Theoretical and Empirical Researches in Urban Management
Volume 15 Issue 4 / November 2020

SPATIAL EFFECTS OF INFORMAL EMPLOYMENT AND PRECARIZATION IN URBAN CENTRES AND REGIONS

Vyacheslav VOLCHIK
Southern Federal University, Bolshaya Sadovaya str. 105, Rostov-on -Don 344006, Russian Federation
volchik@sfedu.ru

Elena MASLYUKOVA
Southern Federal University, Bolshaya Sadovaya str. 105, Rostov-on -Don 344006, Russian Federation
maslyukova@sfedu.ru

Wadim STRIELKOWSKI
Cambridge Institute for Advanced Studies, 23 King Street, CB1 1AH Cambridge, United Kingdom
strielkowski@cantab.net

Abstract
Informal employment constitutes a significant factor in economic development of large cities and regions. In this paper, we examine the informal employment within the context of instability and precarization of labor in the Russian cities and regions. We consider the negative effects in the higher education system as one of the factors in the formation of the precariat and informal employment. Universities and higher educational institutes have always been associated with the cities and their steady urban development.
The aim of our study is to identify and assess the influence of the determinants of the development of employment in the informal sector in the Russian regions, taking into account the influence of spatial effects using spatial regression models and classical panel data models. The paper compares the use of spatial econometric models with classical panel data models to analyze the dependence of employment in the informal sector on various characteristics of regions. In order test the hypothesis of the influence of the spatial location of regions on the distribution of the share of employees in the informal sector, we employ the values of Moran and Geary indices of the global spatial autocorrelation. We use a matrix of inverse geographic distances between the centroids of the corresponding administrative units and a matrix of inverse shortest automobile distances as spatial weights. The persistently positive statistically significant values of the Moran and Geary indices confirm the presence of spatial autocorrelation. Moreover, the use of spatial econometric models also made it possible to obtain estimates of the coefficients taking into account the presence of positive spatial autocorrelation. Our results can be used for studying the instability in the labor market in the context of the formation of a stable precariat. Spatial effects can also be considered in relation to the evolution of the local institutional and organizational structure of the training system for regional labor markets.
Keywords: informal employment, spatial effects, urban development, spatial lags, precariat, higher education, spatial econometrics, labor market

1. INTRODUCTION

Informal (or unregular) employment contrasts with the relative security that stable employment provides. Economic and institutional changes taking place in many economics in transition that are visible in the recent years have an impact on the growth of employment in the informal sector which is one of the most

difficult socio-economic problems from the point of view of the methodology for studying it and adequately assessing various prospects and social consequences. This informal sector is often present in large cities and urban centers where it is easier to keep off the grid (see e.g. Baptista, 2019; or Ahmed et al., 2020).

Informal employment is a global problem with a wide range of implications covering many areas of interest to economists. Consequently, it becomes increasingly important to understand the new mechanisms in the labor market that generate it.

A key sign of the informality of hiring is the absence of a formal (written) contract which states the existence of an employment relationship between a specific employee and an employer (Yahmed, 2018). In this case, the contract can exist in various forms provided for by law: fixed-term or unlimited employment contract; civil contract; record in the work book; an order for employment based on the employee's personal application.

In the Russian Federation, those employed in the informal sector are persons who, during the survey period, were employed in at least one of the production units of the informal sector, regardless of their employment status and whether this job was their main or additional job. The criterion of the absence of state registration as a legal entity was adopted as a criterion for determining the units of the informal sector (as it stems from the results of a sample survey of the labor force II quarter of 2019) (see Federal State Statistics Service, 2019a).

Empirical studies conducted on Russian data focus on assessing the extent and different forms of precarious employment (precarity employment) (see e.g. Bobkov et al., 2018; Toshchenko, 2015; Volchik and Posukhova, 2016; Strielkowski et al., 2019 and others). In the studies of Gimpel'son and Zudina (2012) on the basis of panel data, estimates of the size and dynamics of the informal sector in Russia are presented, components of the informal sector in the Russian economy, its socio-demographic features, characteristics of jobs and factors of involvement in the informal sector, as well as an analysis of the factors of interregional differentiation in the development of the Russian informal sector. Kapeliushnikov (2013) offers four alternative approaches to defining the scale and socio-demographic profile of informal employment. There are also empirical studies based on aggregated Russian data, where factors influencing the development of informal employment are assessed (for example, Nureev and Akhmadeev, 2019; Simutina et al., 2018 and others.). Oshchepkov and Kapeliushnikov (2015) analyzed the level and dynamics of differences between labor markets of Russian regions as the constituent entities of the Russian Federation in the period from 2000 to 2014 as one of the main indicators of the functioning of labor markets and singled out the prevalence of informal employment.

The importance of taking into account regional differences in the study and modeling of market parameters is noted in the works of Elhorst (2003), Zierahn (2012), Lottmann (2012), Omelyanenko et al.

Theoretical and Empirical Researches in Urban Management
Volume 15 Issue 4 / November 2020

(2018), Fedorov and Mikhaylov (2019), as well as others. Research on the global labor market emphasizes the need to account for cross-country differences to explain global inequality. Thus, Chung et al. (2010), or Muntaner et al. (2012) note that the labor markets of countries tend to grouped according to geographical, historical and developing directions. There are relatively few empirical spatial and econometric studies devoted to the study of various aspects of the Russian labor market. Thus, in the works of Semerikova and Demidova (2016) the influence of various factors on the unemployment rate in the Russian regions for 2005–2010 is identified and assessed. using spatial regression models and classic panel data models. Demidova (2014) based on the generalization of the spatial autoregression model, an analysis of three macroeconomic indicators (unemployment rate, relative wages, and GRP growth) was carried out for Russian regions, preliminarily divided into Western and Eastern. With regard to the above, Rusanovskiy and Markov (2016) use spatial autoregression models to assess the impact of urbanization and agglomeration factors on the level and interregional differentiation of unemployment (see Rusanovskiy and Markov, 2016; Markov, 2015).

In the works devoted to the analysis of employment in the informal sector, performed on Russian regional data, the regional component is ignored, that is, it is not taken into account that changes in employment in the informal sector of one region may affect the labor market of neighboring regions. Ignoring spatial relationships between variables can lead to biased estimates. The purpose of this work is to identify and assess the influence of the determinants of the development of employment in the informal sector in the Russian regions, taking into account the influence of spatial effects using spatial regression models and classical panel data models. The study covers the period from 2010 to 2016. and is based on annual official statistics for 80 subjects of the federation. Our work compares the use of spatial econometric models with classical panel data models to analyze the dependence of employment in the informal sector on various characteristics of regions.

2. HIGHER EDUCATION AND REGIONAL LABOR MARKETS

In general, one would agree that the functioning of universities is the most important factor in regional and urban development. Moreover, universities have an impact on various spheres of society, from the labor market to the development of cultural and tourism industries. It can be said that the presence of a well-known and productive university in the region is associated with significant externalities that have a positive effect on regional development. However, in modern university education there is a problem of a gap between the fundamental theoretical knowledge of the scientific community and the requirements of industry (Etzkowitz, 2019:40), which makes the problem of the practical use of academic knowledge by students in their working careers significant. The development of higher education can also be associated

with the evolution of inclusive institutions that promote sustainable development, which can also be considered in connection with positive externalities (Bertolin, 2018).

Regional and urban development are closely related to the state of the vocational education system at all levels. However, the imbalances that arise between the needs of the labor market and the structure of training in educational institutions are associated with issues of both a fundamental economic nature and the specifics of state planning and decentralized decision-making in a market economy.

In complex systems represented by the regional and urban economies, there is a constant adaptation to the emerging imbalances in the labor market. We proceed from the assumption that informal employment is one of the factors characterizing such disparities. Informal employment is associated with the growth of instability in the labor market, which in modern social sciences is associated with the formation of the precariat. The precariat, as a new social phenomenon, is becoming a significant factor influencing the indicators of socio-economic development embracing people involved in flexible and insecure labor relations (see Standing, 2013). Therefore, the negative effects of informal employment on regional economies can be viewed in the context of employment precarization. The processes of precarization of employment are associated with imbalances in the labor market, in particular, arising from the decline in the quality of higher education.

The functioning of regional universities is associated with several significant issues (issues). First, the education system generates significant positive externalities that are significantly associated with regional and urban communities. Such externalities improve the social climate, reduce the likelihood of deviant behavior, positively affect the characteristics of human capital and the quality of the workforce, and also contribute to a decrease in the impact on the unemployment rate (Titus, 2009: 457). Secondly, university graduates find jobs not only within a particular region or a city (consider large agglomerations such as Beijing, New York, London, or Moscow), but also have a significant impact on the supply of highly skilled labor in neighboring regions. Thus, according to the Portal for monitoring the employment of graduates, the majority of graduates who graduated from universities in the Southern Federal District (SFD) prefer to seek employment in Moscow, but a significant part of graduates, having received a higher education in the capital, returns to the SFD. In second place in terms of the number of visitors to the Southern Federal District are graduates of the universities of the North Caucasus Federal District. It is adjacent to the Southern Federal District and most likely has fewer job opportunities, so graduates are forced to migrate. Almost the same number of arrivals and departures is observed with the Far Eastern, Northwestern and Ural federal districts. 48% more graduates migrate from the Central Federal District to the Southern Federal District in order to find employment than from the Southern Federal District to the Central Federal District (seeMaslyukov and Maskaev, 2019).

Theoretical and Empirical Researches in Urban Management
Volume 15 Issue 4 / November 2020

TABLE 1 - MIGRATION OF UNIVERSITY GRADUATES

	The number of university graduates from other federal districts who came to the Southern Federal District	The number of university graduates who left the Southern Federal District for other federal districts
Saint Petersburg	462	2140
Moscow	4403	8877
Central Federal District	2443	1644
Northwestern Federal District	311	277
Volga Federal District	2521	1348
North Caucasian Federal District	3123	1292
Ural federal district	663	817
Siberian Federal District	885	263
Far Eastern Federal District	216	205

SOURCE: Own results based on data from the Graduate Employment Portal (2020)

In the event of negative changes in the higher education system in the region, there may be an increase in official unemployment and informal employment, which also affect the unemployment and informal employment rates in neighboring regions. In Russian conditions, there are alarming trends in the development of the higher education system associated with a reduction in the number of educational institutions and students. These trends are a consequence of the policy of optimization of the Russian higher education system, which has been pursued since 2012. Thus, the total number of educational institutions of higher education and scientific organizations at the beginning of the 2010/2011 academic year in the Southern Federal District was 85, at the beginning of the 2018/2019 academic year - 61, and the total number of students enrolled in undergraduate, specialist, and graduate programs has decreased during this period from 490.9 thousand people. Up to 418.3 thousand people (Federal State Statistics Service, 2019b).

Thus, negative changes in higher education in one region are associated with the growing formation of the precariat in neighboring regions, which requires an assessment of the spatial effects of informal employment.

3. DATA AND VARIABLES

The empirical base of the study was formed on the basis of information presented on the official website of the Federal State Statistics Service for the period from 2010 to 2016. Our model includes the following variables (for constituent entities of the Russian Federation, a total of 80 constituent entities[1]):

[1] In the study, the constituent regions - the Tyumen region and the Arkhangelsk region are considered as single regions. The Republic of Crimea and the city of Sevastopol were excluded from the analysis due to the lack of statistical data on individual innovators.

d_inf_emp – Employed in the informal sector in% of the total employed population *(dependent variable)*

Independent variables:

unemp - unemployment rate, %;

rGRPpc – logarithm of Gross Regional Product per capita (in 2010 prices);

rInv – the logarithm of the volume of investment in fixed assets per capita (in 2010 prices);

wage – logarithm of the average monthly accrued wages of employees of organizations (in 2010 prices)

enterprise – the logarithm of the average annual number of enterprises and organizations;

avtime – average time of job search by the unemployed, months;

over_year – share of unemployed looking for work 12 months. and more, %

imigr – coefficients of migration growth per 10,000 people.

Table 1 shows the coefficients of variation of the indicator ***d_inf_emp*** – employed in the informal sector as% of the total employed population of the regions in the period 2010-2016 As can be seen from the table, in general, despite the observed slight decrease in the variation of this indicator, there is a heterogeneity of regions in terms of the level of employment development in the informal vector.

TABLE 1 - COEFFICIENTS OF VARIATION OF THE INDICATOR D_INF_EMP (EMPLOYED IN THE INFORMAL SECTOR IN% OF THE TOTAL EMPLOYED POPULATION)

2010	2011	2012	2013	2014	2015	2016
0,482	0,424	0,415	0,450	0,444	0,443	0,429

SOURCE: Own results

Spatial autocorrelation of the share of employment in the informal sector. To test the hypothesis about the influence of the spatial location of regions on the distribution of the share of employees in the informal sector, let us consider the values of the global spatial autocorrelation indices of Moran and Geary:

$$Moran's\ I = \frac{N}{\sum_i \sum_j w_{ij}} * \frac{\sum_i \sum_j w_{ij}\,(y_i - \bar{y})(y_j - \bar{y})}{\sum_i (y_i - \bar{y})^2}$$

$$Geary's\ C = \frac{N-1}{2\sum_i \sum_j w_{ij}} * \frac{\sum_i \sum_j w_{ij}\,(y_i - y_j)^2}{\sum_i (y_i - \bar{y})^2}$$

Where N – sample size, w_{ij} – matrix element W spatial interaction of regions i and j, y_i – indicator value y in the region i, $\bar{y}$ – mean y.

We will use the following matrices as spatial weights:

1. matrix of inverse geographic distances between the centroids of the corresponding administrative units W^c:

Theoretical and Empirical Researches in Urban Management
Volume 15 Issue 4 / November 2020

$$w_{ij}^{c} = \frac{1}{dist_{ij}}$$

where $dist_{ij}$ is the geographical distance between the centroids of regions i and j ($i \neq j$).

2. matrix of inverse shortest road distances W^a:

$$w_{ij}^{a} = \frac{1}{dist\_avto_{ij}}$$

where $dist\_avto_{ij}$ – the shortest distance between the administrative centers of regions i and j ($i \neq j$) by road, calculated using the information resource Avtodispetccher (2020).

Since the regions of Moscow and the Moscow Region, St. Petersburg and the Leningrad Region have the same administrative centers, for calculating purposes the coordinates of the cities of federal significance were set so that the distance to the corresponding administrative center was not zero, but equal to 1 km.

The values of the Moran and Geary indices for the variable **d_inf_emp** (employed in the informal sector as a% of the total employed population) are shown in Table 2.

TABLE 2 - MORAN'S AND GEARY'S INDICES FOR THE D_INF_EMP VARIABLE

year	W^c	z	p-value*	W^a	z	p-value*
$Moran's\ I$						
2010	0,290	14,563	0,000	0,338	9,258	0,000
2011	0,235	11,880	0,000	0,304	8,338	0,000
2012	0,249	12,476	0,000	0,317	8,630	0,000
2013	0,265	13,426	0,000	0,316	8,747	0,000
2014	0,281	14,310	0,000	0,321	8,927	0,000
2015	0,279	14,129	0,000	0,319	8,828	0,000
2016	0,266	13,524	0,000	0,294	8,174	0,000
$Geary's\ C$						
2010	0,723	-7,321	0,000	0,692	-5,500	0,000
2011	0,766	-6,577	0,000	0,734	-4,972	0,000
2012	0,760	-7,349	0,000	0,729	-5,389	0,000
2013	0,764	-5,870	0,000	0,732	-4,562	0,000
2014	0,748	-5,919	0,000	0,728	-4,414	0,000
2015	0,743	-6,325	0,000	0,721	-4,707	0,000
2016	0,754	-6,005	0,000	0,730	-4,507	0,000

Note: *2-tail test
SOURCE: Own results

Moran's diagrams (for spatial matrices of inverse geographic distances between the centroids of the corresponding administrative units Wc and inverse shortest road distances Wa) for the variable d_inf_emp (Employed in the informal sector in% of the total employed population) are presented in Fig. 1-2. Most regions are located in the first and third quadrants. The upper right quadrant includes regions with relatively high values of their own indicator, surrounded by regions with also high values of the analyzed

indicator. In the lower left quadrant, regions are grouped that are characterized by relatively low values of their own indicator surrounded by neighbors with also low values of the analyzed indicator.

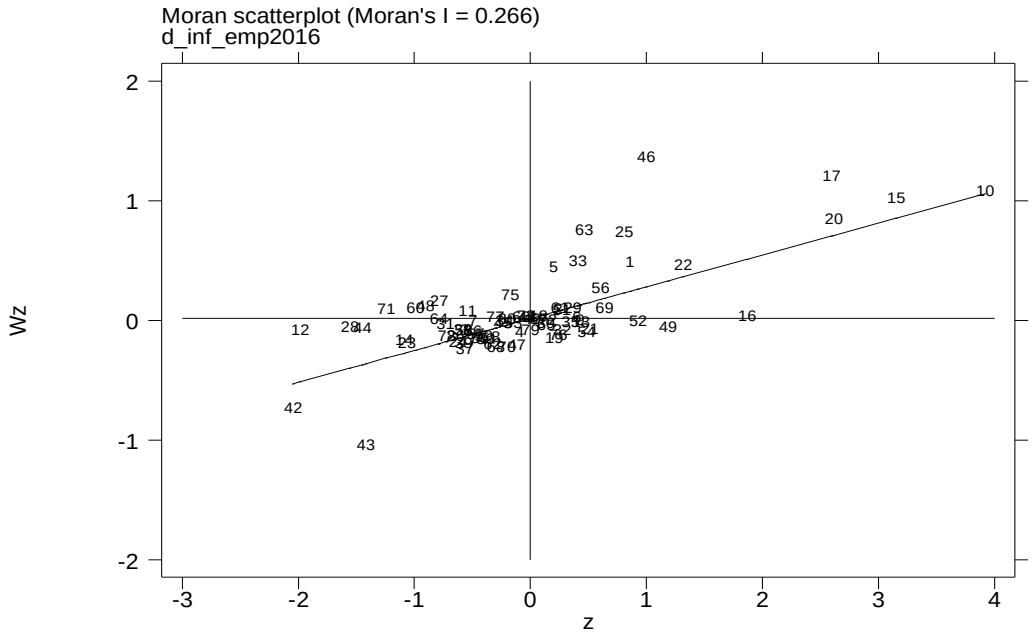

FIGURE 1- MORAN'S SCATTER PLOT FOR THE VARIABLE D_INF_EMP (EMPLOYED IN THE INFORMAL SECTOR IN% OF THE TOTAL EMPLOYED POPULATION), 2016, A MATRIX OF INVERSE GEOGRAPHIC DISTANCES BETWEEN THE CENTROIDS OF THE REGIONS WC WAS USED
SOURCE: Own results

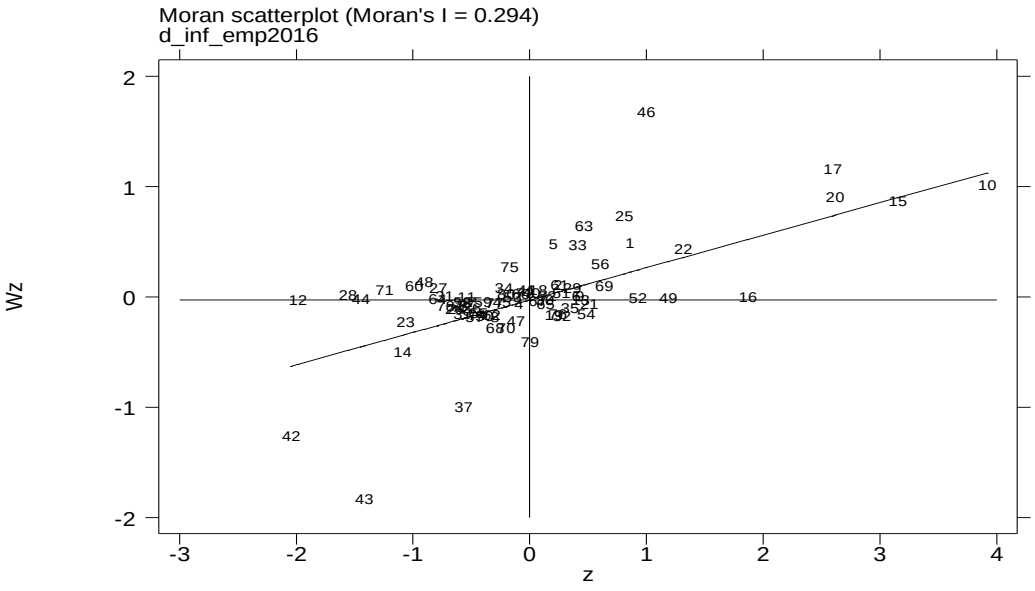

FIGURE 2- MORAN'S SCATTER PLOT FOR THE VARIABLE D_INF_EMP (EMPLOYED IN THE INFORMAL SECTOR IN% OF THE TOTAL EMPLOYED POPULATION), 2016, USING THE MATRIX OF INVERSE SHORTEST ROAD DISTANCES WA
SOURCE: Own results

Theoretical and Empirical Researches in Urban Management
Volume 15 Issue 4 / November 2020

Theoretical and Empirical Researches in Urban Management
Volume 15 Issue 4 / November 2020

The persistently positive statistically significant values of the Moran and Geary indices for the variable d_inf_emp indicate the presence of spatial autocorrelation, which allows us to make the assumption that the indicators of informal employment in neighboring regions are positively correlated.

4. SPATIAL MODELS ON PANEL DATA

Following Elhorst (2014), we analyze the influence of the selected characteristics on the level of employment development in the informal sector by considering a generalized spatial model with a spatial lag of the dependent and independent variables of the following form as the basic equation:

$$y = \rho W y + X\beta + WX\gamma + u,$$
$$u = \lambda W u + \varepsilon$$

where Y - dependent variable;

X - independent or explanatory variables;

W – spatial matrix of weights;

ρ – spatial correlation coefficient;

λ - spatial correlation coefficient in residuals;

γ - spatial correlation coefficient for independent variables;

β – the vector of the estimated regression coefficients for the X factors;

ε – regression residuals.

The calculations were performed using different spatial weighting matrices (matrices of inverse geographic distances between the centroids of the corresponding administrative units W^c and matrices of inverse shortest road distances W^a). Then, using LM tests and Hausman tests for random and fixed effects, a procedure was carried out to find the best model specification. The best model for describing data is the Spatial Durbin Model (SDM):

$$y = \rho W y + X\beta + WX\gamma + \varepsilon,$$
$$\varepsilon \sim N(0, \sigma^2 I_N)$$

In the specification under consideration, the model includes the spatial lag of the dependent variable and the spatial lags of the independent variables *avtime* (average time of finding a job by the unemployed), *over_year* (the proportion of unemployed looking for work for 12 months or more) and *imigr* (coefficients of migration growth per 10,000 population). The results of evaluating the SDM model using spatial weighting matrices are shown in Tables 3-4.

TABLE 3 - RESULTS OF SDM-MODEL ASSESSMENT USING THE MATRIX OF INVERSE GEOGRAPHIC DISTANCES BETWEEN THE CENTROIDS OF THE CORRESPONDING ADMINISTRATIVE UNITS Wc

Variables	odds	Direct effects	Indirect effects	General effects
Unemployment rate, *unemp*	-0,4747450*** (0,0707607)	-0,7318214*** (0,256957942)	-0,084483579 (0,0643876507)	-0,81630499*** (0,21169023)
Logarithm of GRP per capita, *log(rGRPpc)*	3,8847153* (2,0292432)	5,98830478* (4,133720201)	0,6913072078 (0,7159132014)	6,679611984* (3,93370059)
Logarithm of the volume of investments in fixed assets per capita, *log(rInv)*	-2,5761297*** (0,6455050)	-3,9711146*** (1,669250373)	-0,458436944 (0,3956039861)	-4,42955154*** (1,46852069)
Logarithm of the average monthly wages of employees of organizations, *log(wage)*	6,2464603** (2,8722177)	9,62894461* (5,484690780)	1,1115931904 (0,9187584119)	10,740537800** (5,46668699)
Logarithm of the average annual number of enterprises and organizations, *log(enterprise)*	-4,8111693** (2,1271148)	-7,41643743* (4,279438295)	-0,856174969 (0,6972608156)	-8,272612403** (4,19392901)
Average time spent looking for a job by the unemployed, *avtime*	0,2301986 (0,4356542)	0,35485208 (0,853101502)	0,0409651497 (0,1289882321)	0,395817231 (0,85650609)
Share of unemployed looking for work 12 months and more, *over_year*	-0,0478521 (0,0535139)	-0,07376423 (0,113212272)	-0,008515556 (0,0189530843)	-0,082279787 (0,11034704)
Migration growth rate, *imigr*	-0,0025425 (0,0046096)	-0,00391932 (0,008156687)	-0,000452458 (0,0008349095)	-0,004371778 (0,00870329)
Spatial lag of the variable Average time spent looking for a job by the unemployed, *slag(avtime)*	4,5491020** (1,8965740)	7,01245967** (4,087189215)	0,8095386079 (0,7290558387)	7,821998276** (3,92059467)
Spatial lag of the variable Share of unemployed looking for work 12 months and more, *slag(over_year)*	-0,5053361** (0,2322987)	-0,77897771* (0,506363283)	-0,089927438 (0,0871775243)	-0,868905149** (0,48736257)
Spatial lag of the variable Coefficient of migration growth, *slag(imigr)*	-0,0350048 (0,0241407)	-0,05396000 (0,047785698)	-0,006229298 (0,0059973792)	-0,060189296 (0,04944811)
Spatial autoregressive coefficient ρ *(Spatial autoregressive coefficient ρ)*	0,418422*** (0,092532)			

Note: Standard errors are shown in parentheses. *, **, *** - significance at 10, 5, 1st significance level, respectively.
SOURCE: Own results

Theoretical and Empirical Researches in Urban Management
Volume 15 Issue 4 / November 2020

TABLE 4 - THE RESULTS OF EVALUATING THE SDM-MODEL USING THE MATRIX OF INVERSE SHORTEST ROAD DISTANCES WA:

Variables	odds	Direct effects	Indirect effects	General effects
Unemployment rate, *unemp*	-0,491178*** (0,0701533)	-0,671708*** (0,151451452)	-0,0971548*** (0,0228113088)	-0,76886329*** (0,149809996)
Logarithm of GRP per capita, *log(rGRPpc)*	4,1121873** (2,0100597)	5,623604248* (3,124746519)	0,8133889591* (0,3945852108)	6,436993207* (3,431999261)
Logarithm of the volume of investments in fixed assets per capita, *log(rInv)*	-2,676898*** (0,6380717)	-3,6607809*** (1,113331729)	-0,52948938*** (0,1533784154)	-4,1902702*** (1,160498306)
Logarithm of the average monthly wages of employees of organizations, *log(wage)*	7,4676267*** (2,7597962)	10,212321247** (4,231285166)	1,4770935121** (0,5732095701)	11,689414759** (4,548889030)
Logarithm of the average annual number of enterprises and organizations, *log(enterprise)*	-4,4136442** (2,1199046)	-6,035860445** (3,166310945)	-0,8730170239* (0,4069748202)	-6,908877469** (3,501430237)
Average time spent looking for a job by the unemployed, *avtime*	0,2639316 (0,4339274)	0,360938523 (0,648168770)	0,0522055601 (0,0837027171)	0,413144083 (0,727408114)
Share of unemployed looking for work 12 months and more, *over_year*	-0,0501443 (0,0533249)	-0,068574690 (0,079982718)	-0,0099185315 (0,0101119231)	-0,078493222 (0,089123080)
Migration growth rate, *imigr*	-0,0024576 (0,0045967)	-0,003360815 (0,006732909)	-0,0004861028 (0,0008507266)	-0,003846918 (0,007518205)
Spatial lag of the variable Average time spent looking for a job by the unemployed, *slag(avtime)*	4,9520034*** (1,8742766)	6,772091174** (2,827489716)	0,9795042376** (0,3733848473)	7,751595412** (3,052786637)
Spatial lag of the variable Share of unemployed looking for work 12 months and more, *slag(over_year)*	-0,5574197** (0,2283150)	-0,762296967** (0,350902220)	-0,110257392** (0,0455998039)	-0,872554359** (0,381647077)
Spatial lag of the variable Coefficient of migration growth, *slag(imigr)*	-0,0357616 (0,0240471)	-0,048905690 (0,034515314)	-0,0070736394 (0,0041668429)	-0,055979330 (0,037725786)
Spatial autoregressive coefficient ρ *(Spatial autoregressive coefficient ρ)*	0,361163*** (0,075323)			

Note: Standard errors are shown in parentheses. *, **, *** - significance at 10, 5, 1% significance level, respectively.

To interpret the results of estimates of spatial models, the values of direct, indirect and general effects are used. The direct effect is defined as the average (across all regions) change in the level of informal

employment in a region when the ith factor changes in the same region. An indirect effect (overflow effect) is the average change in the level of informal employment in a region with a change in the ith factor in all other regions. The overall effect is the sum of direct and indirect effects, i.e. the average change in the level of informal employment in a given region in the event of a change in the ith factor in all regions. The marginal effects for the variable unemployment rate have the same signs and are statistically significant, which suggests that higher unemployment rates in this and other regions lead to lower informal employment in this region. It is believed that an increase in unemployment means a decrease in employment opportunities in the formal sector, and therefore, has a positive effect on the development of informal employment. However, this conclusion was not confirmed on Russian data. The unemployment rate allows us to characterize the macroeconomic situation. With an increase in unemployment, the demand for employment, both formal and informal, will decrease. Accordingly, the more economically attractive a region is, the more attractive it becomes for the development of not only the formal but also the informal sectors of the economy. This conclusion is consistent with the results presented in the work of Nureev and Akhmadeev (2019).

Gross regional product per capita is the most well-known and widely used indicator that measures the results of aggregate economic activity in a region. The positive influence of the gross regional product per capita on the level of development of informal employment can be explained by the fact that the higher the level of development of the regional economy, the more reason to expect large-scale development of both the formal and informal sectors. Similar conclusions were made in a study by Gimpelson and Zudina (2011).

The direction of the influence of investment in fixed assets per capita corresponds to the expected one: it is traditionally believed that there is an inverse relationship between the amount of investment and informal employment, which is also confirmed by the results of this study.

The value of the average monthly accrued wages of employees of organizations in a constituent entity of the federation allows us to imagine the degree of attractiveness of the formal sector for employees. In this case, based on the revealed positive influence of this factor on the development of informal employment, it can be assumed that with the growth of this indicator in the region there are more funds and opportunities to use them in the informal sector. “The peculiarity of Russia is that the legalization of a number of sectors of the service sector has not yet been completed. Therefore, the growth of incomes of the population can be expressed in the fact that a number of services they need are not accompanied by the observance of all formalities, i.e. is actually carried out illegally " (Nureev and Akhmadeev, 2015).

An increase in the average annual number of enterprises and organizations in the region contributes to a decrease in the level of informal employment. This fact indicates that the growth in the number of

Theoretical and Empirical Researches in Urban Management
Volume 15 Issue 4 / November 2020

enterprises and organizations contributes to the legalization of business, and, accordingly, reduces the level of informal employment.

The indicators avtime (the average time of finding a job by the unemployed), over_year (the proportion of unemployed looking for a job for 12 months or more), and imigr (coefficients of migration growth) turned out to be statistically insignificant. However, a significant positive coefficient was found in the spatial lag of the avtime variable: with an increase in the average time of job search for unemployed people in neighboring regions, the level of informal employment in other regions increases. This conclusion may be related to the fact that people are forced to temporarily move to informal places in neighboring regions until they find a suitable legal job in their region. There is also a significant negative coefficient for the spatial lag of the over_year variable: an increase in the proportion of unemployed looking for work for 12 months. and more, the region increases the level of informal employment in neighboring regions, which can also be explained by the fact that a long search for work inclines individuals to informal employment, and it significantly increases only in neighboring regions: people desperate to find work in their region, hoping to find workplace ready to move to neighboring regions.

5. FIXED EFFECTS MODEL WITHOUT SPATIAL STRUCTURE

Let us compare the results obtained in the previous paragraph with the results obtained using the fixed effects model. The results of estimating the model using the standard method for estimating panel data with fixed effects - “within” estimates, are presented in Table 5.

The signs of the coefficients of the model with fixed effects without taking into account the spatial structure coincide with the signs of the coefficients of the SDM models, however, the statistically significant coefficients are the variables unemp (unemployment rate), log(rGRPpc) (logarithm of GRP per capita), log(rInv) (logarithm of the volume of investment in fixed assets per capita) and log(wage) (logarithm of the average monthly wages of employees of organizations). It should be noted that in the model with fixed effects without taking into account the spatial structure, the coefficients for these variables are higher in absolute value than in spatial models. Perhaps due to the lack of consideration of the spatial structure, they are displaced.

In the case of modeling employment in the informal sector using the classical model with fixed effects without taking into account the spatial structure, the coefficient of the variable log(enterprise) (the logarithm of the average annual number of enterprises and organizations) is not statistically significant. Taking into account spatial dependence makes it possible to reveal this relationship, which is important to consider when choosing a regional policy.

TABLE 5 - RESULTS OF EVALUATING THE MODEL WITH FIXED EFFECTS (EXCLUDING SPATIAL STRUCTURE)

Variables	Fixed Effects Model
constant	-
Unemployment rate, *unemp*	-0,55213754*** (0,07753402)
Logarithm of GRP per capita, *log(rGRPpc)*	7,62347594*** (2,16696167)
Logarithm of the volume of investments in fixed assets per capita, *log(rInv)*	-3,91920333*** (0,66352809)
Logarithm of the average monthly wages of employees of organizations, *log(wage)*	9,44799681*** (2,61019770)
Logarithm of the average annual number of enterprises and organizations, *log(enterprise)*	-3,43195004 (2,36380348)
Average time spent looking for a job by the unemployed, *avtime*	0,70488296 (0,47568729)
Share of unemployed looking for work 12 months and more, *over_year*	-0,09731364 (0,05916848)
Migration growth rate, *imigr*	-0,00068178 (0,00513737)
R-Squared: 0,33357 Adj. R-Squared: 0,21073 F-statistic: 29,5312 on 8 and 472 DF, p-value: < 2,22e-16	

Note: Standard errors are shown in parentheses. ·, *, **, *** - significance at 10, 5, 1% significance level, respectively.
SOURCE: Own results

6. CONCLUSIONS

Overall, it appears such factors as the employment in the informal sector and the lack of decent working conditions have a negative impact on the quality of human capital and social interaction in society. Studying employment in the informal sector can help to understand its role as a social indicator of inequality and precarization, and a general decline in the level of employment in the informal sector can significantly improve the welfare and standard of living of the population in urban and regional centers.

Our results show that the estimates obtained using the SDM model, taking into account spatial effects, make it possible to reveal the influence on employment in the informal sector of the variable “average annual number of enterprises and organizations in the city or region”, as well as spatial lags of the variables “average time of job search unemployed "and" the share of unemployed looking for work 12 months. and more”, which was not possible in the case of model estimation without including spatial effects. The statistical significance of the corresponding coefficients in the SDM model, taking into account spatial effects, allows us to draw the following conclusions: First, the growth of the average annual number of enterprises and organizations in the region contributes to a decrease in the level of informal employment in this region. Second, with an increase in the average time of finding a job for the unemployed in neighboring regions, the level of informal employment in other regions increases. Third, an increase in the share of unemployed looking for work 12 months and more, the city or region increases the level of informal employment in neighboring cities or regions.

Theoretical and Empirical Researches in Urban Management
Volume 15 Issue 4 / November 2020

Significant influence of the factors unemp (unemployment rate), log (rGRPpc) (logarithm of GRP per capita), log (rInv) (logarithm of the volume of investments in fixed assets per capita) and log (wage) (logarithm of the average monthly accrued wages of employees of organizations) the level of informal employment in the region is confirmed both in the classical model with fixed effects without taking into account the spatial structure, and in SDM-models, however, in the classical model with fixed effects, the coefficients for these variables are higher in modulus than in spatial SDM-models, which can be associated with obtaining biased estimates without taking into account the spatial structure.

The significance of the weighted value of the level of informal employment in other cities and regions included in the regression model (the spatial lag of the dependent variable) indicates the presence of mutual spatial correlation between neighboring regions. Therefore, measures aimed at reducing the level of informal employment in the city or region would have an impact on neighboring cities and regions, while the closer the region is, the stronger this impact. An important future research goal is the development and evaluation of government programs, both at the macro and regional levels, that effectively reduce informal employment and labor market tensions and their associated impact on living standards. What is needed is not isolated measures, but the implementation of a systemic state policy that affects groups of regions and takes into account the impact of measures applied to specific regions on neighboring labor markets.

The most important of these measures can be considered measures for the development and adaptation of higher education programs to changes in regional labor markets. Therefore, the dynamics of the number of graduates should be considered along with changes in the number of enterprises and indicators of employment in the region and adjoining regions. In the case of multidirectional changes: an increase in the number of graduates and a decrease in employment and enterprises, this can lead to an increase in informal employment and, consequently, the precarization of university graduates.

The employment insecurity that accompanies informal employment can be viewed in the context of spatial effects. Therefore, changes in supply and demand in the labor market can also be viewed through the prism of spatial overflows of university graduates looking for the most profitable ways of employment, taking into account the qualifications obtained by the parameters of regional labor markets. Thus, the instability of employment in one region may be associated with precarization in another region. Consequently, the policy of reducing the negative effects of precarization of employment should take into account spatial regional characteristics which can serve as a subject for further research.

ACKNOWLEDGMENTS

This research was supported by the Russian Foundation for Basic Research (project No. 19-010-00651) “University graduates as a new precariat”.

REFERENCES

Ahmed, A., Korah, P. I., Dongzagla, A., Nunbogu, A. M., Niminga-Beka, R., Kuusaana, E. D., & Abubakari, Z. (2020). City profile: Wa, Ghana. *Cities*, 97, 102524. https://doi.org/10.1016/j.cities.2019.102524

Avtodispetccher (2020). *Cargo and loads database*. Available at: https://www.avtodispetcher.ru. Accessed on 06 August 2020

Baptista, I. (2019). Electricity services always in the making: Informality and the work of infrastructure maintenance and repair in an African city. *Urban Studies*, 56(3), 510-525. https://doi.org/10.1177/0042098018776921

Bertolin, J. (2018). Higher Education and Development in the Knowledge Society. *Higher Education for the Future*, 5(2), 122–141. https://doi.org/10.1177/2347631118767279

Bobkov, V. N., Odegov, Y. G., & Pavlova, V. V. (2018). Precarious employment in present-day Russia: Relevant worker profiles. *International Journal of Engineering & Technology*, 7(4.38), 72-77. https://doi.org/10.14419/ijet.v7i4.38.24325

Chung, H., Muntaner, C., Benach, J., & EMCONET Network. (2010). Employment relations and global health: a typological study of world labor markets. *International Journal of Health Services*, 40(2), 229-253. https://doi.org/10.2190/HS.40.2.e

Demidova, O. (2014). Spatial-autoregressive model for the two groups of related regions (eastern and western parts of Russia). *Applied Econometrics*, 34(2), 19-35.

Elhorst, J. P. (2003). The mystery of regional unemployment differentials: Theoretical and empirical explanations. *Journal of Economic Surveys*, 17(5), 709-748. https://doi.org/10.1046/j.1467-6419.2003.00211.x

Elhorst, J. P. (2014). *Spatial econometrics: from cross-sectional data to spatial panels*: Berlin: Springer.

Etzkowitz, H. (2019). The second academic revolution: antecedents and consequences of academic entrepreneurship. In *Handbook of Universities and Regional Development* (pp. 29–43). https://doi.org/10.4337/9781784715717.00009

Federal State Statistics Service (2019a). *Labor Survey 2019*. Available at: https://rosstat.gov.ru/folder/11110/document/13265 Accessed on 29 July 2020

Federal State Statistics Service (2019b). *Regions of Russia. Social and Economic Indicators*. Available at: https://gks.ru/bgd/regl/b19_14p/Main.htm Accessed on 04 August 2020

Fedorov, G., Mikhaylov, A. (2019). Socioeconomic asymmetry in regional development across Russia, *Theoretical and Empirical Researches in Urban Management*, 14(4), 35-52.

Gimpelson, V., & Zudina, A. (2011). Informal Workers in the Russian Economy: Who Are They and How Many? *Voprosy Economiki*, 10, 53-76. https://doi.org/10.32609/0042-8736-2011-10-53-76

Gimpel'son, V., & Zudina, A. (2012). " Informals" in the Russian Economy: How Many of Them and Who Are They? *Problems of Economic Transition*, 55(5), 26-57. https://doi.org/10.2753/PET1061-1991550502

Graduate Employment Portal (2020) *Data on the higher education*. Available at: http://graduate.edu.ru/ Accessed on 05 August 2020

Kapeliushnikov, I. (2013). Informality in the Russian Labor Market: What Do Alternative Definitions Tell Us? *Journal of the New Economic Association*, 20(4), 52-83.

Lottmann, F. (2012). Spatial dependencies in German matching functions. *Regional Science and Urban Economics*, 42(1-2), 27-41. https://doi.org/10.1016/j.regsciurbeco.2011.04.007

Theoretical and Empirical Researches in Urban Management
Volume 15 Issue 4 / November 2020

Markov V. A. (2015) Information technology and spatial models in the analysis of regional localization and globalization of unemployment. *Information Security of Regions*, 2 (19), 21-27.

Maslyukova, E. V., Maskaev, A. I. (2019). Institutional change in higher education and precariat. *Journal of Institutional Studies*, 11(4), 141-155. https://doi.org/10.17835/2076-6297.2019.11.4.141-155

Muntaner, C., Chung, H., Benach, J., & Ng, E. (2012). Hierarchical cluster analysis of labour market regulations and population health: a taxonomy of low-and middle-income countries. *BMC Public Health*, 12(1), 286. https://doi.org/10.1186/1471-2458-12-286

Nureev, R. M., & Akhmadeev, D. R. (2015). Formal and Informal Employment as' Twins Brothers': Modern Russian Practice. *Terra Economicus*, 13(3), 16-33. https://doi.org/10.18522/2073-6606-2015-3-16-33

Nureev, R. M. and Akhmadeev, D. R. (2018). *Informal employment: origins, current state and development prospects (experience of institutional analysis*) : KNORUS.

Omelyanenko, V., Semenets-Orlova, I., Khomeriki, O., Lyasota, L., & Medviedieva, Y. (2018). Technology transfer management culture (education-based approach). *Problems and Perspectives in Management*, 16(3), 454-463. https://doi.org/10.21511/ppm.16(3).2018.36

Oshchepkov, A. Y., & Kapeliushnikov, R. I. (2015). *Regional labour markets: 15 years of differences*: Working paper WP3/2015/10. Moscow, HSE Publ. House.

Rusanovskiy, V. A., & Markov, V. A. (2016). Influence of the spatial factor on the regional differentiation of unemployment in the Russian economy. *Studies on Russian Economic Development*, 27(5), 593-604. https://doi.org/10.1134/S1075700716050129

Semerikova, E. V., & Demidova, O. A. (2016). Interaction of Regional Labour Markets in Russia: Spatial Econometric Analysis. *Prostranstvennaya Ekonomika*, (3), 57-80. https://doi.org/10.14530/se.2016.3.057-080

Simutina, N. L., Leventov, N. N., & Puzikova, O. P. (2018). The Impact of Economic Factors on the Employment Rate in the Informal Sector: Regional Aspect. *Prostranstvennaya Ekonomika*, (1), 83-100. https://doi.org/10.14530/se.2018.1.083-100

Standing, G. (2013). Inequality, Class and the 'Precariat.' In Work after Globalization. https://doi.org/10.4337/9781849802376.00009

Strielkowski W, Kalyugina S, Mukhoryanova O (2019) Managing human potential and youth social entrepreneurship in peripheral regions. *Management Research & Practice* 11(3):41-51

Titus, M. A. (2009). The Production of Bachelor's Degrees and Financial Aspects of State Higher Education Policy: A Dynamic Analysis. *The Journal of Higher Education*, 80(4), 439–468. https://doi.org/10.1080/00221546.2009.11779024

Toshchenko, Z. T. (2015). Precariat-new social class. *Sotsiologicheskiya issledovaniya*, 6, 3-13.

Volchik, V. V., & Posukhova, O. Y. (2016). Precarity and professional identity in the context of institutional change. *Terra Economicus*, 14(2), 159-173. https://doi.org/10.18522/2073-6606-2016-14-2-159-173

Yahmed, S. B. (2018). Formal but less equal. Gender wage gaps in formal and informal jobs in urban Brazil. *World Development*, 101, 73-87. https://doi.org/10.1016/j.worlddev.2017.08.012

Zierahn, U. (2012). The importance of spatial autocorrelation for regional employment growth in Germany. *Jahrbuch für Regionalwissenschaft*, 32(1), 19-43. https://doi.org/10.1007/s10037-011-0062-x