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# Unemployment and online job boards in Russia: A Beveridge curve perspective[1]

**Abstract**. This paper investigates the relationship between online recruitment and unemployment in Russia within the Beveridge curve (the unemployment–vacancy curve) framework. Using panel data for 81 Russian regions over the period 2006–2022, we examine how the expansion of online job boards affects regional unemployment dynamics. The empirical analysis is based on fixed-effects and instrumental-variable specifications that account for regional heterogeneity, time effects, and potential endogeneity. The results confirm the validity of the Beveridge curve in the Russian context and reveal a statistically significant negative association between online vacancy rates and unemployment. While traditional vacancies reported to public employment services remain important, the role of online platforms has strengthened notably in recent years, particularly during and after the COVID-19 period. The effect of online recruitment is heterogeneous across demographic groups: it is the strongest among younger workers (age 20–39), women, and individuals with lower levels of education. The findings highlight the growing importance of digital matching mechanisms and suggest that a balanced combination of traditional and online recruitment channels can enhance labor market efficiency and inform employment policy.

**Keywords:** *online recruitment; unemployment–vacancy curve; online job boards; Beveridge curve; Russian labour market.*

JEL Classification: J64, E24, L86.

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## 1. Introduction

Since the seminal contribution of the Diamond–Mortensen–Pissarides framework (Diamond, 1982; Mortensen, Pissarides, 1994), the discussion on job search and matching theory has become one of the central topics in labour economics. A lot of efforts were made by scholars to develop this model in different directions (e.g. (Yashiv, 2007)) and to verify it in various environments (e.g. (Elhorst, 2003)). With the origination and spread of the Internet, it deserves attention to analyse the labour market and job matching process under these new conditions.

The growing penetration and popularity of the Internet has led to an increase in the number of online job boards. Companies use such job boards to post their vacancies online and job seekers are able to share their *curriculums vitae* (CVs) and apply for unfilled vacancies. In Russia, for example, the proportion of unemployed people who

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look for a job using the Internet increased from 4% to around 18% in 2006–2018[2], while other channels for job seeking (personal networks, job agencies and offline job advertisement) showed a downward trend in the same period.

Such developments are expected to have an impact on the process of matching employers and job seekers for several reasons. On the one hand, online recruitment saves time and money for job searching and matching for both employers and employees (Autor, 2001; Freeman, 2002; Stevenson, 2009) and it encourages the dissemination of information about unfilled vacancies and about unemployed people actively looking for a job (Bagues, Labini, 2009; Mang, 2012).

On the other hand, one can argue that the Internet might have the opposite effect on the labour market and job matching. Lower costs of job searches through the Internet are associated with a higher number of alternatives and might lead to an increase in the time spent for job seeking (Freeman, 2002). P. Kuhn and M. Skuterud (Kuhn, Skuterud, 2004) provide empirical evidence of increased unemployment duration due to online job searching. In addition, coordination problems between companies might arise as a result of higher search intensity (Gautier, Moraga-González, 2018).

As the Internet continues to evolve and more employees and companies use this channel to find each other, the question about the nature of online job boards and their impact on unemployment is still a matter to be addressed. The aim of this paper is to analyse the relationship between online recruitment and unemployment from a macroeconomic perspective in the case of Russia. We use the concept of the unemployment–vacancy curve (UV curve, or Beveridge curve) which describes the relationship between unemployment rate and job vacancy rate.

This paper contributes to the investigation of how new technologies, in particular online recruitment, influence job searching and matching processes. The approach of the UV curve is to analyse unemployment and vacancy rates at the regional level. This macro perspective provides several advantages. In comparison with survey data that are usually used for such studies, the use of macro data is less biased and less exposed to measurement errors. The results of the study could be used for policymaking related to labour markets and mechanisms of job searching.

To answer the question posed in the study, we analyse data from 81 Russian regions from 2006 to 2022. Two main sources of data are: Russian Federal State Statistics Service and vacancy data from one of the largest job boards in Russia.

This paper is structured as follows. Section 2 contains an analysis of relevant literature about the foundation of the UV curve, job matching process and the role of online job boards. This section also includes a description of the Russian context. Section 3 describes the methodology and Section 4 presents data used in this study. The empirical results are provided and analysed in Section 5. Section 6 concludes and discusses possible limitations and future perspectives of the research.

[2] Authors' calculations based on "Russia Longitudinal Monitoring survey, RLMS–HSE", conducted by National Research University "Higher School of Economics" and "Demoscope" LLC together with Carolina Population Center, University of North Carolina at Chapel Hill and the branch of Institute of Sociology RAS. (Russia Longitudinal Monitoring Survey – Higher School of Economics web sites: https://rlms-hse.cpc.unc.edu, https://www.hse.ru/org/hse/rlms) of Russian Longitudinal Monitoring Survey (https://www.hse.ru/en/rlms/).

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## 2. Related literature

### 2.1. From unemployment–vacancy curve to job searching and matching theories

Half a century ago, macroeconomic theory was enriched with the appearance and development of an empirical relationship between unemployment and job vacancy rates (unemployment–vacancy, or UV curve). Following the Keynesianism framework, (Dow, Dicks-Mireaux, 1958) analysed data on job vacancy and unemployment rates to measure excess demand in the labour market as a proxy for the excess demand in the goods market. This idea was empirical rather than theoretical; however, the UV curve gained popularity since it provides a practical mechanism to guide economic policy (Börsch-Supan, 1991; Gujarati, 1972; Jackman, Pissarides, Savouri, 1990; Pissarides, 1986).

The UV curve is also known in economic theory as the Beveridge curve. W. Beveridge (Beveridge, 1944) described the relationship between unemployment and job vacancy rates and discussed some issues relating to it; however, he did not provide a graphical representation of the curve. In this paper, we consider the UV curve and Beveridge curve as the same concept and use it for analysis of the Russian labour market and the role of online job boards.

The UV curve was developed in both theoretical and empirical directions. The transformation of the UV curve in economic theory was described in detail in papers by (Rodenburg, 2011; Elsby, Michaels, Ratner, 2015). In this paper we focus on job searching and matching processes.

Towards the end of the last century scholars analysed and developed these theories describing how individuals look for a job and how they and potential employers are matched (Cahuc, 2014). One of the most widely adopted contributions in this field was made by (Diamond, 1982; McCall, 1970; Mortensen, Pissarides, 1994). Concerning these ideas, one can describe the process of matching companies and workers as a matching function (Rogerson, Shimer, Wright, 2005). This function is treated as a 'production function' of the labour market and is presented as $M = M(U,V)$, where the output $M$ is the number of matches between employers and employees and the inputs are job vacancy ($V$) and unemployment rates ($U$).

One of the crucial empirical questions is related to the functional form of the matching function (Eckstein, Berg, 2007; Fahr, Sunde, 2005; Sunde, 2007). B. Petrongolo and C. Pissarides (Petrongolo, Pissarides, 2001) provided a comprehensive discussion about theoretical foundations of the matching function and presented empirical results of its estimation. They concluded that the most precise estimation of the matching function can be obtained through the Cobb–Douglas function. Later, (Kohlbrecher, Merkl, Nordmeier, 2016) extended the understanding of what lay behind the matching function and validated a traditional model with idiosyncratic productivity shocks for new jobs. For the purposes of this paper, we analyzed several functional forms and carried formal tests to choose the one that fits the data best.

### 2.2. Job matching and online job boards

This paper aims to investigate the effect of online recruitment on unemployment. On the one hand, online job boards provide a more efficient way of job post-

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ing and searching in terms of both money and time (Autor, 2001; Freeman, 2002; Stevenson, 2009). In addition, the Internet promotes job mobility due to dissemination of information (Bagues, Labini, 2009; Mang, 2012). Thus, it is likely that job matching is increasing, and the quality of such matches is expected to be higher.

On the other hand, there is some empirical evidence that job searching through the Internet has negative consequences for the labour market. For instance, the Internet lowers the cost of searching, but might increase the time spent for job seeking because workers search through more jobs and companies review more applicants (Freeman, 2002). Wage structure is also influenced by Internet usage (Lee, Kim, 2004). Higher search intensity might cause fewer matches due to coordination problems between the companies (Gautier, Moraga-González, 2018). A study by (Kuhn, Skuterud, 2004) showed that Internet job searches are associated with longer periods of unemployment. However, this relationship was tested on more recent data and contradictory results were obtained (Kuhn, Mansour, 2014).

### **2.3.** The Russian context

To investigate whether online job boards influence the process of matching between unemployed persons and unfilled vacancies, we used a dataset from the Russian labour market at a regional level during the 17 years from 2006 to 2022. We believe that the Russian context is an interesting and fruitful environment to investigate such issues about the labour market for several reasons.

Russia is a developing country and is often characterized as having an unfavourable institutional environment, in particular in the context of the labour market and its legislation. Whilst labour legislation was significantly transformed since the 1990s, it retains a legacy of the former Soviet Union and has some of the weaknesses of that system (Kapelyushnikov, Kuznetsov, Kuznetsova, 2011; Gimpelson, Kapeliushnikov, Lukyanova, 2010). As a consequence, poor legislative provision of social guarantees leads to a low quality of work life in modern Russia (Fakhrutdinova et al., 2013). In addition, trade unions as social institutions also experience difficulties, facing distrust from employees and confrontation from the companies' management (Chetvernina, 2009).

These issues inevitably influence the performance of the Federal Employment Service, the state mechanism for job searching and matching in Russia. Fewer unemployed people now use the Federal Employment Service to find a job. In 2006 almost a third of unemployed people (35%) used this service for job searching, whilst in 2015 this value had fallen to 27%[3]. Studies show that unemployed people do not trust this institution and it plays a minor training role (Clarke, 1999; Gimpelson, Kapeliushnikov, 2013).

Russia is characterized by having a high level of information and communication technology (ICT) infrastructure development that can potentially help to overcome some imperfections of social institutions (Nelson R., Nelson K., 2002). In 2017, according to the Global ICT Development Index (Measuring the Information Society Report, 2017) Russia was in the top 50 countries in the development of information and communication technologies. The report showed that more than 70% of Russian citizens use computers and the Internet. Russia has relatively cheap Internet (McCarthy, 2019) which makes it accessible to more people.

[3] Authors' calculations are based on data from Russian Federal State Statistics Service (https://eng.gks.ru/).

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In addition, the developed ICT infrastructure in Russia is supported by high quality and quantity of human capital[4]. This in turn provides opportunities for an improvement in labour market outcomes under the influence of new technologies (Freeman, 2002). This study aims to investigate the impact of online recruitment on job matching. We suppose that with increasing ICT skills and access to the Internet (and hence to online recruitment platforms), the number of matches between employees and employers will be higher. Therefore, Russia as a country with weak social institutions and high levels of development of ICT infrastructure and human capital provides an interesting setting to analyse this phenomenon.

**3. Data**

The database for this study was compiled from two sources. The first source is the Russian Federal State Statistics Service[5], also known as Rosstat, which is the governmental statistics agency of Russia. This source provided data on unemployment (both overall and for different population groups), demographic structure, and economic development at the regional level. One of the key indicators in this study is the number of vacancies, which represents the demand (declared need) for workers as reported by organizations to employment service authorities. Its ratio to the labor force serves as a proxy for the *vacancy rate*, making it comparable to similar metrics in the academic literature. However, it is important to note that this variable does not necessarily reflect the full and actual level of labor demand.

To address the research question, we also compiled a unique dataset of online vacancies posted by companies on Russia's leading job search and recruitment platform. We analyzed various job features and descriptions for all vacancies published between 2006 and 2022. The dataset includes the following details: position name and vacancy description, employer name, date of publication, workplace address, salary range and currency, required experience and skills, work schedule, and professional area. Duplicate vacancies were removed based on the following rule: if the same company posted two or more identical vacancies with the same job title and workplace address on the same day, these vacancies were considered duplicates, and only the most recently published vacancy was retained in the sample. According to this rule, 0.7% of duplicate vacancies were removed. After deduplication, the final dataset comprised 19 373 724 online vacancies in the Russian labor market over 17 years.

The ratio of the total number of online vacancies to the regional labor force numbers is referred to as the *online vacancy rate*. This variable partially overlaps with the general *vacancy rate*. In other words, organizations may report vacant job to official services while simultaneously posting advertisements on online platforms. However, we will not adjust the variables to account for potential duplication assuming a cumulative effect from various recruitment channels. Additionally, there is no available information on vacancies duplication, either in Rosstat data or on the online platform. The correlation between announced vacancies and online vacancies is quite weak ($R^2 = 8.7\%$).

The collected database has a panel structure and includes data from 81 regions between 2006 and 2022. Almost all regions are covered, except for the capital cities (Moscow and St. Petersburg) and regions with a relatively short historical record (the Republic of Crimea and Sevastopol). The Arkhangelsk and Tyumen regions are treated

[4] World development report 2019: The changing nature of work. Retrieved November 22, 2024, (https://www.worldbank.org/en/publication/wdr2019).

[5] https://eng.gks.ru/

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as separate federal subjects from their respective autonomous okrugs, meaning their statistical and administrative data do not include those autonomous areas.

Table 1 presents the descriptive statistics of the database. Some variables with high skewness were transformed using logarithms and winsorizing[6] (at 0.5% and 99.5% of distribution) to reduce heteroscedasticity and minimize the impact of outliers. The analysis reveals a high variance in unemployment, reflecting strong regional and intertemporal heterogeneity driven by demographics, business activity, and economic structure. Significant differences in unemployment rates are observed across various labor force groups. The rate declines with age, likely due to the accumulation of professional skills and experience, as well as psychological factors such as a preference for stable employment and reduced ambition in job selection. Similarly, unemployment rates decrease with higher education levels, as advanced education generally correlates with better skills and competencies. Table 2 presents the dynamics of both vacancy rates over time. It shows the aggregated numbers for all regions in the sample for each year.

**Table 1.**

Descriptive statistics

| Variable | Description | Number of observations | Minimum | Mean | Maximum | Standard deviation |
|---|---|---|---|---|---|---|
| *Online rate* | Number of online vacancies per labour force, % | 1377 | 0.00 | 1.37 | 7.86 | 1.96 |
| *Vacancy rate* | Number of vacancies (need for workers declared by firms to the employment service authorities) per regional labour force, % | 1377 | 0.00 | 1.76 | 10.01 | 1.33 |
| Log(*Online rate*) | Logarithm of online rate | 1377 | −7.00 | −1.09 | 2.06 | 2.09 |
| Log(*Vacancy rate*) | Logarithm of vacancy rate | 1377 | −3.34 | 0.30 | 2.30 | 0.82 |
| **Unemployment and related variables** | | | | | | |
| *UR* | Unemployment rate, % | 1377 | 1.60 | 7.31 | 67.70 | 5.55 |
| *UR men* | Male unemployment rate, % | 1377 | 0.60 | 7.69 | 69.30 | 5.26 |
| *UR women* | Female unemployment rate, % | 1377 | 1.70 | 6.96 | 69.80 | 6.11 |
| *UR urban* | Urban unemployment rate, % | 729 | 1.53 | 5.66 | 26.95 | 3.30 |
| *UR rural* | Rural unemployment rate, % | 729 | 1.40 | 7.89 | 35.93 | 4.50 |
| *Job search time* | Average job search time, months | 1366 | 2.80 | 7.61 | 13.50 | 1.47 |
| *U long* | Long–term unemployment, the share of unemployed seeking work for more than 12 months, % | 1366 | 0.50 | 30.60 | 82.90 | 11.82 |
| **Regional variables** | | | | | | |
| Log(*Labor force*) | Number of labor force aged 15–72 years (according to sample surveys), thousand (logarithm) | 1377 | 3.06 | 6.35 | 8.42 | 0.92 |
| *Rural* | Rural population share, % | 1377 | 3.50 | 30.78 | 73.30 | 12.20 |
| *Women* | Female share in population, % | 1377 | 48.77 | 53.42 | 55.54 | 1.18 |

[6] Winsorizing – statistical measure replacing extremes with nearest values; method of averaging that initially replaces the smallest and largest values with the observations closest to them.

**Continuation of Table 1.**

| Variable | Description | Number of observations | Minimum | Mean | Maximum | Standard deviation |
|---|---|---|---|---|---|---|
| Log*(GRP)* | Gross regional product per capita, thousand rubles in nominal prices (logarithm) | 1377 | 3.09 | 5.69 | 9.37 | 0.85 |
| *Internet* | Use of broadband internet access in organizations, share of surveyed organizations,% | 1377 | 4.40 | 64.74 | 97.70 | 22.25 |
| **Labor force, by age, %** | | | | | | |
| *Age* 15–19 | 15–19 years | 1377 | 0.00 | 1.30 | 8.88 | 1.04 |
| *Age* 20–29 | 20–29 years | 1377 | 12.08 | 22.03 | 34.36 | 3.63 |
| *Age* 30–39 | 30–39 years | 1377 | 20.94 | 26.51 | 35.33 | 2.58 |
| *Age* 40–49 | 40–49 years | 1377 | 17.24 | 24.97 | 32.88 | 2.05 |
| *Age* 50–59 | 50–59 years | 1377 | 8.03 | 20.39 | 25.24 | 2.47 |
| *Age* 60–72 | 60–72 years | 1377 | 0.41 | 4.80 | 12.22 | 1.86 |
| **Unemployment rate, by age, %** | | | | | | |
| *UR* 15–19 | 15–19 years | 890 | 0.00 | 28.04 | 94.00 | 12.39 |
| *UR* 20–29 | 20–29 years | 891 | 2.90 | 10.08 | 78.30 | 6.72 |
| *UR* 30–39 | 30–39 years | 891 | 0.90 | 5.78 | 41.50 | 4.06 |
| *UR* 40–49 | 40–49 years | 891 | 0.40 | 5.00 | 25.90 | 2.98 |
| *UR* 50–59 | 50–59 years | 890 | 0.00 | 5.00 | 22.80 | 2.57 |
| *UR* 60–72 | 60–72 years | 867 | 0.00 | 3.72 | 46.30 | 3.07 |
| **Labor force, by education, %** | | | | | | |
| *Educ*5 | Higher education | 1377 | 11.59 | 28.03 | 50.13 | 5.39 |
| *Educ*4 | Secondary vocational education | 1377 | 6.12 | 45.36 | 66.48 | 7.20 |
| *Educ*3 | Secondary general education | 1377 | 6.39 | 21.04 | 68.05 | 6.81 |
| *Educ*2 | Basic general education | 1377 | 0.10 | 5.13 | 17.70 | 2.32 |
| *Educ*1 | Without education | 1377 | 0.00 | 0.44 | 5.75 | 0.42 |
| **Unemployment by education, %** | | | | | | |
| *UR educ*5 | Higher education | 1377 | 0.27 | 4.35 | 58.93 | 4.15 |
| *UR educ*4 | Secondary vocational education | 1377 | 0.85 | 6.55 | 60.42 | 4.81 |
| *UR educ*3 | Secondary general education | 1377 | 2.54 | 10.38 | 77.82 | 7.29 |
| *UR educ*2 | Basic general education | 1377 | 0.00 | 14.52 | 79.58 | 7.24 |
| *UR educ*1 | Without education | 1343 | 0.00 | 20.08 | 100.00 | 20.43 |
| **Sector share* in GRP, %** | | | | | | |
| *Sector* 1 | Mining and quarrying | 1377 | 0.00 | 10.24 | 1.70 | 86.00 |
| *Sector* 2 | Manufacturing | 1377 | 0.10 | 17.33 | 17.20 | 55.60 |
| *Sector* 3 | Electricity, gas, steam, water and air conditioning supply; sewerage, waste management and remediation | 1377 | 0.70 | 4.36 | 3.80 | 18.70 |
| *Sector* 4 | Construction | 1377 | 1.60 | 7.28 | 6.40 | 31.50 |

**End of Table 1.**

| Variable | Description | Number of observations | Minimum | Mean | Maximum | Standard deviation |
|---|---|---|---|---|---|---|
| *Sector* 5 | Wholesale and retail trade | 1377 | 0.40 | 12.71 | 12.60 | 57.50 |
| *Sector* 6 | Transporting and storage | 1377 | 1.60 | 9.08 | 8.00 | 29.60 |
| *Sector* 7 | Public administration and defense; compulsory social security | 1377 | 1.10 | 8.05 | 6.90 | 39.20 |
| *Sector* 8 | Financial, insurance and real estate activities | 1377 | 0.70 | 8.44 | 8.20 | 24.70 |
| *Sector* 9 | Other services | 1377 | 2.30 | 13.80 | 13.10 | 34.30 |

**Note.** *The sector "Agriculture, forestry and fishing" is the basic category.

**Table 2.**

Number of regular and online vacancies by years

| Year | Number of vacancies (declared need) | Number of online vacancies | Vacancy rate, % | Online rate, % |
|---|---|---|---|---|
| 2006 | 703 454 | 141 493 | 0.817 | 0.053 |
| 2007 | 862 342 | 186 094 | 0.971 | 0.081 |
| 2008 | 660 667 | 371 593 | 0.804 | 0.193 |
| 2009 | 521 595 | 152 308 | 0.680 | 0.089 |
| 2010 | 772 802 | 297 898 | 0.931 | 0.167 |
| 2011 | 964 310 | 648 189 | 1.172 | 0.388 |
| 2012 | 1 098 416 | 572 953 | 1.404 | 0.377 |
| 2013 | 1 157 478 | 721 570 | 1.508 | 0.524 |
| 2014 | 1 174 257 | 469 639 | 1.584 | 0.394 |
| 2015 | 935 223 | 496 593 | 1.288 | 0.464 |
| 2016 | 1 004 882 | 637 791 | 1.393 | 0.567 |
| 2017 | 1 174 972 | 925 293 | 1.612 | 0.792 |
| 2018 | 1 271 177 | 3 161 061 | 1.742 | 3.371 |
| 2019 | 1 281 054 | 3 104 945 | 1.802 | 3.336 |
| 2020 | 1 537 256 | 3 756 352 | 2.191 | 4.060 |
| 2021 | 1 725 303 | 980 439 | 2.331 | 1.031 |
| 2022 | 1 452 878 | 2 749 513 | 1.987 | 2.989 |

Overall, there is a noticeable trend of increasing employers' demand for the labor force in both indicators. This trend can be attributed to both economic development and the more active behavior of companies in actively seeking workers. At the same time, online vacancies are growing significantly faster and are more volatile. In particular, there was a significant decline in 2021, which may be due to the lagging impact of COVID-19. The pandemic affected firms by restructuring their business processes and increasing digital literacy. This may have led to more conscious and effective behavior when searching for employees online.

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Figure 1 illustrates the empirical unemployment–vacancy (UV) curve for Russian regions. To the best of the authors' knowledge, this is the first attempt to depict the Russian UV curve. It appears to follow the expected functional form and is similar to the results from Britain (Pissarides, 1986), the United States (Blanchard, Diamond, 1989) and OECD countries (Nickell et al., 2003).

Figure 2 shows a similar relationship between online vacancies and unemployment rates. To our knowledge, this is the first attempt in the literature to construct a curve specifically for online vacancies. Notably, it closely resembles the common UV curve. Therefore, general considerations regarding the matching function in the labor

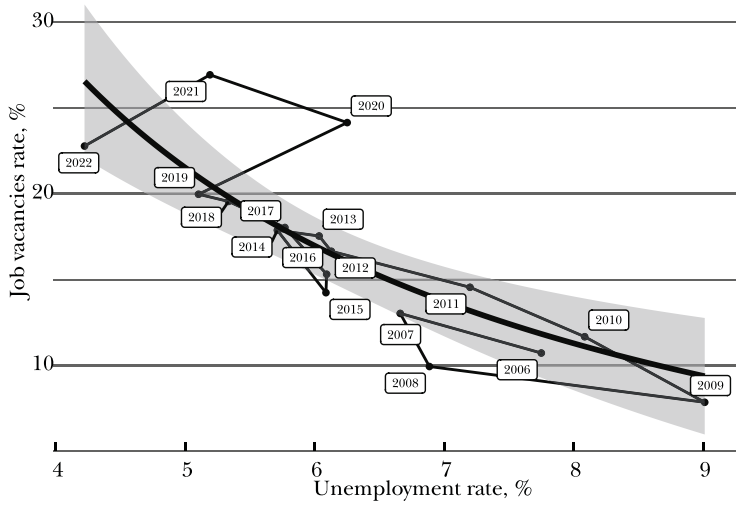


**Figure 1.**
*Empirical UV curve for Russian regions from 2006 to 2022*

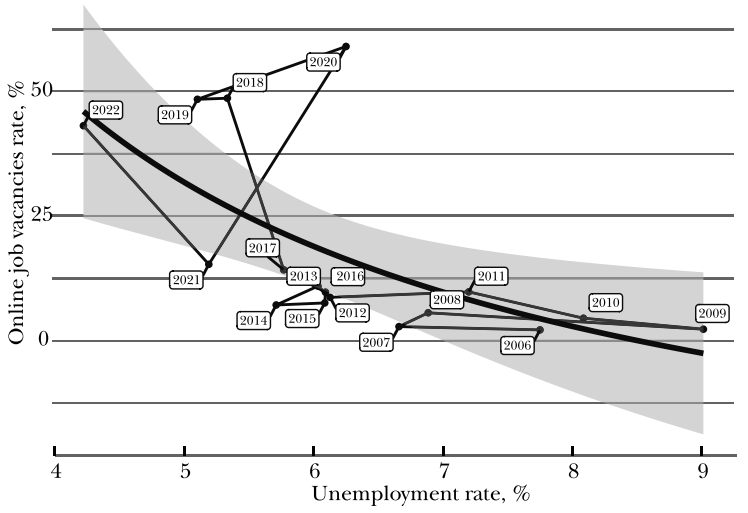


**Figure 2.**
*Unemployment and online vacancies rates for Russian regions from 2006 to 2022*

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market may also apply to more specific recruiting channels. These figures further suggest that the UV curves for Russia are likely nonlinear (Figures 1 and 2).

**4. Methodology**

We use regression analysis to estimate the UV curve empirically and analyze the impact of online recruitment on unemployment. Following the discussion in the review of (Petrongolo, Pissarides, 2001), we are concerned about the possible nonlinearity in the relationship between variables in the matching function. Therefore, a number of alternative specifications were estimated: using logarithmic and linear forms of key variables (unemployment, vacancy, and online vacancy), as well as quadratic terms for the factors. These models were compared both for quality (adjusted $R^2$) and based on Projection matrix Extended test (PE-test) for functional form (MacKinnon, White, Davidson, 1983). Experiments have shown an advantage of the semi-logarithmic functional form. Hence, the basic regression equation is as follows:

$$u_{it} = \beta_0 + \beta_1 \log\left(vacancy\,rate_{it-1}\right) + \beta_2 \log\left(online\,rate_{it-1}\right) + \\ + \beta_3 CV_{it-1} + \beta_4 region_i + \beta_5 year_t + \varepsilon_{it}, \quad (1)$$

where $u_{it}$ is the unemployment rate in region $i$ in year $t$; *vacancy rate* is the number of vacancies (declared need for workers) divided by labour force number (the latter includes employed and unemployed people); *online rate* is the number of online vacancies divided by labour force, *CV* is the vector of control variables; $\rho_i$ is an individual regional effect; $year_t$ is a time effect; $\varepsilon_{it}$ is a stochastic error. The vector of control variables includes log of labour force (proxy for effect of size), log of GRP[7] per capita (economic development), shares of sectors in GRP (proxies for economic structure), access to broadband internet (usage in organizations) and demographic structure (shares of women and rural population).

The basic regression is a two-way fixed effect model: it enables us to account for strong heterogeneity between regions and across time and it also reduces endogeneity related to omitted variable bias. Additionally, to reduce endogeneity (simultaneity bias) all the factors are taken with a one-year lag.

Based on the literature review, we expect $\beta_1$ to be statistically significant and negative. This would mean that our results are in line with established theory. The same results are expected for the effect of the online vacancy rate ($\beta_2$).

In the first stage of the analysis, we estimate the basic model (equation 1), as well as some alternative models that differ in their approaches to accounting for endogeneity. We consider simple OLS, two-step instrumental variable estimation without (IV) and with individual effects (IV FE), and a dynamic model with a lagged dependent variable and fixed effects, which is estimated by the system generalized method of moments (FE–GMM). The latter model allows us to directly account for the "path dependence effect", which is important since the level of regional unemployment is very stable over time ($R^2$ between unemployment rate and its lagged value is 92.2%). In the last three models based on IV estimation, factors are taken without a lag, and their lags are used as instruments[8].

We further deepen our analysis by examining unemployment from various perspectives, namely: intertemporal analysis of unemployment factors; analysis of unemploy-

[7] Nominal values; since we apply logarithms, factor of price index is captured by year dummies.

[8] For more possible tests (such as overidentifying restrictions tests) we also included long-term unemployment (U long) as one additional instrument.

ment duration (job search time and long-term unemployment); analysis by major demographic groups, including gender (men and women) and settlement type (urban and rural populations); analysis of major workforce groups by age; analysis by educational level.

### 5. Empirical results

The results of the econometric analysis are presented in tables below. Table 3 contains the results of estimating the baseline model (column 1) and alternative models for the full sample.

Despite differences between the models, almost all of them show a strong and significant impact of both vacancy rates on reducing unemployment. However, the effect of online vacancies appears somewhat weaker than that of traditionally

**Table 3.**

Basic results

| Variable | FE | OLS | IV (2SLS) | FE–IV | FE–GMM**** |
|---|---|---|---|---|---|
| | 1 | 2 | 3 | 4 | 5 |
| Log(*Online rate*) | −0.402*<br>(0.205) | −0.607***<br>(0.142) | −0.814***<br>(0.175) | −0.614**<br>(0.300) | −0.225<br>(0.183) |
| Log(*Vacancy rate*) | −0.735*<br>(0.415) | −1.559***<br>(0.233) | −1.705***<br>(0.230) | −0.962<br>(0.774) | −1.067***<br>(0.331) |
| Log(*Labor force*) | −12.001***<br>(3.811) | 0.983***<br>(0.208) | 1.301***<br>(0.319) | −13.226***<br>(4.957) | 0.479+<br>(0.327) |
| Log(*GRP*) | −2.826+<br>(1.869) | −0.623<br>(0.506) | −0.129<br>(0.660) | −1.835<br>(2.622) | 0.298<br>(0.457) |
| Internet | −0.035**<br>(0.016) | −0.006<br>(0.009) | −0.016<br>(0.013) | −0.047**<br>(0.022) | −0.013<br>(0.012) |
| Rural | 0.246**<br>(0.122) | 0.076***<br>(0.013) | 0.085***<br>(0.016) | 0.241+<br>(0.155) | 0.033*<br>(0.019) |
| Women | 0.789<br>(0.719) | 0.804***<br>(0.250) | 0.969***<br>(0.297) | 0.805<br>(0.964) | 0.405**<br>(0.192) |
| UR lagged | | | | | 0.577***<br>(0.112) |
| GRP structure variables | Yes | Yes | Yes | Yes | Yes |
| Regional fixed effects | Yes | No | Yes | Yes | Yes |
| Year fixed effects | Yes | Yes | Yes | Yes | Yes |
| N | 1296 | 1296 | 1285 | 1285 | 1285 |
| $R^2$ | 0.545 | 0.764 | 0.755 | | |
| $R^2$ within | 0.545 | | | 0.431 | |
| $R^2$ between | 0.253 | | | 0.267 | |
| $R^2$ overall | 0.240 | | | 0.249 | |
| Log likelihood | −2403.796 | −3038.711 | −3041.516 | | |

**Notes.** Robust standard errors are in parentheses. Symbols "+", "*", "**" and "***" denote a significance at the 15, 10, 5 and 1% level. FE stands for Fixed Effects model, OLS for Ordinary Least Squares model, IV (2SLS) for Instrumental Variables (Two-Stage Least Squares) model, FE–IV for Fixed Effects Instrumental Variables model, and FE–GMM for Fixed Effects Generalized Method of Moments model. **** The results were tested for endogeneity and autocorrelation. The robust Hansen test of overidentifying restrictions gives the values of the chi-square statistics 7.54 (p-value = 0.056). The Arellano–Bond autocorrelation test of order 1 and 2 gives the corresponding values of the test z-statistics of –6.35 (p-value = 0.000) and 0.68 (p-value = 0.499).

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announced vacancies, which can be explained by the use of data from only one online platform and the fact that the development of digital technologies has increased the importance of online social interactions only in recent years. Other key generalized findings include the insignificance of economic development, the rather positive role of Internet penetration in reducing unemployment, and greater difficulties in job searching for women and the rural population. The most controversial effect is observed in relation to the labor force, which, as we suggest, negatively influences the unemployment rate in line with the basic model (column 1). A higher concentration of people, despite internal competition, fosters the accumulation of human capital (the size effect), stimulates economic activity, and boosts regional employment, while also enhancing the diversity of professional skills and competencies, thereby increasing the likelihood of successful matches between labor supply and demand.

The differences in the results of the alternative models (columns 2–5) stem from their assumptions regarding endogeneity. The OLS and IV estimates (columns 2–3) generally produce biased coefficients, as they fail to account for omitted variable bias, which is controlled for by regional fixed effects. The Wald test confirmed the significance of these fixed effects in models presented in columns 1 and 4. Notably, model in column 4 produces coefficients very close to those of the baseline model (column 1), despite being noticeably less accurate. This suggests that to address simultaneity bias, simply using lagged factors is sufficient, eliminating the need for a specialized instrumental approach. The dynamic model presented in column 5 includes a significant lag of the dependent variable, reflecting strong true state dependence. While this model better accounts for endogeneity, it still produces results statistically similar to the basic model (column 1) for most variables. Moreover, it is less convenient for interpretation and economic policy, as it primarily highlights the persistence of unemployment over time rather than demonstrating how this indicator can be changed in the long run. Consequently, further analysis is based entirely on the simple FE model in column 1 as the baseline.

The next stage of the study involves an intertemporal analysis of the basic model (column 1, Table 3). To achieve this, the observed period was divided into five time intervals: 2007–2010 (reflecting the impact of the 2008 financial crisis), 2011–2013, 2014–2016 (economic sanctions), 2017–2019, and 2020–2022 (COVID-19 and new sanctions). The modeling results are presented in Table 4.

**Table 4.**

Unemployment model in dynamics

| Variable | 2007–2010 | 2011–2013 | 2014–2016 | 2017–2019 | 2020–2022 |
|---|---|---|---|---|---|
| | 1 | 2 | 3 | 4 | 5 |
| Log(*Online rate*) | 0.027<br>(0.324) | −0.074<br>(0.304) | 0.293<br>(0.362) | −0.159<br>(0.158) | −1.476*<br>(0.779) |
| Log(*Vacancy rate*) | −0.602*<br>(0.306) | −0.916**<br>(0.458) | −0.501**<br>(0.201) | 0.286<br>(0.286) | 0.283<br>(0.249) |
| Log(*Labor force*) | 1.312<br>(4.070) | −6.538<br>(5.869) | −0.536<br>(3.869) | 3.516<br>(2.623) | −11.980***<br>(4.136) |
| Log(*GRP*) | −3.750<br>(3.212) | −1.740<br>(1.431) | −1.771<br>(2.373) | 0.751<br>(2.786) | 0.765<br>(1.120) |
| Internet | 0.050<br>(0.045) | 0.010<br>(0.030) | −0.019+<br>(0.013) | 0.028*<br>(0.016) | −0.030**<br>(0.014) |

**End of Table 4.**

| Variable | 2007–2010 | 2011–2013 | 2014–2016 | 2017–2019 | 2020–2022 |
|---|---|---|---|---|---|
| | 1 | 2 | 3 | 4 | 5 |
| Rural | −0.271 (0.377) | 0.125 (0.133) | −0.186 (0.222) | 0.019 (0.144) | −0.137 (0.282) |
| Women | −0.817 (1.682) | 1.016 (0.872) | −0.138 (0.665) | −0.898 (0.665) | −0.637 (0.975) |
| GRP structure variables | Yes | Yes | Yes | Yes | Yes |
| Regional fixed effects | Yes | Yes | Yes | Yes | Yes |
| Year fixed effects | Yes | Yes | Yes | Yes | Yes |
| N | 324 | 243 | 243 | 243 | 243 |
| R2 within | 0.341 | 0.516 | 0.371 | 0.476 | 0.747 |
| R2 between | 0.024 | 0.226 | 0.011 | 0.010 | 0.057 |
| R2 overall | 0.011 | 0.229 | 0.008 | 0.012 | 0.061 |
| Log likelihood | −557.058 | −220.676 | −135.077 | −92.205 | −200.799 |

**Notes.** Robust standard errors are in parentheses. Symbols "+", "*", "**" and "***" denote a significance at the 15, 10, 5 and 1% level.

**Table 5.**

Specific models of unemployment

| Variable | *Job search time* | *U long* | *UR urban* | *UR rural* | *UR men* | *UR women* |
|---|---|---|---|---|---|---|
| | 1 | 2 | 3 | 4 | 5 | 6 |
| Log(*Online rate*) | −0.095 (0.069) | −0.872+ (0.527) | 0.029 (0.203) | −0.080 (0.303) | −0.298+ (0.198) | −0.540** (0.239) |
| Log(*Vacancy rate*) | −0.120 (0.132) | −0.590 (1.036) | −0.283+ (0.181) | 0.241 (0.334) | −0.843** (0.398) | −0.720* (0.410) |
| Log(*Labor force*) | −3.136*** (1.086) | −25.061*** (9.013) | −1.676 (2.298) | −1.522 (3.324) | −10.885*** (3.641) | −14.605*** (4.388) |
| Log(*GRP*) | 0.406 (0.500) | 0.252 (3.529) | −0.036 (0.932) | −2.968+ (1.875) | −3.568* (1.878) | −1.983 (1.897) |
| Internet | −0.006 (0.007) | −0.053 (0.057) | −0.019 (0.017) | −0.048** (0.021) | −0.039** (0.016) | −0.036* (0.019) |
| Rural | 0.017 (0.042) | −0.188 (0.301) | 0.158* (0.084) | 0.044 (0.140) | 0.153 (0.128) | 0.387*** (0.146) |
| Women | 0.024 (0.206) | 0.242 (1.260) | −0.672* (0.366) | −1.179** (0.574) | 0.486 (0.663) | 1.526* (0.888) |
| *GRP structure variables* | Yes | Yes | Yes | Yes | Yes | Yes |
| *Regional fixed effects* | Yes | Yes | Yes | Yes | Yes | Yes |
| Year fixed effects | Yes | Yes | Yes | Yes | Yes | Yes |
| N | 1296 | 1296 | 729 | 729 | 1296 | 1296 |
| $R^2$ within | 0.339 | 0.412 | 0.378 | 0.343 | 0.540 | 0.525 |
| $R^2$ between | 0.134 | 0.101 | 0.300 | 0.454 | 0.317 | 0.184 |
| $R^2$ overall | 0.108 | 0.098 | 0.301 | 0.440 | 0.291 | 0.175 |
| Log likelihood | −1588.058 | −4230.564 | −897.408 | −1210.769 | −2477.337 | −2547.147 |

**Notes.** Robust standard errors are in parentheses. Symbols "+", "*", "**" and "***" denote a significance at the 15, 10, 5 and 1% level.

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The models for different periods were estimated using relatively small samples, resulting in generally weaker effects compared to the basic model and lower overall accuracy. However, the intertemporal analysis revealed shifts in the role of unemployment factors over time. Vacancies registered with employment services had a strong effect from 2007 to 2016 but later lost their significance. Conversely, online vacancies remained insignificant for an extended period but began to play a significant role in reducing unemployment during 2020–2022, coinciding with the expansion of Internet access. This shift can be attributed to the impact of the COVID-19 pandemic, which underscored the importance of digital technologies and online interactions in the economy. As a result, recent years have seen a decline in the role of traditional recruitment channels and a growing reliance on online recruitment.

Table 5 summarizes the results of specific models, including average job search time, long-term unemployment, and analyses through key demographic groups, categorized by type of settlement and gender.

The estimation results for the average time for job search and long-term unemployment models (columns 1 and 2 respectively) indicate no significant effects of different types of recruiting services. This can be attributed to the fact that prolonged job searches are driven not primarily by information asymmetry in the labor market but by deeper underlying factors. These include specific employer requirements in the region, insufficient worker competences and qualifications, the necessary time for training and preparation, and psychological aspects influencing job-seeking behavior.

The models for the urban (column 3) and rural (column 4) populations do not show significant effects from declared vacancies or online vacancies. This result is somewhat unexpected and warrants further investigation. However, it is important to highlight the significant positive impact of Internet development on the employment of the rural population. This finding is quite natural, given the strong local constraints faced by this group in job selection and their higher level of information deficit.

The models for men (column 5) and women (column 6) are generally straightforward to interpret and align with the basic model (column 1, Table 3). Declared vacancies, online vacancies, and Internet penetration all have a negative effect on unemployment for both groups. The coefficients in both models are statistically similar, though some minor differences exist. Notably, regional economic growth positively impacts men's employment, while women face greater challenges in securing jobs, particularly in rural areas, and are more sensitive to the availability of online vacancies.

The models for the main age groups of the workforce are presented in Table 6. In general, the unemployment rate shows significant volatility across various groups and weak dependence on different drivers compared to the base model. It is worth noting the generally low values of all effects, as well as the relatively low accuracy of the models (with $R^2$ within). At the same time, there are some noticeable differences between groups. The results indicate that online recruitment has the greatest effect on the 20–29 and 30–39 age groups, which supports the idea that younger people are more engaged in social interaction through online channels, including for employment purposes. The spread of the Internet has a particularly strong effect on individuals aged 30–59, a significant portion of the workforce. This makes sense, as the Internet offers extensive opportunities for interaction between companies, workers, and educational institutions. The lack of significance of this factor for the 20–29 age group could be

**Table 6.**

Models by age groups

| Variable | *UR* 15–19 | *UR* 20–29 | *UR* 30–39 | *UR* 40–49 | *UR* 50–59 | *UR* 60–69 |
|---|---|---|---|---|---|---|
| | 1 | 2 | 3 | 4 | 5 | 6 |
| Log(*Online rate*) | 1.213 (1.378) | −1.020** (0.434) | −0.536* (0.304) | 0.050 (0.240) | 0.027 (0.243) | −0.422 (0.395) |
| Log(*Vacancy rate*) | 0.022 (1.457) | −0.051 (0.376) | −0.249 (0.254) | −0.173 (0.231) | −0.094 (0.230) | 0.021 (0.345) |
| Log(*Labor force*) | 4.945 (11.233) | −5.449 (4.959) | −6.394+ (3.882) | −4.771* (2.500) | −3.192+ (2.086) | −7.142+ (4.388) |
| Log(*GRP*) | −12.295+ (7.456) | −3.422 (2.566) | −2.896+ (1.987) | −2.219* (1.255) | −4.012*** (1.441) | −3.941* (2.152) |
| Internet | −0.066 (0.096) | −0.033 (0.030) | −0.040* (0.021) | −0.039** (0.017) | −0.040* (0.022) | −0.006 (0.020) |
| Rural | 1.212* (0.643) | 0.702*** (0.186) | 0.312*** (0.104) | 0.224*** (0.066) | 0.338*** (0.128) | 0.610* (0.338) |
| Women | 1.935 (2.370) | 1.471* (0.765) | −0.438 (0.499) | −0.132 (0.292) | −0.695 (0.514) | 2.050 (1.480) |
| *Age* 15–19 | −0.450 (0.877) | | | | | |
| *Age* 20–29 | | −0.051 (0.149) | | | | |
| *Age* 30–39 | | | −0.100 (0.178) | | | |
| *Age* 40–49 | | | | −0.223*** (0.069) | | |
| *Age* 50–59 | | | | | −0.029 (0.144) | |
| *Age* 60–72 | | | | | | 0.589*** (0.210) |
| GRP structure variables | Yes | Yes | Yes | Yes | Yes | Yes |
| Regional fixed effects | Yes | Yes | Yes | Yes | Yes | Yes |
| Year fixed effects | Yes | Yes | Yes | Yes | Yes | Yes |
| N | 890 | 891 | 891 | 891 | 890 | 867 |
| $R^2$ within | 0.120 | 0.276 | 0.265 | 0.260 | 0.203 | 0.166 |
| $R^2$ between | 0.007 | 0.310 | 0.370 | 0.480 | 0.413 | 0.034 |
| $R^2$ overall | 0.000 | 0.291 | 0.336 | 0.418 | 0.308 | 0.023 |
| Log likelihood | −3200.939 | −1823.444 | −1491.385 | −1334.364 | −1492.936 | −1927.064 |

**Notes.** Robust standard errors are in parentheses. Symbols "+", "*", "**" and "***" denote a significance at the 15, 10, 5 and 1% level.

explained by their inherently high level of digital competences. Additionally, the weak effects of vacancy levels (both declared and online) for the youngest (15–19) and oldest (60–72) age groups, along with the low accuracy of the related models, are expected, as these groups generally exhibit low labor market participation and make up a small share of the workforce.

Table 7 reports the estimation results of the models by education groups. In general, these models differ significantly. Online vacancies have a negative effect on groups with lower levels of education (columns 3–4). This can be explained by the high information asymmetry in the market segments for semi- and low-skilled labor,

**Table 7.**

Models by education groups

| Variable | *UR educ*5 | *UR educ*4 | *UR educ*3 | *UR educ*2 | *UR educ*1 |
|---|---|---|---|---|---|
| | 1 | 2 | 3 | 4 | 5 |
| Log(*Online rate*) | −0.137<br>(0.148) | −0.158<br>(0.177) | −0.747***<br>(0.276) | −0.717*<br>(0.421) | −0.704<br>(1.552) |
| Log(*Vacancy rate*) | −0.720***<br>(0.231) | −0.233<br>(0.270) | −1.038*<br>(0.588) | −0.294<br>(0.999) | −2.728+<br>(1.645) |
| Log(*Labor force*) | −11.876**<br>(4.823) | −12.832***<br>(4.703) | −7.197<br>(7.017) | −13.273*<br>(7.290) | −6.142<br>(16.132) |
| Log(*GRP*) | −2.952*<br>(1.484) | −2.860*<br>(1.596) | −3.384+<br>(2.203) | −1.601<br>(3.921) | −1.813<br>(8.075) |
| Internet | −0.020<br>(0.016) | −0.027<br>(0.021) | −0.055** (0.021) | −0.053<br>(0.048) | −0.013<br>(0.124) |
| Rural | 0.157**<br>(0.060) | 0.273**<br>(0.128) | 0.019<br>(0.158) | 0.353<br>(0.271) | 1.317**<br>(0.660) |
| Women | 0.491+<br>(0.300) | 0.497<br>(0.600) | 0.670<br>(0.816) | 1.148<br>(1.675) | −2.290<br>(3.463) |
| *Educ*5 | 0.143<br>(0.122) | | | | |
| *Educ*4 | | 0.006<br>(0.031) | | | |
| *Educ*3 | | | −0.158***<br>(0.036) | | |
| *Educ*2 | | | | −0.316<br>(0.264) | |
| *Educ*1 | | | | | −1.929<br>(1.601) |
| GRP structure variables | Yes | Yes | Yes | Yes | Yes |
| Regional fixed effects | Yes | Yes | Yes | Yes | Yes |
| Year fixed effects | Yes | Yes | Yes | Yes | Yes |
| N | 1296 | 1296 | 1296 | 1296 | 1263 |
| $R^2$ within | 0.387 | 0.422 | 0.411 | 0.286 | 0.055 |
| $R^2$ between | 0.148 | 0.232 | 0.270 | 0.250 | 0.001 |
| $R^2$ overall | 0.132 | 0.202 | 0.273 | 0.166 | 0.001 |
| Log likelihood | −2349.718 | −2549.985 | −2938.319 | −3714.628 | −5455.384 |

**Notes.** Robust standard errors are in parentheses. Symbols "+", "*", "**" and "***" denote a significance at the 15, 10, 5 and 1% level.

where online recruitment helps bridge this gap. At the same time, common vacancies show a heterogeneous effect, with significant impacts for groups with higher education (column 1) and complete secondary education (column 3), and a marginally significant effect for the "no education" group (column 5). This result can be attributed to the imbalances between supply and demand in these specific segments. This is further supported by the absence of effects for the largest group of the workforce (secondary vocational education) in model (column 2). Among the other coefficients, the Internet

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is significant only in model for complete secondary education (column 3), although it is statistically similar for all groups. GRP has a negative effect on unemployment for the most educated groups (columns 1–2), reflecting the importance of professional skills and competence for economic growth. Additionally, the low accuracy of model (column 5) should be noted, which is due to the very small share of people without education in the labor force and the high volatility in their statistics.

Summarizing the results of the analysis by demographic groups (settlement, age, education), we observe generally weak effects and low accuracy of the models (based on $R^2$ within) compared to the basic model (column 1, Table 3). This can be explained by several factors. First, the available information is not sufficiently detailed for these specific groups. In particular, the data on vacancies is generalized and does not account for the specific demands of employers for particular categories of workers. Second, information about individual population groups may be less accurate, and the subsamples by settlement and age are significantly smaller than in the basic model. Third, job seekers may move from one group to another (e.g., from rural areas to cities, or from one educational level to another) or relocate to a different region, with varying levels of mobility across groups. Therefore, while the differences between the models do not contradict the basic model, they highlight the need for more in-depth future research.

A potential issue with the current study lies in the choice of model specification. To address this, we conducted several robustness checks. First, we compared the semi-logarithmic form used in our analysis with the more commonly applied logarithmic form (Cobb–Douglas model) found in related studies. For this purpose, we re-estimated all equations using the logarithm of unemployment as the dependent variable. The key results are presented in Appendix A. Overall, the coefficients and p-values for the key variables $\log(\textit{Vacancy rate})$ and $\log(\textit{Online rate})$ are similar to those obtained in the main analysis. It is also worth noting that, although the accuracy of the alternative models is comparable to that of the original model, the results for most variables in the Cobb–Douglas models are significantly less robust.

Beyond the form of the dependent variable, we also tested for nonlinearity in relation to the explanatory variables in both the basic model (column 1, Table 3) and the Cobb–Douglas model with fixed effects. For each factor, we considered linear, polynomial (including both linear and squared terms), and logarithmic forms as alternatives. These experiments revealed that the alternative forms were generally less significant, and the variable specifications used in the basic model provided the highest level of accuracy. In conclusion, the results appear robust with respect to the choice of model specification.

## 6. Conclusion

This study was designed to analyze the relationship between online job search and unemployment from a macroeconomic perspective. The empirical analysis is based on data from 81 Russian regions over the period from 2006 to 2022. The study reveals a significant impact of posted vacancies — including those on online platforms — on reducing regional unemployment. Our empirical tests demonstrate that the UV curve framework is applicable in the Russian context. The main finding is that online job boards have a positive impact on reducing unemployment in the Russian labor market.

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While the effect of online vacancies between 2007 and 2022 was generally weaker than that of traditional vacancies, this trend has changed in recent years. At the same time, there was a gradual decline in the role of traditional recruitment channels and a growing influence of online recruitment.

The analysis revealed a highly heterogeneous influence of traditional and online vacancies across various demographic groups. Both gender groups are strongly affected by job postings; however, the impact of online job postings is more significant for women. The effect of online vacancies is notably stronger for younger workers (aged 20–39), reflecting their greater engagement with online and social media platforms. At the same time, there are no clear differences in the impact of traditional vacancies on unemployment across age groups. Online employment services have a strong influence on workers with secondary general and basic general education, whereas traditional agencies are more influential among those with higher or secondary vocational education.

There are several practical implications of our findings for both employers and policymakers. From the perspective of companies, greater emphasis should be put on recruiting workers through online platforms. However, the effectiveness of different employment services varies significantly across demographic groups. Online platforms offer the greatest advantages for targeting women, younger workers, and semi- or low-skilled labor. At the same time, traditional recruitment agencies remain effective, particularly when hiring men and workers across all skill levels, including high-, semi-, and low-skilled labor. Therefore, firms should adopt a mixed recruitment strategy, utilizing both online and traditional channels to optimize hiring outcomes. Additionally, employers should strive to articulate their requirements for potential employees more clearly and specifically to enhance the efficiency of the recruitment process.

From a government policy perspective, our results highlight the importance of supporting digital employment platforms, which are becoming increasingly vital. For Russia and other developing countries with underdeveloped formal labor markets and weak social institutions, advancements in IT infrastructure and digitalization can help address some of the structural weaknesses in the labor market. Therefore, the creation of new digital institutions within the labor market, along with comprehensive support for existing ones, could contribute to improving job matching efficiency and reducing unemployment. Additionally, authorities should work to enhance the effectiveness of public employment services by moving them to online platforms, improving their quality, and increasing transparency. The relatively low impact of online tools for certain groups — particularly older workers — may be due to a lack of digital literacy and competence. As such, policymakers should shift a focus on developing the digital skills of the population and ensuring that clear, accessible information about online employment services is widely available.

This study has several limitations. First, we analyzed online vacancies from only a single online recruitment platform. It would be beneficial to collect and analyze data from all major online employment agencies in Russia to obtain a more comprehensive view. Second, the available statistics on online vacancies are aggregated and do not capture the specific requirements of employers. In particular, the dataset does not include employer preferences regarding education level, age, or industry, which may explain the lower accuracy of models tailored to individual demographic groups. Third, there

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may be some overlap between online and traditional vacancy rates. As a result, we may have underestimated the effects of both types of vacancies. Separating their influence is challenging, as employers often post the same vacancy across multiple platforms, and such duplication cannot be precisely identified. Despite these limitations, the findings still fit the Beveridge curve framework and show the positive effect of online job boards on reducing the unemployment. Addressing the issues outlined above could allow for a more accurate and detailed identification of these effects, providing a solid foundation for future research on this topic.

## APPENDIX

**A.** Robustness checks

Robust standard errors are in parentheses. Symbols "+", "*", "**" and "***" denote a significance at the 15, 10, 5 and 1% level. All the regressions are similar to the estimated in the study (Tables A1–A5) excluding the form of the dependent variable. Other variables are omitted.

**Table A1.**

Basic results. Key results for models of the logarithm of unemployment (the Cobb–Douglas functional form)

| Variable | FE | OLS | IV (2SLS) | FE–IV | FE–GMM |
|---|---|---|---|---|---|
| Log(*Online rate*) | −0.077***<br>(0.013) | −0.019<br>(0.016) | −0.096***<br>(0.016) | −0.037+<br>(0.024) | −0.041**<br>(0.020) |
| Log(*Vacancy rate*) | −0.094***<br>(0.014) | −0.035<br>(0.025) | −0.107***<br>(0.018) | −0.056<br>(0.050) | −0.094***<br>(0.035) |
| $R^2$ | 0.743 | 0.602 | 0.749 | | |
| $R^2$ within | | 0.602 | 0.592 | 0.602 | |

**Table A2.**

Unemployment model in dynamics

| Variable | 2007–2010 | 2011–2013 | 2014–2016 | 2017–2019 | 2020–2022 |
|---|---|---|---|---|---|
| Log(*Online rate*) | −0.037<br>(0.032) | −0.040<br>(0.040) | −0.024<br>(0.050) | −0.016<br>(0.026) | −0.239**<br>(0.102) |
| Log(*Vacancy rate*) | −0.096**<br>(0.039) | −0.082**<br>(0.040) | −0.044*<br>(0.024) | 0.027<br>(0.028) | 0.004<br>(0.040) |
| $R^2$ within | 0.472 | 0.628 | 0.329 | 0.542 | 0.816 |

**Table A3.**

Specific models of unemployment

| Variable | *Job search time* | *U long* | *UR urban* | *UR rural* | *UR men* | *UR women* |
|---|---|---|---|---|---|---|
| Log(*Online rate*) | −0.040<br>(0.038) | −0.004<br>(0.043) | −0.007<br>(0.010) | −0.004<br>(0.022) | −0.007<br>(0.017) | −0.030*<br>(0.017) |
| Log(*Vacancy rate*) | −0.016<br>(0.025) | 0.027<br>(0.032) | −0.011<br>(0.017) | 0.015<br>(0.037) | −0.046*<br>(0.026) | −0.021<br>(0.026) |
| $R^2$ within | 0.466 | 0.423 | 0.334 | 0.421 | 0.597 | 0.484 |

**Table A4.**

Models by age groups

| Variable | *UR* 15–19 | *UR* 20–29 | *UR* 30–39 | *UR* 40–49 | *UR* 50–59 | *UR* 60–69 |
|---|---|---|---|---|---|---|
| Log(*Online rate*) | 0.064<br>(0.059) | −0.083**<br>(0.037) | −0.086*<br>(0.045) | 0.067<br>(0.061) | 0.042<br>(0.043) | −0.038<br>(0.091) |
| Log(*Vacancy rate*) | −0.069<br>(0.056) | 0.007<br>(0.034) | −0.038<br>(0.038) | −0.007<br>(0.041) | −0.005<br>(0.035) | −0.015<br>(0.102) |
| $R^2$ within | 0.107 | 0.202 | 0.298 | 0.321 | 0.242 | 0.118 |

**Table A5.**

Models by education groups

| Variable | *UR educ* 5 | *UR educ* 4 | *UR educ* 3 | *UR educ* 2 | *UR educ* 1 |
|---|---|---|---|---|---|
| Log(*Online rate*) | 0.019<br>(0.023) | 0.018+<br>(0.013) | −0.022+<br>(0.014) | 0.062**<br>(0.025) | 0.190***<br>(0.059) |
| Log(*Vacancy rate*) | −0.031+<br>(0.019) | 0.003<br>(0.013) | 0.003<br>(0.017) | 0.113**<br>(0.049) | 0.164*<br>(0.098) |
| $R^2$ within | 0.423 | 0.113 | 0.304 | 0.187 | 0.091 |

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# Безработица и онлайн-платформы вакансий в России: анализ кривой Бевериджа

**Аннотация**. Целью данной статьи является анализ взаимосвязи между онлайн-платформами для поиска работы и уровнем безработицы в России с использованием модели кривой Бевериджа (кривой безработицы и вакансий). На основе панельных данных по 81 региону России за период 2006–2022 гг. анализируется влияние расширения онлайн-платформ вакансий на динамику региональной безработицы. Эмпирическое исследование базируется на моделях с фиксированными эффектами и инструментальными переменными, что позволяет учесть региональную гетерогенность, временные эффекты и потенциальную эндогенность факторов. Полученные результаты подтверждают применимость концепции кривой Бевериджа к российскому рынку труда и выявляют статистически значимую отрицательную связь между уровнем онлайн-вакансий и безработицей. Несмотря на сохраняющуюся значимость традиционных вакансий, заявляемых в государственные службы занятости, роль онлайн-платформ заметно возросла в последние годы, особенно в период и после пандемии COVID-19. Эффект онлайн-рекрутинга имеет неоднородный характер: он наиболее выражен среди молодых работников (20–39 лет), женщин и лиц с более низким уровнем образования. Результаты подчеркивают возрастающую значимость цифровых механизмов подбора персонала и свидетельствуют о целесообразности сочетания традиционных и онлайн-каналов найма для повышения эффективности рынка труда и совершенствования государственной политики занятости.

**Ключевые слова:** *онлайн-рекрутинг; онлайн-платформы вакансий; кривая Бевериджа; российский рынок труда.*

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