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Does Digitalization Boost Unemployment: Spatial Effects and COVID-19 Case

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ABSTRACT

The labor market always presupposes a collision of the supply and demand forces. Sharp fluctuations in the economic environment can reduce the demand for labor. In the article, the authors discuss how digitalization changes the labor market, increases its efficiency, but also creates negative effects for its equilibrium. The purpose of the study is authors` measurement of the impact of digitalization of households on the unemployment rate, taking into account the spatial heterogeneity of Russian regions on panel data for two periods: 2016-2019 and 2020-2021. We used Moran and Geary spatial correlation indices, an econometric model with spatial lags, and the maximum likelihood method. Also, we show clustering of Russian regions by unemployment rate, strengthening of spatial cooperation of regions by unemployment rate and digitalization of households during the coronacrisis. The findings distinguish that the influence of digitalization of households on the reduction of unemployment existed during the coronacrisis, and it absented in the period preceding the pandemic. The scientific novelty of the study is the measuring the impact of household digitalization on the unemployment rate in the regions of Russia, taking into account spatial effects. The main conclusions of the investigation can be used in scientific and practical activities for the implementation of institutional measures for the development of regional labor markets, considering spatial differentiation of Russian regions.

Keywords: Applied Statistics & Data Mining, Business & Information Systems, Environment and Energy, Unemployment, Labor Market, Digitalization, Regions, Spatial Economic Models, Russia

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1. INTRODUCTION

Serious technological changes in society aimed at achieving sustainable development goals (Brundtland, 1987) through innovations in the energy and information and communication industries affect economic growth in general (Bhuiyan *et al.*, 2022), investment markets (Dinçer *et al.*, 2022), food and resource markets (de Clercq, 2023; Skare *et al.*, 2023; Zhang *et al.*, 2021; Myovella *et al.*, 2020). Therefore, research on renewable energy sources and digital technologies is in demand. The corona crisis has proven the stability of renewable energy development (Bhuiyan *et al.*, 2022; RECAI, 2020) and has triggered an expansion of the data economy (Ganichev and Koshovets, 2021). In particular, the number of contactless services has increased in the Russian economy (HSE ISSEK, 2021a), organizations' spending on the purchase of digital content has tripled, household spending on the purchase of digital equipment has increased by a third (HSE ISSEK, 2021b), in 2021 the value of the index of digitalization of economic sectors increased by 0.4 points and amounted to 15.7 points (HSE ISSEK, 2022c).

Along with the above trends, the corona crisis has become a source of cyclical fluctuations in the labor market: first, in the direction of rising unemployment, and then in the direction of reducing it (Kapeliushnikov, 2022;

Kadochnikova *et al.*, 2022). Cyclical fluctuations in aggregate demand affect the level of labor force participation, and the supply of labor by household members is primarily explained by the theory of consumer choice due to the desire of each individual to maximize utility. In general, the Russian labor market has established institutional frameworks for employment regulation, redistribution of employment in the service and construction sectors, flexibility and reduction in wage inequality, a mismatch between supply and demand due to the large number of highly educated labor resources, shrinkage of the low-paid segment and growth of share of highly skilled professions in 2020 by 10 percentage points compared to 2000. Men, persons of mature age, with higher education, urban residents, and those who employed in mining, financial activities, and business services are more likely to enter the highest paying jobs (Gimpelson and Kapeliushnikov, 2022; Gimpelson, 2023).

In this study, we explore spatial interactions in the labor market and in Internet-users in order to assess the impact of household digitalization on unemployment, considering the spatial heterogeneity of Russian regions, especially during the Covid-19 pandemic. At the beginning of the study, a spatial autocorrelation analysis was performed, then a spatial econometric model of the SAR type was used to measure relationships, and direct and indirect marginal effects were calculated to determine the spillover effect in the impact of digitalization on unemployment.

Negative trends in the transformation of the labor market under the influence of digitalization are detailed in theoretical studies. Thus, scientists suggest structural unemployment and income inequality as a result of the digital divide and the replacement of low-income human capital by machines, as the labor supply structure responds slowly to a rapidly changing demand structure (Huws, 2014; Christensen, 2003; De Groot *et al.*, 2009; Vial, 2019; Gong *et al.*, 2020). Based on the reasoning of Keynes and Schwab assumes technological unemployment in the short term, “since the discovery of economical use of labor methods outstrips the pace of identifying new labor applications” (Keynes, 1931; Schwab, 2016), but the replacement of labor with capital is accompanied by an increase in demand for innovations and the creation of new jobs, companies and industries, introduction of machine learning technologies (An *et al.*, 2020) and optimization of costs for the production of energy resources from renewable sources (Li *et al.*, 2022). A theoretical study (Acemoglu and Restrepo, 2018) describes that exogenous technologies at a fixed capital level reduce employment and wages, while endogenous capital accumulation and the creation of new automation tasks form advantages for the workforce. The authors of studies (Dosi *et al.*, 2021; Pasqualino *et al.*, 2021) suggesting that digitalization could increase inequality between asset owners and workers, lowering wages in real terms and potentially causing a significant increase in technological unemployment. A number of scientists call digitalization a factor of technological unemployment and economic injustice (Coyle, 1999; Frey and Osborne, 2013; Moretti and Thulin, 2013; Brynjolfsson and McAfee, 2014; Florida, 2017).

Among the positive consequences of digitalization in the labor market, scientists point to the creation of new jobs for the economy, an increase in labor productivity, increased labor mobility and competition, and a reduction in transaction costs (Safronchuk *et al.*, 2022). Based on Keynes' theory and a review of 86 articles on the Fourth Industrial Revolution in research, the authors (Annunziata and Biller, 2014; Pfeiffer and Suphan, 2015; Szabó-Szentgróti *et al.*, 2021) formulated a theoretical conclusion about reducing the required labor force and working time and obtaining new opportunities for development and life, creativity and entrepreneurship, increasing economic efficiency through more intensive work (Bag *et al.*, 2020; Gualtieri *et al.*, 2020) concluded that new employment opportunities, new professions as a result of the increase in the complexity of production systems.

Empirical studies on country, regional and microdata samples show a predominantly positive impact of digitalization on the labor market. Few works predict technological unemployment: for developed countries, a significant negative correlation was found between intangible investments (including information and communication technologies, software and databases) and total factor productivity after the 2008 financial crisis (Bertani *et al.*, 2020); the study (Lastauskaite and Krusinskas, 2021) shows a negative correlation of average personnel costs for manufacturing companies with the general labor cost index in the EU states. On the contrary, for the EU member states, a strong positive correlation was found between the digitalization index and the share of the employed population, as well as the level of participation of the population in the labor force (Bogoslov *et al.*, 2022). The positive impact of digital technologies on productivity and employment growth in Europe has been proven in (Evangelista *et al.*, 2014). Based on a panel regression model for a sample of 28 European countries, the authors showed that the transformation of activities under the influence of technology, the increase in technological personnel, contributes to the growth of activity in the labor market (Bănescu *et al.*, 2022). The researchers used the proportion of people aged 15 to 64 in the labor market as the dependent variable; as factors to explain labor activity: the weighted average index of e-commerce adoption with values from 0 to 100 and the weighted average index of advanced technical skills of human resources. A similar conclusion was obtained in (Mirgorodskaya *et al.*, 2020; Litvintseva and Karelin, 2022) for Russian regional data based on panel regression.

A separate group of empirical studies is devoted to the impact of the COVID-19 pandemic and interregional interactions in the labor market. Assuming that restrictive strategies have reduced sustainable demand for renewable energy sources and led to a drop in economic growth (Bhuiyan *et al.*, 2021), increased financial turbulence (Liu *et al.*, 2022), we can suppose a reduction in demand for the labor force. In the study (Vakulenko and Gurvich, 2015), the authors find the effect of a regional buffer or regional absorption of asymmetry in the labor market, taking into account spatial interaction: regions with a more prosperous situation mitigate crisis shocks in neighboring regions. Increasing labor mobility both within and between countries is reflected in (Baldwin, 2016).

In general, researchers point to an impressive contribution of theoretical research and a clear lack of empirical arguments for the impact of digitalization on the economy and social environment (Ching *et al.*, 2022). There is limited empirical evidence for the impact of digitalization on the labor market in Russia. A study for Russia from 2015 to 2018 found a significant negative correlation between the indicator of the development of the digital economy and the number of unemployed by education level (Litvintseva and Karelin, 2022). The conclusion about the creation of new jobs, the replacement of traditional labor with digital technologies for Russian regional data based on panel regression was obtained in (Mirgorodskaya *et al.*, 2020). In the study (Dubrovskaya and Kozonogova, 2021), the authors found a high spatial heterogeneity in the level of registered unemployment, its increase in peripheral territories, a high demand for specialists in the "Information Technology" group in areas with a high level of registered unemployment.

In order to expand empirical work for Russian regional data on measuring the social effect of digitalization on the labor market, we evaluate the impact of digitalization on the unemployment rate, taking into account the spatial heterogeneity of Russian regions. We test two research hypotheses:

- assumption of stable regional clusters and spatial relationships of regions in terms of unemployment and digitalization;
- the assumption of a reduction in the unemployment rate under the influence of digitalization, considering spatial interaction, especially during the period of the COVID-19 coronacrisis.

2. DATA AND METHODOLOGY

A sample of data was obtained on the official website of the Federal Statistical Office of the Russian Federation by region (Rosstat, 2022a) and, in particular, the authors used the results of Monitoring the development of the Information Society in the Russian Federation (Rosstat, 2022b). Two periods were used to measure the effects: 2016-2019 and 2020-2021. The first period is characterized as a stage of recovery of the Russian economy after the geopolitical crisis of 2014, the effect of which was most clearly manifested in 2015. The second period is 2020-2021 – it reflects the effect of the COVID-19 coronacrisis in Russia, which was accompanied by a lockdown and a serious adaptation of the Russian labor market, which made it possible to maintain a relatively low unemployment rate due to the spread of part-time and remote employment (Kapeliushnikov, 2022). The study presents 85 regions of Russia – administrative subjects of the Russian Federation. Data for the Arkhangelsk and Tyumen regions are presented separately from their autonomous districts (a list of regions is provided in the Appendix). Descriptive statistics and description of variables are provided in Table 1.

The dependent variable is the labor force unemployment rate. The independent variable of research interest is the number of Internet users (*l_users*), which is a proxy for assessing the level of digitalization of households in Russian regions. In the previous study (Kadochnikova and Suyucheva, 2022), as well as on the example of a cointegration analysis of five indicators of household digitalization, it was shown that the share of households using the Internet and the number of active subscribers of fixed Internet access have a predominant impact on the socio-economic characteristics of unemployment. These variables are closely correlated with each other. We use the variable "the number of Internet users" (l_users), because the use of the Internet by households as a source of access to network platform resources and other digital services is the final result of their digitalization through gadgets, training, and changes in behavior in the labor market. A set of independent control variables was formed based on the socio-economic factors of unemployment systematized in scientific studies and literature review (Figure 1). First of all, the situation in the labor market is determined by the demographic situation, therefore, the control variables include: population (*population*), expected sign "minus" (Bogoslov *et al.*, 2022), demographic structure of the population using variables younger than working age (*below*), expected sign "plus" (Ivanova and Burmistrova, 2016) and older than working age (*above*), expected sign "plus" (Ivanova and Burmistrova, 2016), migration (*migration*), expected sign "minus" (Ivanova and Burmistrova, 2016). The economic development of the region determines the situation on the labor market, therefore, to control the main effect, wages *(wage_fix*), expected sign "minus" (Gurvich and Vakulenko, 2018; Zubarevich and Safronov, 2020) and gross regional product (*l_grp_fix*), expected sign "minus" (Gurvich and Vakulenko, 2018; Zubarevich and Safronov, 2020) were introduced as regressors. The number of Internet users and the gross regional product are used with the first lag to avoid the problem of endogeneity. The quality of human capital is represented in the model by the proportion of the employed population with higher education (*education*), expected sign "plus" (Zemtsov, 2017; Mirgorodskaya *et al*., 2020).

The unemployment rate is influenced by various groups of factors. The review of theoretical and empirical studies made it possible to single out three groups of factors influencing unemployment at the regional level (see Figure 1). The demographic characteristics of the regions associated with the population, its mechanical growth under the influence of migration, the structure of the population, reflecting the natural growth and historical development of the region, determine the supply of labor resources in the labor market. The level of socio-economic

Table 1. Descriptive statistics of the main variables

Variable	Description		Mean	Std. Dev.	Min	Max	Observations
unempl	Labor force unemployment rate, in %	overall	6.307	3.696	1.200	30.900	N = 510
		between		3.633	1.833	28.333	n = 85
		within		0.770	2.774	9.807	T = 6
population	Average annual population, thousands of people	overall	1724.385	1788.948	43.900	12666.6	N = 510
		between		1797.602	44.083	12553.08	n = 85
		within		26.514	1517.235	1884.835	T = 6
below	The proportion of the population younger than the working age, in %	overall	19.463	3.563	14.700	34.600	N =510
		between		3.573	14.933	34.316	n = 85
		within		0.232	18.313	20.513	T = 6
above	The proportion of the population older than working age, in %	overall	24.318	4.566	9.900	31.300	N = 510
		between		4.549	10.316	30.350	n = 85
		within		0.595	21.984	25.484	T = 6
wage_fix	The average monthly nominal salary of organizations employees divided by the cost of a fixed set of consumer products and services	overall	2.474	0.666	1.541	5.523	N = 510
		between		0.647	1.720	5.059	n = 85
		within		0.172	1.891	2.937	T = 6
education	The share of the employed population aged 25-64 years with higher education in the total number of employed population of the corresponding age group, in %	overall	33.269	5.448	22.559	52.500	N = 510
		between		5.111	25.160	50.802	n = 85
		within		1.954	23.055	42.931	T = 6
migration	Migration growth rate per 10,000 population	overall	3.299	80.901	-187	1313	N = 510
		between		62.308	-90.333	410.666	n = 85
		within		51.968	-240.367	905.632	T = 6
l_grp_fix	Gross regional product divided by the cost of a fixed set of consumer products and services (first lag)	overall	40.478	57.695	3.232	831.925	N = 510
		between		41.957	9.391	269.550	n = 85
		within		39.820	-218.206	681.551	T = 6
l_users	Number of Internet users per 100 people (first lag)	overall	76.447	7.705	51	98	N = 510
		between		4.774	68	93	n = 85
		within		6.065	51.113	91.947	T = 6

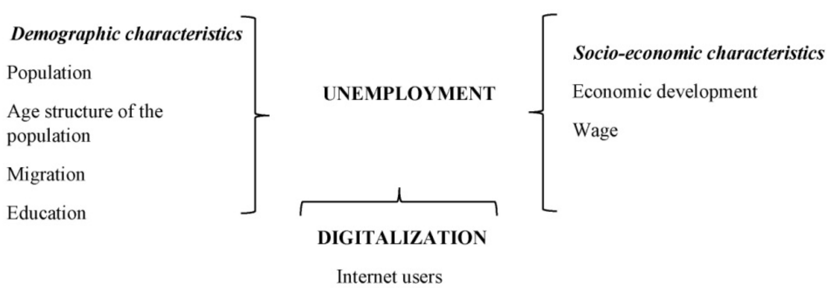


Figure 1. Exploratory model of the relationship between variables.

development of the region affects the demand for labor resources in the labor market. The ubiquity of digital technologies may have an impact on the unemployment rate in the region, this hypothesis is being tested as part of the ongoing study.

The heterogeneity of Russian regions, which was shown by descriptive statistics in Table 1, suggests having spatial effects reflecting the interdependence and mutual influence of regional labor markets. The mutual influence of regions on each other can be a significant external determinant of labor supply and demand, therefore, to obtain unbiased estimates of explanatory factors, it is advisable to model using a spatial lag (Anselin, 2006; Elhorst, 2009). In order to detect spatial relationships in the digitalization of households and in the unemployment rate, we carried out spatial autocorrelation analysis using Moran's and Geary's global indices (Anselin, 1995; LeSage and Pace, 2009):

$$I(X)=\frac{N}{\sum_{i,j} w_{ij}}\cdot\frac{\sum_{i,j} w_{ij}(X_i-\bar{X})(X_j-\bar{X})}{\sum_{i}(X_i-\bar{X})^2}, \quad (1)$$

where N is the number of regions, and $\bar{X}$ is the average value of the X (in this study: unempl - the unemployment rate; l_users - number of Internet users, w_{ij} - elements of the boundary matrix of weights.

$$C=\frac{(\mathrm{n}-1)\sum_{i=1}^{n}\sum_{j=1}^{n} w_{ij}(\mathrm{X}_i-X_j)^2}{2W\sum_{i=1}^{n}(\mathrm{X}_i-\bar{X})^2}, \quad (2)$$

where W denotes the sum over all w_{ij}, other notations correspond to the notation of the Moran index.

The Moran index takes values in the range of [-1; 1]. The Geary index takes values in the range of [0; 2], where values from 0 to 1 indicate a positive spatial correlation, and values from 1 to 2 indicate a negative spatial correlation. The statistical significance of the indices allows substantiating the existence of a spatial relationship between the region and its neighbors according to this indicator. Thus, a positive spatial correlation coefficient means that a growing region contributes to the growth labor market of its neighbors, a negative value indicates that a growing region "takes" the resources of its neighbors. The insignificance of the coefficient indicates the absence of processes interconnection in different regions.

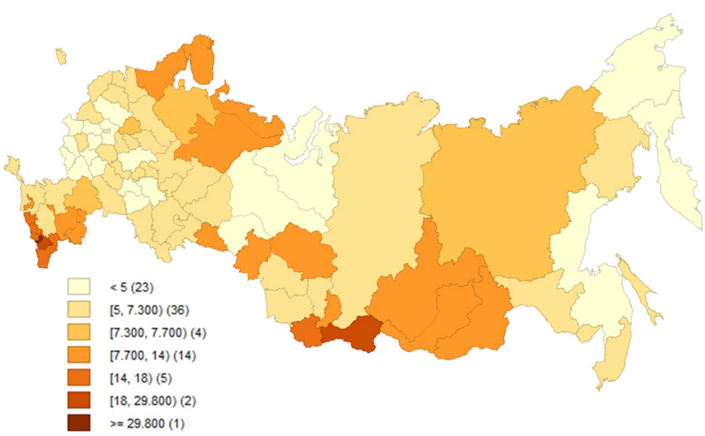
Using the (Elhorst, 2014) scheme to select a spatial panel model, we settled the SAR (Spatial Autoregression Model) with random effects model in the form:

$$\begin{aligned} &unempl_{it}=\rho Wunempl_{it}+\beta X_{it}+u_{it},\\ &u_{it}=\alpha_i+\varepsilon_{it} \end{aligned} \quad (3)$$

where $unempl_{it}$ is dependent variable, X_{it} is the vector of independent variables (detailed description of variables is given in Table 1), α_i reflects random individual differences between regions, ε_{it} is a normally distributed error term, W is the spatial matrix for the autoregressive component. In order to be able to talk about spatial effects, it is necessary that spatial "rho" will be significant. In addition to answering the question whether there are spatial effects in the impact of digitalization on unemployment at the level of the Russian regions, we would like to determine the direction of this influence: is this influence concentrated within the region or is there an overflow effect of the digitalization impact on unemployment from neighboring regions. For this purpose, we calculated direct and indirect marginal effects.

3. RESULTS AND DISCUSSION

The cartogram in Figures 2 reflects the uneven de-



Source: obtained by the authors on the data of Federal Statistical Office of the Russian Federation (Rosstat, 2022a).

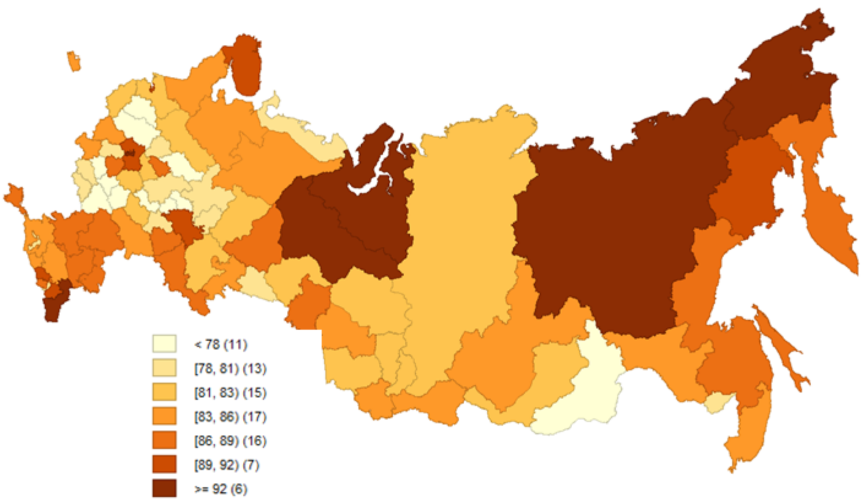
Figure 2. The unemployment rate in 2020 by regions of Russia, in %.

mand for labor in the Russian regions. The highest unemployment rate in 2020 was in the Republic of Ingushetia, the Chechen Republic and the Tuva Republic.

For the southern regions, high unemployment is typical not only in 2020. The southern regions are traditionally characterized by a high level of unemployment, which is associated with the traditions and institutional conditions in the labor market in these regions.

Figure 3 demonstrates heterogeneity in the Internet-users among regions. The highest number of Internet users is in the Republic of Dagestan, the Khanty-Mansi Autonomous Okrug, the Republic of Sakha, the Yamalo-Nenets Autonomous Okrug, the Chukotka Autonomous Okrug and Moscow. At the same time, it is worth paying attention to the fact that the highest values of Internet use are observed in hard-to-reach, northern regions of Russia. The lowest values are in the Orel Oblast, the Republic of Mordovia, the Tambov Oblast, the Lipetsk Oblast, the Novgorod Oblast, the Voronezh Oblast, the Zabaykalsky Krai, the Tver Oblast, the Republic of Mari El, Chuvashia, and the Kostroma Oblast. Almost all regions with a low value of the indicator, with the exception of the Zabaykalsky Krai, are located in the European part of Russia.

The values of Global spatial autocorrelation of Moran's and Geary's indices obtained in the study are presented in Table 2. The statistical significance of Moran's and Geary's indices confirms the hypothesis of the positive autocorrelation and regions clustering by the unemployment rate and by the Internet-users. In other words, regions with a high unemployment rate are surrounded by neighbor regions with a high unemployment rate, and regions with a low level are similarly surrounded by regions with a low unemployment rate. This result is consistent with the work of (Dubrovskaya and Kozonogova, 2021). Indeed, regions with developed infrastructure, high production potential, favorable social conditions for self-realization attract labor resources and provide a high level of employment in the relevant territory. And regions with a high level of registered unemployment do not have sufficient resources and conditions for employment and self-realization. Similar relationships can be traced in relation to Internet access in households. Spatial interaction intensified in 2020, during the coronacrisis. This may be a consequence of more active use of online services both for searching the work and work itself. The spatial autocorrelation makes it possible to assess the impact of In-



Source: obtained by the authors on the data of Federal Statistical Office of the Russian Federation (Rosstat, 2022a)

Figure 3. Number of Internet users per 100 people in 2020 by regions of Russia, %.

Table 2. Global spatial autocorrelation Moran's and Geary's indexes

Variable	Index	2016	2017	2018	2019	2020	2021
unempl	Moran's I	0.412 (0.000)	0.434 (0.000)	0.436 (0.000)	0.482 (0.000)	0.533 (0.000)	0.470 (0.000)
	Geary's c	0.456 (0.000)	0.455 (0.000)	0.439 (0.000)	0.384 (0.000)	0.363 (0.000)	0.395 (0.000)
users	Moran's I	0.345 (0.000)	0.152 (0.032)	0.201 (0.006)	0.163 (0.024)	0.252 (0.001)	0.175 (0.016)
	Geary's c	0.595 (0.000)	0.830 (0.062)	0.747 (0.003)	0.795 (0.013)	0.703 (0.000)	0.760 (0.004)

Note: the value of p-value is indicated in parentheses for Global spatial autocorrelation Moran`s and Geary`s indexes.

ternet access in households on the unemployment rate, taking into account spatial effects.

Positive spatial autocorrelation in the unemployment rate is typical for both the period of 2016-2019 and 2020-2021 – the period of the coronacrisis. Figure 4 shows a scatterplot of local Moran indexes for unemployment rate in 2021. The list of regions is presented in the Appendix.

In the quadrant of high unemployment rates, with high values of this indicator in neighboring regions, there are southern regions of Russia - the Republic of Ingushetia, the Republic of North Ossetia-Alania, the Kabardino-Balkar Republic, the Chechen Republic, the Republic of Dagestan, which confirms the conclusion about the tension in the market labor in these regions of Russia. The second cluster of high unemployment rates are the southern regions of the Siberian part of Russia - Altai Republic, Tuva Republic, Buryatia. In general, the low unemployment rate is confirmed by "low-low" quadrant, in which most regions are concentrated. This fact indirectly shows the maturity of the labor market in the Russian regions and effective institutional measures aimed at regulating supply and demand in the labor market. The Moran scatterplot confirms the conclusions obtained in (Vakulenko and Gurvich, 2015; Vakulenko and Gurvich, 2016; Gorlov *et al.*, 2021).

The next step of the study is to assess the impact of the number of Internet users on the unemployment rate. We used a spatial autoregression model of the SAR type on panel data in the time period 2016-2019 and 2020-2021. The division into two time periods is dictated by the assumption of the impact of the COVID-19 corona crisis in 2020-2021, which was associated with restrictive measures for the mobility of human resources, an increase in morbidity and mortality, and a change in migration flows both at the international and interregional levels. The proposed hypothesis is confirmed by the results of the Chow's test ($F(9, 492) = 5.50$, $Prob > F = 0.0000$). The choice of the random effects model is determined by the results of the Hausman test (Prob>chi2 = 0.0700). The choice of the random effects model is determined by the results of the Hausman test (chi2 = 14.30, Prob>chi2 = 0.0743). Limited sample does not allow for the Hausman test for the model 2020-2021.

The results of the models` evaluation are presented in Table 3. In each of the models, the coefficient with the spatial lag "rho" is statistically significant and takes a positive value, which confirms the positive spatial autocorrelation between the unemployment rate in this region and neighboring regions.

Consequently, regions with high unemployment rates are surrounded by neighbor regions also with high unemployment rates, and regions with low unemployment rates are surrounded by neighbors with similar indicators.

As can be seen from Table 3, in the period of 2016-2019, no statistically significant impact of household digitalization (l_users) on the unemployment rate was found in the regions. However, in 2020-2021, during the coronacrisis, there is a statistically significant negative impact of household digitalization on the unemployment rate in the regions. Therefore, the hypothesis about the catalytic role of digitalization in the impact on the labor market during the pandemic cannot be rejected.

Table 4 contains estimates of marginal effects for the period of the coronacrisis, which reveal the source of the impact on the unemployment rate – the economy of a given region or the effects of overflows from neighboring regions. Marginal effects reveal a stable spatial interaction of regions and reflect the negative impact of households` digitalization in neighboring regions and a given region on the unemployment rate of a given region: if the proportion of households with Internet access both in this

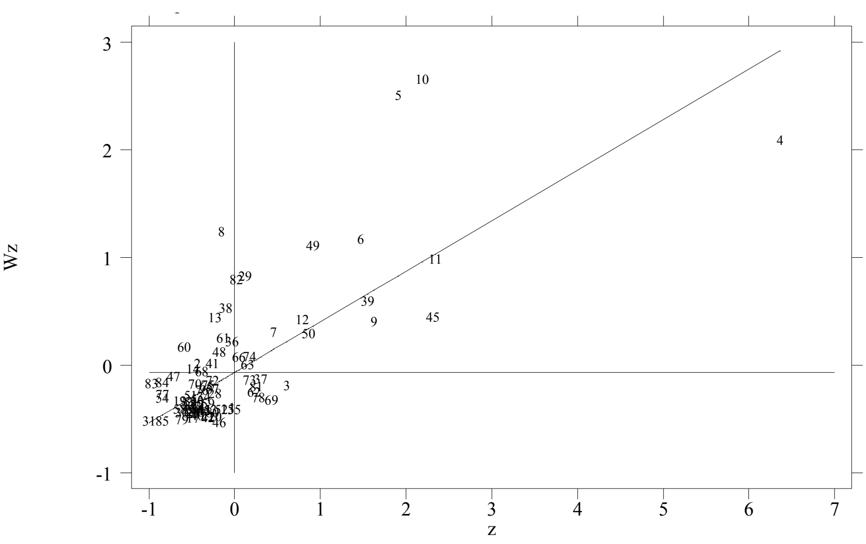


Figure 4. Moran scatterplot for unemployment rate in 2021.

region and in neighboring regions increases, then the unemployment rate as a whole in this region decreases. The decrease in the unemployment rate is dominated by the indirect effect of digitalization of households (l_users) of neighboring regions against the direct effect of digitalization of households in this region (61% vs. 39%, respectively). These effects are observed in 2020-2021. and are not typical for the pre-pandemic period. The obtained results correspond to the conclusions about an increase in activity in the labor market due to the transformation of activities under the influence of technology and a growth in technological personnel, obtained in the work (Bănescu *et al.*, 2022).

It should be noted that modeling the impact of digitalization on the situation in regional labor markets, taking into account spatial effects – the spatial lag of the dependent variable – allowed obtaining more accurate estimates of coefficients with appropriate regressors.

Table 3. Results of SAR modelling (unemployment as dependent variable)

Regressors	Panel data model (2016-2019 years)		Panel data model (2020-2021 years)	
	Coef.	P-value	Coef.	P-value
population	-.0001489	0.229	-.0003121	0.019
below	.427174	0.000	.8272722	0.000
above	-.1425823	0.012	.2315226	0.011
wage_fix	-1.947126	0.000	-1.373154	0.000
education	.0089234	0.603	.1759213	0.000
migration	.0001874	0.882	-.0002582	0.698
l_grp_fix	.0035462	0.401	.0012876	0.104
l_users	-.0122862	0.113	-.0528735	0.026
const	5.340268	0.061	-15.29459	0.008
Rho	.2441325	0.000	.410828	0.000
R-sq.	within	0.3946		0.6759
	between	0.6864		0.7401
	overall	0.6778		0.7382
Hausman test	14.30	0.0743	-	-

Table 4. Marginal effects of SAR models

	Panel data model (2016-2019 years)			Panel data model (2020-2021 years)		
	LR_Direct	LR_Indirect	LR_Total	LR_Direct	LR_Indirect	LR_Total
population	-0.000147 (0.256)	-0.000047 (0.294)	-0.000194 (0.257)	-0.0003233 (0.025)	-0.0002061 (0.068)	-0.0005294 (0.033)
below	0.4315926 (0.000)	0.1329151 (0.006)	0.5645077 (0.000)	0.8632123 (0.000)	0.5336044 (0.000)	1.396817 (0.000)
above	-0.1418302 (0.010)	-0.0422068 (0.029)	-0.184037 (0.008)	0.2443845 (0.007)	0.1475586 (0.006)	0.3919431 (0.003)
wage_fix	-1.974159 (0.000)	-0.5996533 (0.001)	-2.573812 (0.000)	-1.440101 (0.000)	-0.9141887 (0.011)	-2.354289 (0.001)
education	0.0089762 (0.590)	0.0026324 (0.623)	0.0116085 (0.593)	0.1849057 (0.000)	0.1158228 (0.000)	0.3007285 (0.000)
migration	0.0002538 (0.840)	0.0000912 (0.829)	0.000345 (0.836)	-0.0002351 (0.734)	-0.0001428 (0.759)	-0.0003779 (0.742)
l_grp_fix	0.0036529 (0.415)	0.0011362 (0.447)	0.0047891 (0.416)	0.0013546 (0.116)	0.0008621 (0.159)	0.0022168 (0.124)
l_users	-0.0126608 (0.109)	-0.0037787 (0.155)	-0.0164395 (0.108)	-0.0558425 (0.019)	-0.0350845 (0.045)	-0.090927 (0.021)

4. CONCLUSION

The conducted research allowed formulating the following conclusions:

1. Over a long period of time, we have noted spatial interconnection and mutual influence in regional labor markets and in the use of the Internet at the Russian regional level.

2. Global spatial autocorrelation indices revealed an increase in spatial interaction in 2020, during the coronacrisis.

During the coronacrisis that we observe a significant impact of the level of digitalization among the population on the phenomena occurring in regional labor markets. In 2020, household Internet access became the basis for reducing the severity of the situation that arose during the period of restrictions and economic crisis. According to our own calculations, the growth in the number of Internet users contributed to a decrease in unemployment both in a given region and in neighboring regions.

In conclusion, it should be noted that in the conditions of digitalization, the labor market becomes more transparent and symmetrical, the efficiency of job search and hiring increases. However, in some segments of the economy, the demand for medium-skilled labor is interrupted, demand and incomes in the middle-class sector are declining, and the demand for highly qualified, engineering and related specialties with an IT component is growing rapidly.

The study focuses on measuring digitalization through the number of Internet users, which in most cases is related to the skills of the population in finding and processing information. The emphasis in regional policy on providing access to digital technologies at the household level, increasing digital literacy, and training in digital competencies reduces the limitations of local labor markets, creating opportunities for finding work outside the region without the need to change the place of residence. This may contribute to reducing the unemployment rate in the short term and the development of new forms of remote employment. At the same time, regional administrative borders are being erased in the Internet environment and regional labor markets for a number of professions are turning into national markets. Spatial interrelation and mutual influence of regional labor markets and regional economies, demonstrated by the examples of the unemployment rate and Internet users, can provide a synergistic effect in the development of segmental state policy aimed at reducing unemployment, in particular in the regions of the North Caucasus.

The construction of the spatial model made it possible to estimate direct and indirect effects for an average region of the Russian Federation, further development of research can take place by calculating spatial direct and indirect effects for each region separately, which will reflect the specifics and individual characteristics of the regions.

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APPENDIX

1.	Republic of Crimea	44.	Voronezh Oblast
2.	Sevastopol	45.	Tuva Republic
3.	Republic of Adygea	46.	Sakhalin Oblast
4.	Republic of Ingushetia	47.	Khabarovsk Krai
5.	Republic of North Ossetia-Alania	48.	Amur Oblast
6.	Kabardino-Balkar Republic	49.	Buryatia
7.	Astrakhan Oblast	50.	Zabaykalsky Krai
8.	Stavropol Krai	51.	Tver Oblast
9.	Karachay-Cherkess Republic	52.	Mari El
10.	Chechen Republic	53.	Chuvashia
11.	Republic of Dagestan	54.	Tatarstan
12.	Republic of Kalmykia	55.	Vladimir Oblast
13.	Krasnodar Krai	56.	Nizhny Novgorod Oblast
14.	Rostov Oblast	57.	Ulyanovsk Oblast
15.	Jewish Autonomous Oblast	58.	Moscow Oblast
16.	Primorsky Krai	59.	Pskov Oblast
17.	Kaluga Oblast	60.	Krasnoyarsk Krai
18.	Tula Oblast	61.	Kemerovo Oblast
19.	Bryansk Oblast	62.	Tomsk Oblast
20.	Smolensk Oblast	63.	Omsk Oblast
21.	Oryol Oblast	64.	Udmurtia
22.	Republic of Mordovia	65.	Perm Krai
23.	Kursk Oblast	66.	Novosibirsk Oblast
24.	Penza Oblast	67.	Kirov Oblast
25.	Tambov Oblast	68.	Tyumen Oblast
26.	Lipetsk Oblast	69.	Kurgan Oblast
27.	Ryazan Oblast	70.	Sverdlovsk Oblast
28.	Kaliningrad	71.	Bashkortostan
29.	Republic of Khakassia	72.	Chelyabinsk Oblast
30.	Samara Oblast	73.	Republic of Karelia
31.	Saint Petersburg	74.	Arkhangelsk Oblast
32.	Leningrad oblast	75.	Vologda Oblast
33.	Novgorod Oblast	76.	Kostroma Oblast
34.	Ivanovo Oblast	77.	Khanty-Mansiysk Autonomous Okrug ? Ugra
35.	Yaroslavl Oblast	78.	Komi Republic
36.	Murmansk Oblast	79.	Kamchatka Krai
37.	Nenets Autonomous Okrug	80.	Magadan Oblast
38.	Altai Krai	81.	Sakha Republic
39.	Altai Republic	82.	Irkutsk Oblast
40.	Belgorod Oblast	83.	Yamalo-Nenets Autonomous Okrug
41.	Volgograd Oblast	84.	Chukotka Autonomous Okrug
42.	Orenburg Oblast	85.	Moscow
43.	Saratov Oblast	86.	

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