month should be compared with the same period of the previous year, since the demand for some occupations is seasonal.

We identified the requirements of employers by automated processing of data on the two sections: candidate requirements and additional information on the vacancy. To allow further grouping of requirements, the set of skills contained in the vacancy was divided using the "comma", "period" and "semicolon" symbols. The maximum number of keywords for one vacancy was 209. In order to reduce the number of calculations, the first 50 keywords were used. In total, we identified 778 thousand different keywords, and 10 thousand keywords with the highest frequency were taken for analysis (the minimum frequency was 63). Based on the results of the keyword analysis, 4149 requirements were identified, of which 1979 are related to skills.

The requirements for the applicant's education and work experience were analyzed separately. We formed the traditional variables "education" and "work experience" using Mincer-type specification, i.e. measured it by the number of years. In this regard, we transformed the variable "education" as follows: no education requirement – 4 years of study, secondary education-10 years, secondary vocational education - 13 years, higher education - 15 years, incomplete higher education - 12.5 years, postgraduate education - 18 years. If there is no information about education and work experience in the corresponding fields of the vacancy, we tried to receive this information from the "additional information" field using the previously selected keywords. If there is no requirement for work experience, the variable "work experience" was set to zero, and the minimum work experience requirements were counted as the number of years of experience. The most popular requirements are one, two, three, and five years of work experience, while other options are much less common.

To analyze the number of vacancies for individual occupations, the number of vacant jobs was taken into account, i.e. if a vacancy indicated two jobs, it was counted as two vacancies.

We modify the classification by Deming and Kahn (Deming, Kahn, 2018), excluding the project management skills group and adding an additional 4 groups: skills in working with special equipment, skills in working with documents, professional knowledge and other skills. These changes are primarily due to the fact that Deming and Kahn's work analyzed only professional vacancies, while we consider all professional groups in the course of the analysis. Examples of skills assigned to the selected groups are shown in *Table 1*.

The study of the content of vacancies posted on the site allows us to conclude that the assessment of the requirements imposed by employers on applicants should be carried out using all professional competencies (knowledge, skills, abilities) but not limit to skills as in the (Deming, Kahn, 2018).

Separately, we distinguish such requirements as the presence of a certificate of absence of a criminal record, a sanitary (medical) book, certificates, licenses.

Table 1

Classification of professional competencies by employer requirements

n /	a Skill Group	Examples	
Emphasizing the features of personality formation			
1.	Cognitive	- learning ability; - analytical mindset; - ability to work with a large amount of information;	- ability to read drawings; - fast decision-making; - flexibility of thinking.
2.	Social	- sociability; - teamwork; - literate speech;	- non-conflict; - love for children; - neatness.
3.	Character	- responsibility; - discipline; - punctuality;	- initiative; - focus on results; - lack of bad habits.
Pronounced professional character			
4.	Writing	- literacy; - typewriting skills; - high printing speed;	- document processing; - transfer of the author's desired thoughts; - knowledge of translation techniques.
5.	Customer service	- customer orientation; - attentive attitude to patients; - sales skills;	- knowledge of cash discipline; - knowledge of the product range; - ability to communicate with customers.
6.	Management	- organizational abilities; - leadership skills; - ability to work with a large group of people;	- demanding; - ability to resolve disagreements; - skills in monitoring compliance with production technology.
7.	Financial	- preparation of financial statements; - knowledge of tax legislation; - ability to calculate the purchase price; - knowledge of the calculation rules;	- knowledge of the procedure for reflecting operations related to the movement of fixed assets; - readiness to work with cash.
8.	General computer	- knowledge of the basics of working with a computer; - free work with a computer; - office programs; - basics of information security;	- knowledge of modern information technologies; - knowledge of MS Office, Word, Excel, PowerPoint, Outlook, Internet Explorer, Paint, Consultant-Plus.
9.	Special software	- accounting programs; - modern data processing programs; - programming; - client-service technologies;	- skills in preparing encoded information; - knowledge of 1C, AutoCAD, Compass, SAP, CSS, SQL, JavaScript, PhotoShop, HTML, Linux, VLSI, Python, C++
10.	Working with special equipment	- ability to handle power tools; - ability to work with office equipment; - knowledge of cash registers;	- experience with specialized equipment; - skills in adjusting and adjusting equipment; - technical literacy.

11.	Working with documents	-experience working with documents; - ability to work with technical documentation.	
12.	Professional knowledge	- knowledge of the laws of the Russian Federation and other regulatory legal acts; - knowledge of crafts; - knowledge of office work;	- knowledge of the basics of economics; - knowledge of the specifics of production; - knowledge of foreign languages (English, Chinese, etc.).
13.	Other	- driver's license; - qualification category; - service in the armed forces of the Russian Federation;	- electrical safety admission group; - inoculation certificate.

Source: created by the authors.

To estimate the rate of return on skills, we modify the Mincer wage equation as follows:

$$LnWage_i = \beta_0 + \beta_1 educ_i + \beta_2 exper_i + \beta_3 exper_i^2 + \sum_{k=1}^{K} \delta_k S_{ik} + X_i\theta + u_i, \qquad (1)$$

where $Wage_i$ is the salary in rub.; $educ_i$ is the number of years of education; $exper_i$ denotes number of years of work experience; X_i are additional control variables; S_{ik} are skills and competencies groups; $\delta_{\delta k}$ is a rate of return from the *k*-th skill; u_i is an error term.

We used the following workplace characteristics as control variables:

- region;
- locality (urban-type settlement, rural settlement, dummy variables for 1216 cities);
- industry;
- type of employment (traditional, remote, temporary, seasonal, internship);
- work schedule (traditional, shift, irregular, flexible, shift);
- profession (dummy variables for 8,038 occupations).

We exclude part-time vacancies that constitute approximately 6 % of all vacancies. This is due to the absence of information about the length of the working day, which must be taken into account to combine such vacancies with full-time vacancies.

The approach we use has three main differences from previous studies of the Russian labor market based on the Mincer wage regression:

1) using the vacancy database in contrast to household survey data (primarily the RLMS-HSE);
2) applying a different approach to the definition of traditional independent variables, due to the specifics of the database used (for example, minimal work experience instead of actual; a more detailed list of occupations, industries, localities);
3) inclusion of skill requirements in the list of independent variables (which is the main novelty of this study).

In this regard, it is incorrect to assume that the differences between the results obtained and the results obtained earlier on the basis of surveys of Russian households are solely due to the inclusion of skill requirements in the analysis (point 3). To ensure comparability with previous studies, we evaluate model (2) on the basis of the data of the vacancies and the data of the RLMS-HSE.[2]

$$LnWage_i = \beta_0 + \beta_1 educ_i + \beta_2 exper_i + \beta_3 exper_i^2 + Z_i\gamma + u_i, \quad (2)$$

where Z_i is a list of control variables that is comparable to the RLMS-HSE survey.

Model (2) is evaluated separately based on combined data on vacancies for April and December 2019 and data from the representative part of the 28th RLMS-HSE round sample (autumn 2019). We limit the RLMS-HSE sample to full-time workers. The dependent variable in the RLMS-HSE sample is determined on the basis of the average monthly salary in the primary job for the last 12 months. In the case of the absence of data on the specified variable we use the wage in primary job for the last 30 days. This approach provides the comparability of data, taking into account both the period of analysis and the fact that the analyzed vacancies offer both permanent and temporary employment. Actual wages have been adjusted for wage delays. We divided the amount received by 0.87, since the earnings data in the RLMS-HSE sample are collected after paying personal income tax of 13 %, while vacancies, as a rule, contain before-tax salary. We excluded everyone who has less than 30 hours of work per week at their main place of work, to exclude part-time employees. We also excluded all persons under the age of 16.

The list of independent variables of model (2) includes the following:

1) region;
2) type of location (regional center, city, village, village);
3) industry;
4) occupational group (1 – manager, specialist or employee, 0 – all others).

We create the variable "educ" in the RLMS-HSE sample using the similar approach that we use to code education data in the online job database. Persons with incomplete secondary education are assigned 4 years, those with full secondary education – 10 years, professional secondary education - 13 years, higher education - 15 years, incomplete higher education - 12.5 years, postgraduate education -18 years.

The variable "exper"(work experience) is also created taking into account the peculiarities of data encoding for vacancies. All persons with less than one year of work experience are assigned

[2] Source: "Russia Longitudinal Monitoring survey, RLMS-HSE», conducted by National Research University "Higher School of Economics" and OOO “Demoscope” together with Carolina Population Center, University of North Carolina at Chapel Hill and the Institute of Sociology of the Federal Center of Theoretical and Applied Sociology of the Russian Academy of Sciences. (RLMS-HSE web sites: https://rlms-hse.cpc.unc.edu, https://www.hse.ru/org/hse/rlms)

the value 0, from one to two years - 1, from two to three years – 2, from three to 5 years – 3, and over 5 years – 5.

Skill requirements

Table A1 in the Appendix shows the dynamics of the number of vacancies in Russia's most popular occupations. To identify it, we selected Top-40 occupations by the number of vacant jobs at least in one of the periods.

The largest number of vacant jobs in Russia are observed for such occupations as car driver and room cleaner. The data presented in *Table A1* indicate a seasonality of demand for some occupations. Many occupations have not experienced a significant decline in demand during the pandemic. At the same time, in such professions as car driver, yard keeper, loader, concrete finisher, food vendor, bricklayer, carpenter, millwright, plasterer, painter, there is a decrease in the number of vacancies, that reflects, the decline in the demand for these occupations due to the pandemic restrictions.

Table A2 shows the most popular requirements in vacancies. We used a similar selection principle, identifying the Top-40 most common employer requirements in each month. The most common requirements are responsibility, discipline, sociability, punctuality, teamwork and sense of duty. These requirements were among the Top-6, both during the pandemic and before it. The biggest surprise is that in 2020, there was no significant increase in computer skills requirements, despite the transition of many firms to remote operation.

Among the personal characteristics that marked an increase in employers' demand during the pandemic are the absence of bad habits, mindfulness, hardworking, orderliness, and high productivity. The increase in their popularity suggests that these qualities of job seekers are more important for remote work from the point of view of employers.

By the end of 2020, employers have become more likely to require a medical record with an already completed medical examination for occupations with a mandatory medical examination. This requirement may reflect employers' desire to avoid the risks associated with employees' visits to health facilities during a pandemic.

In 2020, such requirements as sociability, teamwork, sense of duty, learning ability, purposefulness, focus on results, activeness, benevolence, Literate speech, and the presence of a Category B driver's license became less common. These changes are also likely to reflect the impact of restrictions during the coronavirus pandemic.

It is interesting to conduct a separate analysis for professionals. We select managers, specialists, and clerks, i.e. professional groups from the first to the fourth in accordance with the

All-Russian Classifier of Occupations (OKZ). For these professional groups we should expect the most substantial transformation of requirements during the pandemic, since they can perform their duties remotely. The number of vacant jobs by these occupational groups for the entire period of analysis is 1,734,717, or about a third of the total number. Table A3 shows the most common requirements for these groups.

Compared to the overall base vacancies for these groups are less likely to have such requirements as the presence of the driver's license, sense of duty, mindfulness, accuracy, physical endurance, absence of bad habits. More often are requirements for communication skills, foreign language skills, fluency in English, computer skills, knowledge of accounting software, knowledge of 1C, knowledge of MS Excel and Word, legal acts knowledge, literacy, imitativeness, stress tolerance, clear diction, literate speech, result orientation, high-level skills.

Table 2 shows the prevalence of the requirements grouped by our classification. The most common requirements are for character skills, which are found in almost 80 % of vacancies. Also quite common are the requirements for social skills, which are mentioned in about 20 % of vacancies. Requirements for other skill groups are much less common. During the pandemic, there is a significant reduction in the frequency of social skills requirements and an increase in personal skills requirements.

Table 2

Requirements by skill group

	Skill group	Frequency, %				Difference 2019-2020, pp.	
		2019		2020			
		April	December	April	December	April	December
1.	Cognitive	5.74	6.13	5.71	5.49	-0.03	-0.64
2.	Social	22.11	21.34	19.50	20.18	-2.61	-1.16
3.	Character	77.38	77.75	77.84	78.26	0.46	0.51
4.	Writing	0.29	0.32	0.32	0.46	0.03	0.14
5.	Customer service	0.24	0.23	0.23	0.22	-0.01	-0.01
6.	Management	0.21	0.14	0.21	0.22	0	0.08
7.	Financial	0.18	0.17	0.25	0.21	0.07	0.04
8.	General computer	6.36	6.58	6.42	6.48	0.06	-0.10
9.	Special software	1.13	1.12	1.17	1.08	0.04	-0.04
10.	Working with special equipment	0.19	0.15	0.20	0.12	0.01	-0.03
11.	Working with documents	0.26	0.23	0.19	0.35	-0.07	0.12
12.	Professional knowledge	6.40	5.89	6.36	5.04	-0.04	-0.85
13.	Other	7.12	9.36	8.13	7.79	1.01	-1.57

Source: authors' calculations based on data from the portal "Work in Russia".

Note: the sum of values in columns is greater than 100, because several requirements can be specified in one vacancy.

Table 3 presents similar results obtained for a sample of managers, specialists, and clerks. For almost all skill groups, the prevalence of requirements for these professions is higher compared to the whole sample. Requirements for other skills are less common, and requirements for character skills and skills in working with special equipment are about the same frequency.

Requirements for social skills and general computer skills, skills in using special software, as well as requirements for professional knowledge are much more prevalent.

Table 3

Requirements by skill group for the professions of managers, specialists, and clerks (OKZ 1-4)

	Skill group	Frequency, %				Difference 2019-2020, pp.	
		2019		2020			
		April	December	April	December	April	December
1.	Cognitive	6.36	7.22	6.81	6.35	0.45	-0.87
2.	Social	28.16	27.15	25.97	26.18	-2.19	-0.97
3.	Character	78.22	76.97	77.51	76.08	-0.71	-0.89
4.	Writing	0.99	0.96	0.93	0.95	-0.06	-0.01
5.	Customer service	0.54	0.56	0.64	0.55	0.10	-0.01
6.	Management	0.54	0.37	0.47	0.47	-0.07	0.10
7.	Financial	0.30	0.32	0.42	0.32	0.12	0
8.	General computer	17.24	18.14	17.51	18.30	0.27	0.16
9.	Special software	3.37	3.21	3.36	3.33	-0.01	0.12
10.	Working with special equipment	0.17	0.16	0.18	0.14	0.01	-0.02
11.	Working with documents	0.33	0.30	0.29	0.47	-0.04	0.17
12.	Professional knowledge	10.23	9.69	9.40	9.09	-0.83	-0.60
13.	Other	2.49	2.71	2.83	2.58	0.34	-0.13

Source: authors' calculations based on data from the portal "Work in Russia".

Note: the sum of values in columns is greater than 100, because several requirements can be specified in one vacancy.

The prevalence of these skill groups differs significantly from that identified by the US data by Deming and Kan (table 4). In Russian vacancies, compared to vacancies from the United States, requirements for character skills are much more common, and requirements for social and general computer skills are somewhat less common. Requirements for all other skill groups in Russian vacancies are much less common.

Table 4

Requirements by skill groups for the professionals

	Skill Group	Russia, 2019	USA, 2010-2015
1.	Cognitive	6.8	37
2.	Social	27.7	36
3.	Character	77.6	30
4.	Writing	1.0	20
5.	Customer service	0.6	20
6.	Project management	–	12
7.	People management	0.5	15
8.	Financial	0.3	16
9.	General computer	17.7	29
10.	Special software	3.3	32

Source: data for Russia are calculated by the authors using the portal "Work in Russia", data for the USA are from Table A2 from the (Deming, Kahn, 2018).

Some other job requirements are also of interest. First of all, these are requirements for the traditional characteristics of human capital that are education and work experience. In addition, we analyzed the dynamics of requirements for having own car and computer, because the pandemic may have caused significant changes in the frequency of these requirements (*Table 5).*

Table 5

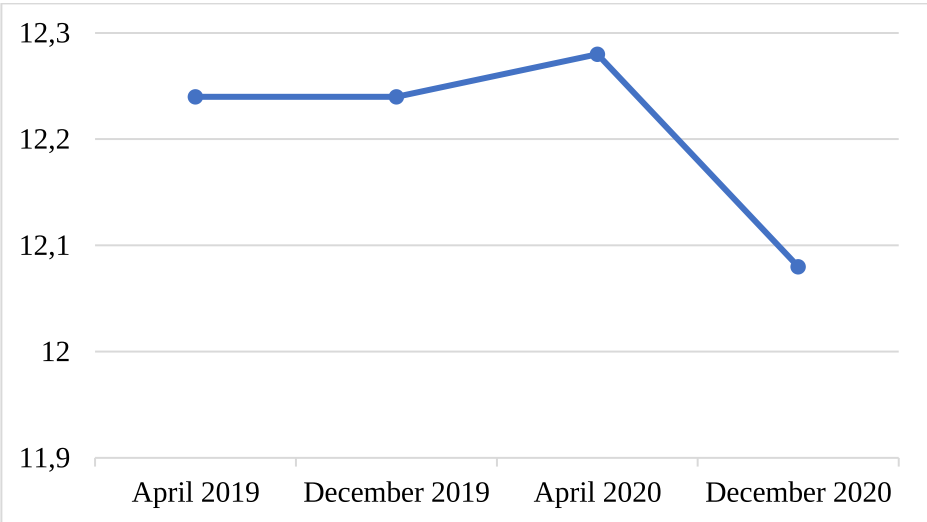
Other requirements

	Requirements	Frequency, %				Difference 2019-2020, pp.	
		2019		2020			
		April	December	April	December	April	December
1.	Higher education	15.85	16.62	17.10	13.49	1.25	-3.13
2.	Secondary vocational education	44.11	43.44	44.29	40.43	0.18	-3.01
3.	Work experience	45.81	42.78	43.28	40.62	-2.53	-2.16
4.	Work experience of 3 years	23.76	19.82	21.01	18.06	-2.75	-1.76
5.	Own car	0.17	0.21	0.13	0.13	-0.04	-0.08
6.	Computer	0.02	0.03	0.02	0.07	0	0.04

Source: authors ' calculations based on data from the portal "Work in Russia".

In 2019, the presence of higher education was a mandatory requirement in approximately 15-17 percent of vacancies, secondary vocational education in 43-44 %. Thus, any professional education was required in about 60 % of vacancies. Approximately 45 % of the vacancies required work experience, and about half of it required at least 3 years of work experience. During the pandemic, the requirements for education and work experience were declined. In December 2020, mandatory professional education was indicated in 54% of vacancies, higher education in 13.5 % of vacancies, and work experience in 41 % of vacancies. In 2019, the average estimated number of years of education required in vacancies was 12.25; by December 2020, it had fallen to 12.08 (*Figure 1*).

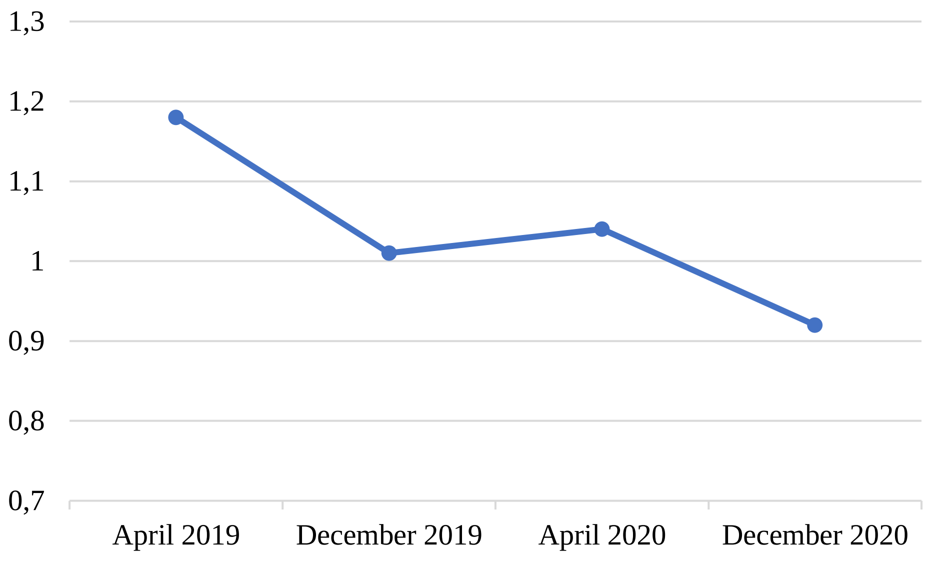
Figure 1. **Average number of years of education required in vacancies**



Source: authors ' calculations based on data from the portal "Work in Russia".

In April 2019, the average number of years of required work experience was 1.18, and by December 2020, it had fallen to 0.92 (*Figure 2*).

Figure 2. **Average number of years of minimum work experience required in vacancies**



Source: authors ' calculations based on data from the portal "Work in Russia".

Having own car and computer is required in a small number of vacancies, less than 0.3% of the total number (*Table 5).* At the same time, there are significant changes in the prevalence of these requirements before and after the pandemic: for example, requiring a car has become less frequent, and the number of vacancies requiring a computer has tripled.

Similar trends are noticeable when the sample is limited to managers, specialists, and clerks (*Table 6*). In these vacancies, professional education is much more often required: in 2019, this requirement was indicated in almost 90 % of vacancies. These differences are primarily explained by the higher prevalence of requirements for higher education, which was indicated as necessary in almost half of vacancies. However, no significant differences were found when analyzing the requirements for work experience. The frequency of work experience requirements in this subsample is approximately the same as the frequency of requirements in the entire sample. During the pandemic, there was a decrease in requirements for education, work experience, car ownership, and an increase in the number of requirements for having a computer.

A decrease in the frequency of requirements for higher education and work experience during the pandemic may mean a decrease in the requirements for formal qualifications with an increase in the requirements for the competence of employees.

However, the observed dynamics in the frequency of requirements may be distorted by the fact that the degree of impact of restrictions during the pandemic varied by region, industry, and occupation. One of the most severe restrictions were introduced in Moscow, a region with higher requirements for job applicants.

Table 6

Other requirements for the professions of managers, specialists and clerks (OKZ 1-4)

	Requirements	Frequency, %				Difference 2019-2020, pp.	
		2019		2020			
		April	December	April	December	April	December
1.	Higher education	46.63	45.55	46.70	42.70	0.07	-2.85
2.	Secondary vocational education	42.16	42.35	42.67	41.45	0.51	-0.90
3.	Work experience	44.76	42.06	40.70	41.39	-4.06	-0.67
4.	Work experience of 3 years	24.69	21.74	21.17	21.46	-3.52	-0.28
5.	Own car	0.31	0.30	0.23	0.27	-0.08	-0.03
6.	Computer	0.04	0.05	0.06	0.17	0.02	0.12

Source: authors ' calculations based on data from the portal "Work in Russia".

To take into account the heterogeneous nature of restrictions, we estimate several linear probability models in which the dependent variables were different job requirements, and the independent variables were region, type of locality, industry, type of employment, as well as dummy variables for the year and month of the vacancy (*Table 7*).

Table 7

Estimates of coefficients for dummy variables of the time period by the professions of managers, specialists, and clerks (OKZ 1-4)

Dependent variable	2020	December
Higher education	-0.010^{***} (0.001)	-0.014^{***} (0.001)
Work experience of at least 3 years	-0.004^{***} (0.001)	-0.008^{***} (0.001)
Cognitive	0.000 (0.000)	0.000 (0.000)
Social	-0.011^{***} (0.001)	-0.010^{***} (0.001)
Character	-0.009^{***} (0.001)	-0.004^{***} (0.001)
Writing	0.001^{***} (0.000)	-0.001^{***} (0.000)
Customer service	0.001^{***} (0.000)	0.000 (0.000)
Management	0.0003^{**} (0.0001)	-0.001^{***} (0.000)
Financial	0.001^{***} (0.000)	0.000 (0.000)
General computer	0.012^{***} (0.001)	0.002^{***} (0.001)
Special software	0.001^{**} (0.000)	-0.001^{***} (0.000)
Working with special equipment	0.000 (0.000)	-0.0003^{***} (0.0001)
Working with documents	0.0005^{***} (0.0001)	0.001^{***} (0.000)
Professional knowledge	-0.004^{***} (0.001)	-0.001^{**} (0.001)
Other	0.001^{***} (0.000)	0.000 (0.000)

Source: The authors' calculations based on data from the portal "Work in Russia".

Table 7 shows the coefficient estimates for the variables “2020” and “December” for a sample of managers, specialists, and clerks. The calculations showed that in 2020 there was a significant increase in the prevalence of requirements for basic computer skills, which is not noticeable in descriptive statistics.

Return to skills

Table 8 shows the results of estimating the parameters of model (2), which allows us to compare data from the online job database with the RLMS-HSE survey. Due to the non-standard approach to determining the main variables, the estimates obtained from the RLMS-HSE data differ substantially from previous studies on this survey. In particular, the estimate of the return to education is much lower, only 2.5 %. The return on work experience is significantly higher, but the maximum return from work experience occurs much earlier. Wages in agriculture are also relatively high.

At the same time, the estimates obtained using the RLMS-HSE are close to the results obtained on the basis of an online vacancies database. Differences in statistical significance are due to different numbers of observations. Using the model (2) based on online vacancies allowed us to get a very close estimate of the rate of return to education of 2.4 %. The estimate of the return to experience is somewhat different, but there is a similar pattern in higher returns from the first year of work experience and faster maximization of returns. Data on relatively higher wages in agriculture compared to traditional models are also consistent. Most of the industry differences are also quite similar in the two samples.

There are also some differences. In the database of vacancies, the difference in wages between professionals and workers is much smaller. Wage differences are less pronounced in the vacancies of employers from settlements of different sizes. Wages in the Moscow Oblast are higher than in Moscow. Wages are lower in the chemical and fuel industries, and higher in civil machine construction.

Table 8

Estimates of Mincer wage equation parameters based on the model (2)

Dependent variable: logarithm of monthly wage

Variable	Online vacancies, 2019	RLMS-HSE, 2019
Education	0.024***	0.025***
	(0.000)	(0.003)
Work experience	0.065***	0.054
	(0.001)	(0.040)
Work experience (squared)	-0.013***	-0.004
	(0.000)	(0.006)
Professional worker	0.008***	0.168***
	(0.001)	(0.017)
type of settlement (base category - village)		
Regional center	0.077***	0.178***
	(0.001)	(0.031)
City	0.077***	0.105***
	(0.001)	(0.027)
Urban-type settlement	0.041***	0.083**
	(0.002)	(0.039)
region (base category – Belgorod oblast)		
Moscow	0.511***	0.645***
	(0.002)	(0.040)
Saint Petersburg	0.203***	0.365***
	(0.003)	(0.047)
Moscow oblast	0.688***	0.312***
	(0.003)	(0.046)
industry (base category - agriculture)		
Construction, real estate operations	0.160***	0.195***
	(0.002)	(0.046)
Chemical, petrochemical, energy industry	0.090***	0.395***
	(0.005)	(0.055)
Housing and communal services	-0.095***	-0.202***
	(0.003)	(0.052)
Education, public health, science, culture,	-0.126***	-0.272***
entertainment, sports, social services	(0.002)	(0.042)
Electric power industry	0.109***	0.076
	(0.009)	(0.062)
Finances	-0.135***	-0.054
	(0.003)	(0.059)
Light and food industry	-0.137***	-0.043
	(0.002)	(0.048)
Forestry and wood industry	-0.033***	-0.083
	(0.002)	(0.128)
Information technology, transportation,	0.196***	0.047
commmunication	(0.002)	(0.045)
Jurisprudence	-0.127***	-0.099
	(0.003)	(0.104)
Marketing, advertising	-0.216***	0.262*
	(0.004)	(0.142)
Civil machine construction	0.403***	0.084
	(0.005)	(0.061)
Trade, consumer services	-0.143***	-0.097**
	(0.002)	(0.041)
Constant	9.602***	9.610***
	(0.003)	(0.073)
R-squared	0.35	0.33
Number of observations	1,852,557	4495

Notes: the authors ' calculations, all estimates are derived from model (2) with a full set of variables, the results for regions and industries are presented selectively.

*), **), ***) This parameter has statistical significance at the level of 10 %, 5 %, and 1 %, respectively.

To estimate the rate of return on skills, we used a modified Mincer wage equation, i.e. model (1). The results of the analysis are presented in *Table 9*. All results are obtained for model (1) with the full set of variables, with the exception of dummy variables for individual occupations.

Table 9

Estimates of return to skills based on the modified Mincer wage equation

Dependent variable: logarithm of monthly salary

Variable	April 2019	December 2019	April 2020	December 2020
Education	0.037*** (0.000)	0.036*** (0.000)	0.036*** (0.000)	0.027*** (0.000)
Work experience	0.024*** (0.001)	0.014*** (0.000)	0.016*** (0.001)	0.012*** (0.000)
Work experience (squared))	-0.002*** (0.000)	-0.001*** (0.000)	-0.001*** (0.000)	-0.001*** (0.000)
Cognitive	0.054*** (0.002)	0.084*** (0.002)	0.046*** (0.002)	0.066*** (0.002)
Social	-0.001 (0.001)	0.024*** (0.001)	0.018*** (0.001)	0.023*** (0.001)
Character	0.008*** (0.001)	-0.006*** (0.001)	0.012*** (0.001)	0.009*** (0.001)
Writing	-0.006 (0.007)	-0.007 (0.007)	-0.083*** (0.008)	-0.034*** (0.007)
Customer service	-0.001 (0.007)	0.005 (0.007)	-0.037*** (0.009)	-0.033*** (0.008)
Management	0.062*** (0.009)	0.051*** (0.013)	0.041*** (0.013)	-0.009*** (0.013)
Financial	-0.002 (0.008)	-0.045*** (0.009)	-0.035*** (0.008)	-0.033*** (0.008)
General computer	-0.032*** (0.002)	-0.048*** (0.002)	-0.037*** (0.002)	-0.067*** (0.002)
Special software	-0.017*** (0.004)	-0.013*** (0.004)	-0.026*** (0.004)	0.009** (0.004)
Working with special equipment	0.010 (0.011)	-0.004 (0.012)	-0.029** (0.013)	-0.152** (0.012)
Working with documents	-0.040*** (0.008)	0.049*** (0.007)	0.039*** (0.009)	-0.063*** (0.007)
Professional knowledge	0.006*** (0.002)	0.040*** (0.002)	0.083*** (0.002)	0.062*** (0.002)
Other	0.080*** (0.002)	0.125*** (0.002)	0.145*** (0.002)	0.170*** (0.002)
Occupation dummies	no	no	no	no
Other dummy variables	yes	yes	yes	yes
R-squared	0.47	0.48	0.46	0.48
Number of observations	722,919	753,887	519,623	824,352

Note: the authors ' calculations, all estimates are derived from model (1) with the full set of variables, except for dummy variables for professions.

*) The parameter has a statistical significance of 10%.

* *) The parameter has a statistical significance of 5%.

***) The parameter has a statistical significance of 1%.

The results of model (1) estimation show that before the pandemic, each additional year of education increased wages by about 3.6–3.7%. The relationship between work experience and earnings, as expected, turned out to be non-linear: having one year of work experience increased wages by 2 % compared to those who had no work experience. With the growth of the work experience the return on each subsequent year quickly decrease.

The results also show that in the Russian labor market, only a part of the skills is rewarded by higher wages. Before the pandemic, cognitive and managerial skills, professional knowledge, and other skills were valued. Interestingly, there was a negative rate of return on character skills.

As a result of the pandemic, there have been significant changes in the rate of return to human capital. The return to education and work experience decreased. The return to management, writing, and customer service skills decreased, and the return on professional knowledge increased.

Table 10 shows estimates for model (1) obtain with the usage of all variables. This analysis allows us to explain within-occupational differences in wages. The inclusion of occupation dummies leads to a significant decrease in estimates of the return to education and work experience. In 2020, their value is reduced to about zero. Thus, the wages of representatives of one occupation did not depend on education and work experience. On the other hand, employees of the same occupation may have significantly different wages depending on the required skills. Cognitive, social, managerial, and financial skills have a fairly high impact within the same occupation. At the same time, in 2020, the return on management skills significantly decreased.

Table 10

Estimates of return to skills based on the modified Mincer wage equation

Dependent variable: logarithm of monthly salary

Variable	April 2019	December 2019	April 2020	December 2020
Education	0.007^{***} (0.000)	0.005^{***} (0.000)	0.000 (0.000)	-0.007^{***} (0.000)
Work experience	0.008^{***} (0.001)	0.006^{***} (0.000)	0.005^{***} (0.001)	-0.002^{***} (0.000)
Work experience (squared))	-0.001^{***} (0.000)	-0.001^{***} (0.000)	-0.001^{***} (0.000)	-0.0002^{***} (0.0000)
Cognitive	0.020^{***} (0.002)	0.043^{***} (0.002)	0.024^{***} (0.002)	0.040^{***} (0.002)
Social	0.010^{***} (0.001)	0.036^{***} (0.001)	0.016^{***} (0.001)	0.028^{***} (0.001)
Character	0.015^{***} (0.001)	0.001 (0.001)	0.017^{***} (0.001)	0.010^{***} (0.001)
Writing	-0.062^{***} (0.006)	-0.051^{***} (0.007)	-0.083^{***} (0.008)	-0.056^{***} (0.007)
Customer service	-0.010 (0.007)	-0.006 (0.007)	-0.043^{***} (0.009)	-0.040^{***} (0.008)
Management	0.070^{***} (0.010)	0.055^{***} (0.012)	0.015 (0.013)	0.005 (0.012)
Financial	0.041^{***} (0.009)	0.026^{**} (0.010)	0.059^{**} (0.010)	0.102^{**} (0.009)
General computer	-0.012^{***} (0.002)	-0.013^{***} (0.002)	-0.016^{***} (0.002)	-0.041^{***} (0.002)
Special software	0.011^{***} (0.003)	0.002^{***} (0.004)	0.001 (0.004)	0.032^{***} (0.003)
Working with special equipment	-0.026^{**} (0.010)	-0.056^{**} (0.011)	-0.088^{**} (0.012)	-0.168^{**} (0.011)
Working with documents	0.003 (0.008)	0.029^{***} (0.008)	0.023^{**} (0.010)	-0.061^{**} (0.007)
Professional knowledge	-0.003 (0.002)	0.038^{***} (0.002)	0.060^{***} (0.002)	0.047^{***} (0.002)
Other	0.054^{***} (0.002)	0.080^{***} (0.002)	0.096^{***} (0.003)	0.078^{***} (0.002)
Occupation dummies	yes	yes	yes	yes
Other dummy variables	yes	yes	yes	yes
R-squared	0.58	0.58	0.57	0.58
Number of observations	722 919	753 887	519 623	824 352

Note: the authors ' calculations, all estimates are derived from model (1) with the full set of variables.

*) The parameter has a statistical significance of 10%.

**) The parameter has a statistical significance of 5%.

***) The parameter has a statistical significance of 1%.

Conclusion

The analysis of more than 5 million vacancies posted by employers on the portal “Work in Russia”, made it possible to identify changes in employers' requirements during the pandemic. It should be noted that the requirements for formal qualification criteria are reduced, which may mean an increase in the importance of professional competencies. These results indicate the need for job seekers to adapt to the new conditions on the labor market.

Among the main problems identified are the following:

1. During the pandemic, there was a sharp decline in the number of vacancies in certain occupations, which limited the employment opportunities for representatives of these occupations. In this regard, the increase in unemployment is due to an increase in structural unemployment, which is longer than frictional.
2. On the one hand, the growth of requirements for occupational competencies can be considered as a positive phenomenon, since it encourages employees to accumulate human capital. On the other hand, in the context of the introduction of restrictions employees with an insufficient level of qualification may have substantial difficulties in improving it. This, in turn, can negatively affect the prospects for further employment and ultimately lead to a decrease in their quality of life.

In this study, a methodology for assessing employers' requirements for human capital and its return was developed and applied. This technique has a potential for the usage in various research of human capital, including studies of economic growth, spatial inequality, income differentiation, etc.

A promising direction is further modification of the developed methodology, which will allow evaluating the effectiveness of the vocational training system based on the analysis of the competencies of graduates of educational organizations of higher and secondary vocational education. Studying and analyzing the data provided in the applicants' CVs will make it possible to assess their perspectives in the labor market, taking into account the transformation of human capital requirements.

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Table A1

Dynamics of the number of vacancies in the most popular occupations

	Occupations	Number of vacant jobs			
		April 2019	December 2019	April 2020	December 2020
1.	Car driver	62,127	77,338	45,719	75,941
2.	Specialist	26,607	28,641	22,571	36,773
3.	Auxiliary worker	38,137	23,143	26,004	34,185
4.	Room cleaner	26,453	25,217	19,225	31,291
5.	Seamstress	28,105	25,679	24,775	28,545
6.	Loader	10,657	13,675	8,715	25,496
7.	Concrete finisher	19,672	17,212	12,044	24,021
8.	Electric and gas welder	16,562	18,964	15,103	22,798
9.	Security guard	15,943	21,609	15,075	21,076
10.	Cook	20,727	18,939	11,957	20,685
11.	Food vendor	17,021	16,945	11,574	19,498
12.	Nurse	17,248	18,434,	15,767	18,475
13.	Bricklayer	17,515	16,295	11,450	18,187
14.	Courier	1,410	5,012	627	14,476
15.	Shooter	12,421	14,708	13,337	14,391
16.	Yard keeper	8,641	9,360	5,673	13,287
17.	Engineer	10,565	11,818	9,703	12,893
18.	Carpenter	11,562	9,528	7,404	12,219
19.	Vegetable grower	9,814	8,125	8,089	11,442
20.	Millwright	9,446	7,752	6,093	11,110
21.	Electrician for repair and maintenance of electrical equipment	8,429	9,999	7,180	11,026
22.	Doctor	10,652	10,914	8,790	10,415
23.	Inspector	11,544	12,422	8,883	10,261
24.	Plasterer	12,643	9,376	5,500	10,113
25.	Painter	9,693	8,227	5,552	10,025
26.	Order picker	3,009	8,178	2,333	10,013
27.	Manager	9,524	9,444	5,417	9,965
28.	Millwright of steel and reinforced concrete structures	8,227	8,324	5,490	9,692
29.	Packager	4,314	3,963	2,983	9,399
30.	Repairman	7,705	8,539	6,464	9,256
31.	Fitter	6,823	5,931	4,832	8,813
32.	Kitchen worker	5,305	5,568	2,959	8,386
33.	Plumber	4,730	5,940	3,484	7,932
34.	Pipeline millwright	11,395	7,066	6,361	7,797
35.	Conductor	7,129	7,040	5,650	7,499
36.	Accountant	6,343	5,834	5,241	7,223
37.	Paramedic	7,112	6,904	6,195	7,081
38.	Tractor driver	7,414	6,333	5,393	6,773
39.	Turner	5,695	6,218	4,812	6,587
40.	Car repair locksmith	4,975	5,747	3,750	6,419
...	Stacker	4,334	4,005	3,781	6,343
...	Tiler	7,144	4,622	2,751	5,812
...	Agricultural machinery operator	7,800	5,667	6,843	5,726
...	Kindergarten teacher	5,959	5,736	4,512	5,676
...	Yard cleaner	6,687	4,348	3,744	5,352
...	Teacher	4,979	4,694	3,933	4,601
...	General practitioner	3,993	4,613	3,887	4,507
...	Road worker	4,389	2,717	4,189	4,324
...	Waiter	6,229	5,520	2,160	3,941
	Total	**1,443,763**	**1,407,319**	**1,027,340**	**1,533,667**

Source: authors ' calculations based on data from the portal "Work in Russia".

Note: professions are sorted by the number of vacant jobs in December 2020; cells for professions that were included in the Top 40 vacancies in the specified month are grayed.

Table A2

The most common employer requirements

	Requirements	Frequency, %				Difference 2019-2020, pp.	
		2019		2020			
		April	December	April	December	April	December
1.	Responsibility	63.39	64.26	63.91	64.44	0.52	0.18
2.	Discipline	34.00	36.56	36.54	35.22	2.54	-1.34
3.	Sociability	13.48	12.08	11.96	12.09	-1.52	0.01
4.	Punctuality	12.25	12.55	12.68	11.49	0.43	-1.06
5.	Ability to work in a team	9.61	10.64	8.87	9.57	-0.74	-1.07
6.	Sense of duty	10.42	8.84	9.41	8.72	-1.01	-0.12
7.	Absence of bad habits	6.49	6.93	7.88	7.44	1.39	0.51
8.	Conscientious performance of duties	7.42	5.86	5.59	6.24	-1.83	0.38
9.	Learning ability	5.38	5.82	5.32	5.15	-0.06	-0.67
10.	Computer skills	4.43	4.96	4.76	4.83	0.33	-0.13
11.	Initiativeness	5.35	5.08	5.21	4.80	-0.14	-0.28
12.	Mindfulness	3.70	3.69	3.95	4.21	0.25	0.52
13.	Purposefulness	4.43	4.21	4.31	3.67	-0.12	-0.54
14.	Accuracy	3.39	3.20	3.40	3.39	0.01	0.19
15.	Driver's license cat. C	3.30	3.46	4.00	3.33	0.70	-0.13
16.	Certificate of no criminal record	2.85	3.37	3.94	3.26	1.09	-0.11
17.	Driver's license cat. B	2.93	4.31	2.82	2.89	-0.11	-1.42
18.	Driver's license cat. D	2.34	2.93	2.73	2.77	0.39	-0.16
19.	High skill level	2.21	2.35	2.41	2.36	0.20	0.01
20.	Medical book with a completed medical examination	2.04	2.00	2.01	2.28	-0.03	0.28
21.	Computer fluency	2.07	1.70	1.88	1.71	-0.19	0.01
22.	Hardworking	1.63	1.56	2.02	1.70	0.39	0.14
23.	High productivity	1.11	1.08	1.06	1.53	-0.05	0.45
24.	Driver's license cat. BE	1.40	1.62	1.89	1.40	0.49	-0.22
25.	Stress tolerance	1.10	1.23	1.14	1.19	0.04	-0.04
26.	English language proficiency	1.02	1.12	1.10	1.10	0.08	-0.02
27.	Chinese language proficiency	1.21	1.23	1.17	1.05	-0.04	-0.18
28.	Craft proficiency	1.31	0.69	0.74	0.82	-0.57	0.13
29.	Activeness	1.17	0.89	0.84	0.79	-0.33	-0.10
30.	1C	0.79	0.78	0.80	0.77	0.01	-0.01
31.	Orderliness	0.73	0.59	0.79	0.74	0.06	0.15
32.	Benevolence	0.81	0.82	0.68	0.71	-0.13	-0.11
33.	Decency	0.71	0.68	0.71	0.70	0	0.02
34.	Military service	0.75	0.88	0.97	0.68	0.22	-0.20
35.	Tractor driver's license	0.71	0.62	0.85	0.66	0.14	0.04
36.	Timely completion of work	0.59	0.41	0.42	0.63	-0.17	0.22
37.	Literate speech	1.07	0.59	0.44	0.58	-0.63	-0.01
38.	MS Excel	0.31	0.33	0.33	0.43	0.02	0.10
39.	Physical endurance	0.29	0.36	0.41	0.40	0.12	0.04
40.	Politeness	0.46	0.35	0.42	0.38	-0.04	0.03
...	Turkish language proficiency	0.37	0.67	1.07	0.36	0.70	-0.31
...	Knowledge of legal acts	0.32	0.36	0.37	0.33	0.05	-0.03
...	Neatness	0.31	0.54	0.29	0.18	-0.02	-0.36
...	Healthy lifestyle	1.51	0.24	0.28	0.18	-1.23	-0.06
...	Result orientation	0.87	0.20	0.24	0.18	-0.63	-0.02

Source: authors ' calculations based on data from the portal "Work in Russia".

Note: the sum of values in columns is greater than 100, because several requirements can be specified in one vacancy. Cells for requirements that were included in the Top-40 in the specified month are grayed.

Table A3

The most common requirements of employers for managers, professionals and clerks (OKZ 1-4)

	Requirements	Frequency, %				Difference 2019-2020, pp.	
		2019		2020			
		April	December	April	December	April	December
1.	Responsibility	64.99	65.13	65.21	63.92	0.22	-1.21
2.	Discipline	32.09	32.34	34.08	32.22	1.99	-0.12
3.	Sociability	20.18	19.45	18.44	18.67	-1.74	-0.78
4.	Computer skills	12.43	13.41	12.73	13.19	0.30	-0.22
5.	Punctuality	13.60	13.70	14.35	11.72	0.75	-1.98
6.	Ability to work in a team	9.41	9.63	8.67	8.58	-0.74	-1.05
7.	Initiativeness	8.14	7.73	7.72	7.05	-0.42	-0.68
8.	Sense of duty	9.07	7.45	8.02	6.65	-1.05	-0.80
9.	Learning ability	6.06	6.90	6.48	5.90	0.42	-1.00
10.	Computer fluency	5.38	4.92	5.40	5.03	0.02	0.11
11.	Conscientious performance of duties	5.47	5.67	5.15	5.03	-0.32	-0.64
12.	Certificate of no criminal record	4.34	4.37	5.42	4.93	1.08	0.56
13.	Purposefulness	6.27	5.90	5.23	4.86	-1.04	-1.04
14.	Absence of bad habits	4.36	4.44	5.00	4.60	0.64	0.16
15.	High qualification level	4.29	4.48	4.32	4.27	0.03	-0.21
16.	Mindfulness	2.77	2.95	3.00	3.10	0.23	0.15
17.	1C	2.27	2.12	2.23	2.22	-0.04	0.10
18.	Accuracy	2.37	2.25	2.18	2.16	-0.19	-0.09
19.	Medical book with a completed medical examination	2.09	2.07	2.12	2.07	0.03	0
20.	English language proficiency	2.15	2.12	1.94	2.07	-0.21	-0.05
21.	Stress tolerance	1.69	1.46	1.44	1.53	-0.25	0.07
22.	Literate speech	1.50	1.41	1.23	1.51	-0.27	0.10
23.	Chinese language proficiency	1.98	1.70	1.53	1.41	-0.45	-0.29
24.	MS Excel	0.97	0.99	0.97	1.41	0	0.42
25.	Benevolence	1.24	1.41	1.46	1.40	0.22	-0.01
26.	Craft proficiency	0.84	0.56	0.55	1.36	-0.29	0.80
27.	Activeness	1.41	1.13	1.29	1.35	-0.12	0.22
28.	Driver's license cat. B	1.04	1.15	1.18	1.24	0.14	0.09
29.	Fluency in English	0.99	0.94	0.66	0.97	-0.33	0.03
30.	High productivity	0.91	0.96	0.92	0.86	0.01	-0.10
31.	Hardworking	0.84	0.80	0.97	0.81	0.13	0.01
32.	Orderliness	0.60	0.56	0.66	0.72	0.06	0.16
33.	Decency	0.65	0.70	0.71	0.68	0.06	-0.02
34.	Knowledge of accounting programs	0.66	0.58	0.64	0.67	-0.02	0.09
35.	Timely completion of work	0.61	0.55	0.54	0.65	-0.07	0.10
36.	Military service	0.73	0.82	0.83	0.64	0.10	-0.18
37.	Knowledge of legislation acts	0.79	0.87	0.77	0.64	-0.02	-0.23
38.	MS Word	0.39	0.39	0.49	0.64	0.10	0.25
39.	Literacy	0.56	0.57	0.54	0.62	-0.02	0.05
40.	MS Office	0.66	0.69	0.67	0.56	0.01	-0.13
...	Honesty	0.44	0.46	0.51	0.44	0.07	-0.02
...	Result orientation	1.64	0.40	0.41	0.42	-1.23	0.02
...	Turkish language proficiency	0.59	0.73	0.82	0.38	0.23	-0.35
...	Clear diction	0.61	0.57	0.39	0.30	-0.22	-0.27

Source: authors ' calculations based on data from the portal "Work in Russia".

Note: the sum of values in columns is greater than 100, because several requirements can be specified in one vacancy. Cells for requirements that were included in the Top-40 in the specified month are grayed.