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MODELING THE INFLUENCE OF SPATIAL FACTORS ON THE SOCIO-ECONOMIC PROCESSES IN A HETEROGENEOUS COUNTRY BY THE EXAMPLE OF RUSSIA

Dissertation Summary

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1. Motivation

The topics related to modeling the main economic indicators, such as the unemployment rate, economic growth rates, etc., will never lose their importance . While previously the corresponding indicators were studied mainly for the country as a whole, in the recent years there has been a trend towards more detailed modeling of these indicators at the regional level. However, regions of one and the same country do not develop in isolation, the processes in them are interconnected, and there are integrated cultural and information fields, flows of goods, services, capital, and migrants between regions, etc. The mutual influence of the regions must be taken into account. It is one of the types of spatial factors which is considered in this study.

In the same way, when studying social processes, for example, the level of citizens' trust in the main socio-political institutions, etc., it is desirable to take into account regional factors. If the study was conducted using the data for residents of different countries (regions), then it is necessary to take into account the fact that some respondents live in the same country (or in the same region). This is another type of a spatial factor that will be discussed. The size of the settlement in which the respondent lives is also important. Residents of large cities and rural areas often have different attitudes towards these institutions, vote differently during elections, etc. Therefore, the factors that make it possible to take into account the place of individuals' residence are also considered in this study as spatial.

If spatial factors are not taken into account in models, then a problem of an omitted variable bias may appear. As a result, when modeling the indicators of interest, the influence of some factors may be mistakenly attributed as insignificant or will be underestimated or overestimated. This can lead to incorrect policy implications. Therefore, it is desirable to assess the scale of the problem arising from the omission of spatial factors.

However, it is rather difficult to assess in detail the mutual influence of regions, of residents of the same countries or regions etc., and it is advisable not to use too cumbersome models with a large number of additional parameters. A compromise option in this case is application of spatial-econometric models, in which the influence of other regions is taken into account by introducing weighting matrices containing pre-fixed weights which reflect the influence of other regions on the selected region (usually, the weights for neighboring regions are larger). At the same time, the number of estimated parameters increases insignificantly. A brief description of classical spatial-econometric models is given in the section "Description of the research methodology", more detailed information can be found, for example, in (Elhorst, 2014), there is also a popular and reproduced in many scientific articles scheme for choosing the specification of a spatial model (Elhorst, 2014 , p.9). However, over time, the mechanical use of the corresponding scheme began to be criticized, even a special issue of the influential in the spatial econometrics field Journal of Regional Science (2012 , vol. 52, No. 2) was published. This special issue was devoted to the criticism of an oversimplified approach. It became obvious that in some cases the assumptions underlying spatial models are too strong and often do not hold for large and heterogeneous countries, including Russia. Different parts of the same country may have different spatial mechanisms, the sensitivity of regions to the influence of other regions may be different for all regions, etc. All of this indicates the need for further development of spatial-econometric models, the use of more flexible functional forms for the study of economic processes taking place in Russia. Most of the dissertation work is devoted to the development of this direction.

In addition, it is important to develop tools that allow taking into account regional factors and assessing their importance (in comparison with the individual characteristics of respondents) when modeling the degree of residents' trust in different countries (including Russia) to the main socio-political institutions, immigrants, etc. This is the subject of the second part of the study.

Based on the foregoing, the goal of the study was formulated.

2. Aim of the research

The aim of this dissertation is to develop econometric tools for modeling socio-economic processes in geographically, economically, in terms of education and cultural values, etc. heterogeneous country Russia, taking into account spatial factors.

Before setting specific objectives to achieve this goal, we will give a brief overview of what has been done in this area and designate the unfilled, but, from our point of view, interesting gaps.

3. Brief literature review

Economic growth rates, unemployment, employment, wages are important regional economic indicators. The first part of this section provides a brief overview of the papers devoted to the modeling of these indicators, using Russian regional data. The emphasis is on the papers that take into account spatial factors. Let us note the important and very common terms in the field of spatial econometrics. Changes that have occurred in a certain region can affect economic processes in this region, and economic processes in other regions. In the first case we talk about direct spatial effects, and in the second case we talk about indirect spatial effects.

The second part of the review is devoted to the modeling the degree of trust to the main socio-political institutions and immigrants for the citizens of different countries and regions, taking into account not only their individual characteristics, but also the socio-economic indicators of the countries or regions in which they live.

3.1. Modeling the economic growth of regions taking into account spatial factors

The spatially econometric approach to modeling the economic growth rates has been applied in articles using empirical data from the United States (Rey, Montouri, 1999; Hammond, Tosun, 2011; Pede, 2013; Ojede et al., 2018), China (Ying, 2003; Yu , Wei, 2008; Tian et al., 2010), the European Union (Armstrong, 1995; López-Bazo et al., 1999; Rodríguez-Pose, 1999; Fingleton, 2001, Arbia, Piras, 2005; Fingleton, López-Bazo , 2006; Olejnik, Olejnik, 2017; Le Gallo, Ertur, 2019; Antunes, 2020; Amidi et al., 2020; Cartone et al., 2021), individual EU countries, in particular Germany (Niebuhr, 2001), Italy (Arbia et al., 2005; Mazzola et al., 2018), Spain (Ramajo et al., 2017).

In all cases, the existence of spatial effects reflecting the influence of regions on each other was empirically demonstrated. Traditional spatial-econometric models and schemes for choosing between them were commonly used in these works (Elhorst, 2014, p. 9). However, many researchers noted that these models and schemes are well suited for homogeneous countries, but require refinement and a more flexible approach for large and heterogeneous countries. As an alternative, a center-periphery model was proposed (Annoni et al., 2019), the division of regions into clubs (Baumont et al., 2003; Postiglione et al., 2013; Fischer, LeSage, 2015; Fiaschi et al., 2018; Zhang et al., 2019; Mazzola, Pizzuto, 2020), but the influence of different groups of regions on each other was usually not modeled. One of the most recent reviews on the spatial aspects of endogenous growth is (Bond-Smith, McCann, 2021). It discusses, among other things, a theoretical model of growth for two interacting regions, the mechanisms due to which spillover effects arise. But this article does not contain empirical calculations.

Another suggestion was to use the Bayesian (Fischer, LeSage, 2015; Piribauer, 2016) or the non-parametric approach (Basile, Gress, 2004; Koroglu, Sun, 2016). However, in this case, the estimation technique and interpretation of the results obtained were significantly complicated.

There is a relatively small number of works devoted to the modeling economic growth in Russian regions using the spatial-econometric approach. Many authors have explored the issues of conditional beta convergence. Buccellato (2007), using data for 77 Russian regions for 1999-2004, emphasized that the spatial dependence of regions must be taken into account: “This paper's intent has been to illustrate the importance of geographic components in studies on the Russian Federation. The spatial dimension appears to be non-negligible and plays a crucial role in the convergence process through the channels of factor mobility, trade relationships and knowledge spill-over, the impact of which is much more evident in neighboring regions". Mobility (labor and capital), trade flows between regions and knowledge exchange were identified as channels for the spread of spatial effects. All formal tests of Lagrange multipliers also confirmed the existence of spatial effects. Without taking spatial factors into account, the rate of beta convergence is overestimated, as well as the costs of research and development (when spatial factors are taken into account, the coefficient for the corresponding variable becomes insignificant). Lugovoy et al. (2007), using data for 79 regions for 1998-2004, also revealed the existence of spatial relationships between Russian regions, but noted that the intensity of these relationships is significantly less in comparison with European ones due to longer distances and weaker transport infrastructure. The authors also noted the expediency of using Moran's diagrams in the spatial analysis of Russian regions. The horizontal axis in such a diagram shows the value of the region's indicator (for example, per capita income) and the vertical axis shows the mean value of this indicator in neighboring regions. These variables are preliminarily centered and are normalized. Observations that fall into each of the four quadrants are considered. A similar division of regions into 4 groups using the Moran's diagram was used in the article (Kholodilin et al., 2013) with the data for 76 Russian regions for 1998–2006. It was shown that for all regions there is beta and sigma convergence in real GRP per capita, but its rate is much higher in the group of regions with a high level of per capita GRP, surrounded by regions with a high level of GRP.

Kolomak (2010) was the first to substantiate the expediency of taking into account the difference between the western and eastern regions of Russia and empirically demonstrated that there are positive spillover effects in the western regions (i.e. if one region starts to grow, then it “pulls along” the neighboring regions), and negative spillovers for the eastern ones, i.e. there is competition for resources.

The authors of the above works often did not assess how much the results change when spatial effects are not taken into account. When dividing regions into groups, their mutual influence, as well as possible differences in the influence of explanatory factors for different groups of regions, were usually not taken into account. In addition, in all the above-mentioned articles, the coefficients for spatial lags were constant, which did not allow taking into account the different sensitivity of Russian regions to the impacts from other regions.

3.2. Modeling the main indicators of regional labor markets

Important indicators of regional labor markets are the unemployment rate, employment, wages. A description of the main theories underlying the models used to explain the differences between regional markets of different countries, or their parts, or associations (the most common example is the European Union) can be found, for example, in the review (Elhorst, 2003), with emphasis countries with economies in transition (Ferragina, Pastore, 2008; Huber, 2007).

One of the first researchers who point out the need to take into account spatial factors when modeling regional unemployment was Molho (1995), who used data from 281 UK regions in 1991.

This idea has been developed in numerous articles and received empirical evidence of the mutual influence of regional labor markets. Spatial factors were taken into account when modeling the level of unemployment or employment in the European Union (in whole or in individual European countries, see Aragon et al., 2003; Niebuhr, 2003; Cracolici et al., 2007; Lottmann, 2012; Mussida, Pastore, 2015; Rios, 2017; Chocolata, Furkova, 2018; Kivi, 2019), USA (Kuscevic, 2014; Basistha, Kuscevic, 2017), etc.

Theoretical aspects explaining the difference between regional unemployment and employment rates are highlighted in the article (Mameli et al., 2021). The authors draw on a classic article (Marston, 1985), which provides two competing explanations for this difference. According to the first, equilibrium theory, «workers migrate in search of better work opportunities until there is no further incentive to move because they feel somehow compensated (e.g., by local amenities and land endowments) ». Each region tends to its own equilibrium unemployment rate. According to the second, non-equilibrium theory, labor flows slowly spread between different regions «because of severe economic and social barriers restricting mobility, which generate persistent unemployment rate differentials between regions.

The authors of many articles noted the heterogeneity of labor markets in different countries, identified clusters of unemployment in Europe (Overman, Puga, 2002; Garcilazo, Spiezia, 2007), the USA (Garcilazo, Spiezia, 2007), China (Wei-Guo, 2006), Japan (Kondo, 2015), etc. There are also articles that consider employment clusters (Ceccato, Persson, 2002; Delgado, 2014; Chatterji, 2014).

A main feature of the Russian labor market is its rapid adjustment to shocks due to wage flexibility (Gimpelson, 2019). As Oshchepkov, Kapelyushnikov (2015) note, there is no single labor market for such a large and heterogeneous country as Russia; regional labor markets should be considered, while for many years there have been stable groups of leading regions and outsider regions. There are only a few studies of the Russian labor market using regional data (Muravyev, Oshchepkov, 2013; Blinova et al., 2016a; Blinova et al., 2016b; Vakulenko, Gurvich, 2016). E. Vakulenko (Vakulenko, 2013; Vakulenko, 2016) studied the convergence of Russian regions in terms of wages, unemployment rates and per capita income. Using panel data from Russian regions for the period 1995–2010, a dynamic model with spatial effects was estimated and significant positive spatial effects on wages and unemployment rates were identified, and it was shown that migration does not contribute to convergence for these indicators.

Note that these studies usually did not consider the influence of different groups of regions on each other, did not focus on the differences in spatial effects and the factors considered in the selected groups of regions.

In addition, when modeling unemployment, the dependence on some factors in spatially econometric models is not always linear, sometimes it is required to use more flexible functional forms. For example, the dependence of the change in unemployment on the degree of economic diversification can be nonlinear and even nonmonotonic due to the overlapping of the effects of (Jacobs, 1969) and (Marshall, 1920). Basile et al. (2012) demonstrated this for Italy using spatial nonparametric models. For Russia, one would expect a similar overlapping of the these effects, but such study has not been carried out. In addition, in times of crises and economic recovery, different effects may prevail; comparison of the assessment results for different time periods has not been carried out.

Another popular area of the labor market research is the estimation of the relationship between wages and regional unemployment. Usually, this dependence is negative and by Blanchflower and Oswald (1989), who estimated this dependence for many countries, including Russia (Blanchflower, 2001; Blanchflower, Oswald, 1995), is called a wage curve. The explanation of the economic mechanisms of the existence of the wage curve in Russia is given in the article (Shilov, Möller, 2008) and the corresponding curve is estimated using panel data for 82 Russian regions for 1995-2005. A detailed analysis of works devoted to modeling wages, as well as an assessment of the corresponding curve using panel data for 78 Russian regions for 2002-2010, is carried out in the article (Vakulenko, Gurvich, 2016). However, the authors of the listed works using Russian data did not take into account the mutual influence of regions, which, as Kosfeld, Dreger (2018, 2019), Ramos (2015) showed, can lead to biased estimation results.

When applying the spatial-econometric approach, the authors usually interpreted the results obtained in terms of "average changes", for example, how the average wages in the region will change when the unemployment rate in the same region changes by 1%, or how the average wages in the region will change when the unemployment rate in all neighboring regions by 1%. However, it is also interesting to assess the consequences of the changes in one region on the specific other regions; this has not been done in the works known to us. In the article (Vakulenko, 2015), the “coefficient of independence and the coefficient of influence of the regions” are introduced, but there is no formula for calculating these indicators and the significance of the corresponding indicators is not checked.

3.3. Modeling the degree of trust in the main socio-economic institutions, taking into account regional factors

(materials from articles (Demidova, 2011), (Demidova, 2012) were used in the text of this paragraph).

Trust in key social, political and financial institutions affects both the rate of countries' economic growth (which was confirmed empirically in the works of Glaeser et al., 2004; Acemoglu et al., 2005; Asoni, 2008; Lee, Kim, 2009). Therefore, it is interesting to identify factors, including spatial ones, that affect the degree of this trust.

Many researchers have used data from various waves of the European Social Survey or the World Value Survey for this purpose. These databases are so popular because they contain answers to a number of questions concerning the attitude of residents of a large number of countries to many socio-economic institutions, immigrants, etc., as well as rich information about the individual characteristics of respondents.

Cammett et al. (2015) based on the data from the 3rd wave of the ESS (European Social Survey) for 2008 demonstrated that private provision and financing of health services reduces the degree of trust in government. Korbiel et al. (2009), also using individual data from the 3rd wave of the ESS, found that only the level of corruption affects the level of trust in the police, the judiciary and parliament, while the gross domestic product, crime rate, and the index of democratic development do not. A similar result was obtained by Kelleher and Wolak (2007).

In Russia, the level of trust in socio-political institutions is lower than in many other countries (Shlapentokh, 2006). I. Denisova with co-authors (Denisova et al., 2007), modeling the attitude of the inhabitants of Russia to transition processes and their role for the country, came to the conclusion that the average Russian is subject to the so-called "cognitive dissonance" - the belief in the need for deep intervention in the economy by the state combined in it with a complete lack of trust in individual political institutions, and the depth of such dissonance varies depending on age, education, work experience.

How do Russian citizens differ from citizens of other countries in matters of trust in socio-political institutions? Which cluster of countries is Russia closest to? Comparative analysis is useful for deciding whether to use the experience of other countries, and if the answer is yes, which ones.

3.4. Modeling the degree of trust in immigrants

(materials from articles (Demidova, 2012, 2014, 2021b) were used in the text of this paragraph).

An important issue, the relevance of which has only increased in recent years, is the identification of micro and macroeconomic factors that affect the attitude of respondents to immigrants, especially in European and neighboring countries. The main theories explaining the attitude of different countries' residents towards immigrants can be divided into two large groups: based on an economic point of view and based on a socio-cultural point of view (Hainmueller, Hopkins, 2014). According to the first group of theories, attitudes towards immigrants mostly depend on the situation in the labor markets of the respondents' countries of residence, the distribution of public goods, etc. (Malchow-Møller et al., 2006; Facchini, Mayda, 2009; Dustman et al., 2013; Llull, 2018).

According to the second group of theories, including Social Identity Theory, Integrated Threat Theory, described in details in (Stephan and Stephan, 2001, 2013; Ward and Masgoret, 2006), self-identification with some socio-cultural group is very important for indigenous respondents. Immigrants often do not belong socio-cultural group (Ramos et al., 2016; Esses et al., 2005, 1998; Hainmueller, Hopkins, 2014; Kustov, 2019). Considering the attitude of respondents to immigrants from the point of view of these theories, in order to identify factors influencing the attitude towards immigrants, the model includes both the individual characteristics of the respondents and the macroeconomic characteristics of the countries of residence of the respondents. However, the listed articles do not define what more strongly affects the attitude towards immigrants - the individual characteristics of the respondents or the macroeconomic situation in the countries where they live.

There are only a few articles devoted to the analysis of the attitude of Russians towards immigrants; their description can be found in the article (Mastikova, Fadeev, 2020). However, as the authors of the article note, the results concerning the influence of factors characterizing the places of residence of immigrants are ambiguous. According to the results of (Bessudnov, 2016), who used the data of the FOM survey for 2011, residents of small towns and villages treat immigrants better than residents of large cities, which, as the author notes, is not typical for residents of European countries, there usually have the opposite trend. Mastikova (2019), according to the data of the 8th wave of the European Social Survey for 2016, showed that "the share of people who are negatively disposed towards migrants is slightly higher in small towns". Therefore, the relevant question cannot be considered resolved. These studies did not take into account that the influence of individual characteristics of respondents (such as age, education, etc.) on their attitude towards immigrants may differ for residents of various regions. None of these studies used geographically weighted regression to perform this analysis.

Taking into account the aim of this study, what has already been done in the areas of the research indicated above, and the gaps identified, objectives of the research were formulated.

4. Objectives of the research

1) Propose modifications of spatial-econometric models for Russia, allowing to identify the difference in the processes taking place in different parts of the country, namely:

a. to develop a new class of spatial-econometric models for two interrelated groups of regions,

b. develop a new class of spatial-econometric models for regions divided into several groups,

c. estimate these models for the main indicators characterizing socio-economic processes in Russian regions and demonstrate the advantages of using the proposed models.

2) Propose modifications of spatial-econometric models for Russia, allowing to reveal the different sensitivity of regions to the processes taking place in neighboring regions, namely:

a. to develop a new class of spatial-econometric models as modification of the spatial autoregression model, with the replacement of the spatial autocorrelation coefficient by a linear function of the selected characteristic of the region;

b. to develop a new class of spatial-econometric models as modification of the spatial Durbin model with the replacement of constant coefficients for spatial lags of the dependent and independent variables by a linear function of the selected characteristic of the region,

c. estimate these models for the growth rates of Russian regions and demonstrate the benefits of these models.

3) Propose modifications of spatial-econometric models for Russia, which would allow not to fix in advance the functional dependence form on the selected factors (nonparametric models).

4) Propose an interpretation of the results of estimation of the traditional spatial-econometric models, which makes it possible to determine how changes that have occurred in one specific region will affect the economic processes in this region and in neighboring regions, without using traditional averaging.

5) Determine how serious the consequences of not taking spatial factors into account when modeling indicators characterizing the economic situation in Russian regions (economic growth, situation on labor markets, etc.).

6) Determine which cluster of countries is closest to Russia in matters relating to the degree of trust of its citizens in the main socio-political institutions and the experience of which countries it makes sense to adopt.

7) Develop models that allow

a. to identify the possible difference in factors affecting the attitude of European and post-Soviet countries citizens towards migrants,

b. to compare the contribution of 1) individual characteristics of respondent (gender, age, education, etc.) and 2) economic and institutional indicators of the respondent's country of residence (gross national product per capita, unemployment rate, corruption perception index, etc.).

8) On the basis of geographically weighted regression, develop models that take into account the difference in the influence of the individual characteristics of respondents from different Russian regions on their attitude towards immigrants.

These problems were solved in 16 articles representing the dissertation.

5. Methodology

5.1. Classical spatial econometric models and their disadvantages

Traditional linear regression panel data models are:

$$Y_t = \alpha + X_t\beta + c_t + \varepsilon_t, \quad (1)$$

where $t = 1, \dots, T$ – time points, n – number of the regions, $Y_t = (Y_{1t}, \dots, Y_{nt})'$ – dependent variable, X_t – matrix of explanatory variables, $\alpha = (\alpha_1, \dots, \alpha_n)'$ - individual fixed effects, c_t – time effects , ε_t is a random error.

If the explanatory variable *Y* is a regional indicator, for example, the unemployment rate or the growth of GRP, then it is necessary to include among the explanatory factors the indicators of this variable for other regions, at least neighboring ones. The channels of influence of neighboring regions are usually identified as the mobility of labor force and capital. Omission of the corresponding variables raises the problem of bias in the estimates of the coefficients with the included factors (omitted variable bias), since the missing variables are usually correlated with regressors. If we add the corresponding variables each with its own coefficient, then the number of estimated parameters will exceed the number of observations and their assessment by classical methods becomes impossible.

In the works of (Paelinsk, Klassen, 1979), (Anselin, 2010), (LeSage, Pace, 2009), (Fischer, Wang, 2009), a toolkit was developed that allows not to increase significantly the number of estimated parameters, but at the same time take into account the mutual influence of regions.

A necessary element of spatial econometric models is a weighting matrix *W* of size *(nxn)*, which is usually exogenously[1], and it reflect the structure of relations between regions.
This matrix has the following properties:
$w_{ii} = 0$, the diagonal elements of the corresponding matrix are equal to 0,
$w_{ij} \geq 0$, non-negativity condition for weighting matrix elements,
$\sum_{j=1}^{n} w_{ij} = 1$, (normalization condition).
The most common types of weighting matrices are:

1) Boundary weighting matrix ($w_{ij} = \frac{1}{n_i}$, if region *j* is a neighbor of region *i* and 0 else, where n_i – is a number of regions - neighbors of the region *i*, these can be regions with common border or regions located no further than a certain distance *d* from the region *i,*
2) Inverted distance weighting matrix, $w_{ij} = \frac{1/d_{ij}}{\sum_{j=1}^{1} 1/d_{ij}}$, where d_{ij} is a distance between regions i and j.

[1] exogenous weighting matrices are used in all the models mentioned in this summary

Using the weighting matrix, we can create spatial lags of the dependent and independent variables. For example, if Y_i is the unemployment rate in region i, and W is the boundary weighting matrix, then WY_i is the average unemployment rate in the neighboring regions.

One of the most popular classical spatial models is the spatial Durbin model (SDM):

$$Y_t = \alpha + X_t\beta + \rho WY_t + WX_t\theta + \mathrm{c}_t + \varepsilon_t, \quad (2)$$

If $\theta = 0$, then this model could be reduced to the spatial autoregressive model (SAR):

$$Y_t = \alpha + X_t\beta + \rho WY_t + \mathrm{c}_t + \varepsilon_t, \quad (3)$$

if $\theta + \rho\beta = 0$, then SDM could be reduced to spatial error model (SEM – model with spatial dependence in errors):

$$Y_t = \alpha + X_t\beta + \mathrm{c}_t + \varepsilon_t,\ \varepsilon_t = \lambda W\varepsilon_t + u_t \quad (4)$$

SAR model contains only one additional parameter — the spatial autocorrelation coefficient ρ. It demonstrates how changes in neighboring regions affect the region in consideration. If the coefficient ρ is insignificant, then no impact occurs. If it is positive and significant, then with an increase in the variable Y (unemployment rate, economic growth rates, etc.) in neighboring regions, similar changes occur in the region under consideration. If the coefficient ρ is negative and significant, then with an increase in the variable Y in the neighboring regions, opposite changes occur in the considered region (for example, if a neighboring region grows and draws on labor and money resources, then a decline may be observed in the considered region). SDM model, contains not only the spatial autocorrelation coefficient ρ, but also coefficients $\theta = (\theta_1, \dots, \theta_k)'$- for spatial lags of the independent variables. These variables reflect the influence of factors included in the model in neighboring regions on the region under consideration.

In estimation of the parameters of spatial econometric models, it is necessary to take into account that the spatial lags of the dependent variable are endogenous. To estimate these models, the maximum likelihood method and the generalized method of moments are usually used. Each of these methods has its own advantages and disadvantages, which are discussed, for example, in (Pace, 2021; Prucha, 2021). To implement the maximum likelihood method, it is necessary to make an assumption about the distribution of errors in the models used. A strong assumption about the normality of the errors is usually used. In practice, this assumption is not always fulfilled. And a large number of observations does not help to solve this problem. If the regression errors do not have the normal distribution, but the likelihood function is used for the normal distribution (as is traditionally done in statistical packages), then the corresponding estimates will be consistent, but not effective. Quasi-maximum likelihood estimates will be effective in this case, but they are much more difficult to obtain from a computational point of view. Another computational problem is to calculate many times the logarithm of the determinant of a high-dimensional matrix $ln\ |I_n - \rho W|$.

Therefore, according to Prucha (2021), for large samples, it is preferable to use the generalized method of moments, for which there are no listed problems. But when applying this method, you also need to be careful, the instruments used in moment conditions must be valid. This condition must be checked using special tests.

There are strong assumptions about the same influence of neighboring regions on each region, which is reflected in the constancy of the ρ and θ coefficients in the SDM and SAR models. These assumptions do not hold in many countries.

It's necessary to weaken this assumption using more flexible models for large and heterogeneous countries like Russia. Different mechanisms of spatial development can be observed in different parts of such countries.

According to (Anselin, 1988), there are two main aspects of spatial heterogeneity. The first type of heterogeneity is associated with the instability of functional form or varying parameters. The second type of spatial heterogeneity arises as a consequence of the omission of essential variables that reflect spatial dependence, including heterogenous one. In this case, the problem of heteroscedasticity of the regression errors arises. In the second case (Anselin, 1988) proposes to use a model similar to SEM, but with a block-diagonal matrix in the formula for regression errors. At the same time, models that take into account both spatial autocorrelation and spatial heterogeneity of observations, as noted by Geniaux, Martinetti (2018), are still very rare.

5.2. Data for the estimation of modified models

To estimate the parameters of the modified econometric models, which we will discuss in this section, three main open access data sources were used:

1) "Regions of Russia. Socio-economic indicators" for 2002–2020, https://rosstat.gov.ru/folder/210/document/13204,

2) World Value Survey (WVS), https://www.worldvaluessurvey.org/wvs.jsp

3) European Social Survey (ESS), https://www.europeansocialsurvey.org/

"Regions of Russia. Socio-economic indicators" contains data on regional indicators for 2000–2018. The articles of O. Demidova and co-authors were written at different times, therefore the considered time intervals are somewhat different. Since during this period there were changes in the administrative-territorial division of regions, the availability of data for some regions (for example, there is no data for the Chechen Republic for some years, data for the autonomous okrugs separately from the large regions to which they are included, appeared only in recent years) , then the number of regions in different articles is slightly different. Each article contains an exact list of the considered regions. The set of regional indicators available in different years also is not exactly the same. The methodology for measuring some indicators has also changed. More detailed information about the data and the reasons for using a certain time interval is available in each article. Unfortunately, Rosstat does not provide free access to information on migration flows between regions, flows of goods and services, etc. Therefore, to describe the relationship between regions, exogenous matrices based on the geographic proximity of regions were used.

The World Values Survey includes data from surveys of residents from more than 120 countries, including Russia, which is carried out approximately every five years. This database contains rich information about the individual characteristics of the respondents (gender, age, educational level, type of settlement, etc.), the values of the respondents, including their attitude to socio-political institutions. Currently, data from seven WVS waves are available, the first wave contains data for 1981–1984, and the seventh wave contains data for 2017–2020.

The European Social Survey includes the data from similar surveys for residents of 40 European countries (not only EU countries, Russia is also included in this survey). Surveys have been conducted every two years since 2002, and 9 ESS waves are currently available (latest wave includes 2018 data).

5.3. Modifications to the spatial autoregressive model and the spatial Durbin model

5.3.1. Modification of the spatial autoregressive model for a group of two interconnected regions

All regions (i is a region number, $i = 1, \dots, n$) were split in two parts: $i = 1, \dots, n_1$, corresponding to the 1st group of regions and $i = n_1 + 1, \dots, n$, corresponding to the 2nd group of regions. For each year $t = 1, \dots, T$ vector of the dependent variable Y_t was split in two parts, Y_t^1 и Y_t^2, corresponding to the observations from the 1st and 2nd groups. Similarly, the matrix of the explanatory variables X_t for each year $t = 1, \dots, T$ also was split in two parts, X^1, X^2, corresponding to the observations for the first and second group of regions, weighting matrix was split into 4 blocks: $W = \begin{pmatrix} W^{11} & W^{12} \\ W^{21} & W^{22} \end{pmatrix}$.

The modified dynamic spatial autoregressive model for two groups of interconnected regions has the following form:

$$\begin{pmatrix} Y_t^1 \\ Y_t^2 \end{pmatrix} = \alpha + \sigma \begin{pmatrix} Y_{t-1}^1 \\ Y_{t-1}^2 \end{pmatrix} + \begin{pmatrix} \rho^{11} W^{11} & \rho^{12} W^{12} \\ \rho^{21} W^{21} & \rho^{22} W^{22} \end{pmatrix} \begin{pmatrix} Y_t^1 \\ Y_t^2 \end{pmatrix} + \begin{pmatrix} X_t^1 \beta^1 \\ X_t^2 \beta^2 \end{pmatrix} + \mathrm{c}_t + \varepsilon_t, \tag{5}$$

where $\alpha = (\alpha_1, \dots, \alpha_n)'$ is a vector of individual fixed effects, c_t – time effect, ε_t is a random error, σ, β^1, β^2 are estimated parameters. Coefficients reflect the influence, respectively, of the regions of the first group on the regions of the first group, regions of the second group on the regions of the first group, regions of the first group on the regions of the second group, regions of the second group on the regions of the second group. $\rho^{11}, \rho^{12}, \rho^{21}, \rho^{22}$. Of particular interest are the significance and signs of the estimates of the coefficients ρ^{12}, ρ^{21}. If they differ, then we can talk about the asymmetric influence of the two groups of regions on each other.

Note that if earlier Anselin (1988) used block-diagonal weighting matrices for errors, then in model (5) we used a block and non-diagonal matrix to create spatial lags of the dependent variable.

Since the spatial lags of the dependent variable on the right-hand side of equation (5) are endogenous, the generalized method of moments was used to estimate the corresponding equation. Time lags of the dependent and independent variables was used as instruments in the framework of Arellano-Bond approach (Arellano, Bond, 1991).

In the article (Demidova, 2014), the western and eastern regions were considered as two groups of regions, including 52 and 23 regions, respectively, for the period of 2000–2010. Unemployment rate, real wages, and GRP growth were used as dependent variables. The share of the urban population, population density, migration growth of the population, GRP per capita (PPP), the ratio of exports and imports to the region's GRP were chosen as explanatory variables.

In the article (Demidova et al., 2013), the Russian regions were also divided into western and eastern, the time period 2000–2009. The level of youth unemployment (group 20–29 years old) was chosen as the dependent variable, and the level of general unemployment, the share of the urban population, the share of the population aged 20–29, the number of students per 10,000 people of the population, the number of pensioners per 1000 people population, migration growth of the population, the share of migrants arriving from other regions, the share of migrants arriving from abroad, GRP per capita (PPP), average monthly pension at PPP, labor productivity, openness of the regional economy to exports and imports were chosen as explanatory variables.

In the article (Demidova et al., 2015) a comparative analysis of youth unemployment was carried out for the northern and southern regions of Russia and Italy (two groups of regions were compared within each country) according to data for 2000–2009 The level of general unemployment, GRP per capita, and population density of the region were used as explanatory variables.

In each of the three articles mentioned in this paragraph, hypotheses about the same spatial effects were tested using the Wald test: $H_0: \rho^{11} = \rho^{12} = \rho^{21} = \rho^{22}$ (with an alternative hypothesis that one of these equalities is rejected) and hypotheses about the same influence of the selected factors: $H_0: \beta^1 = \beta^2$ (with an alternative hypothesis that this equality is rejected for at least one pair of coefficients). And in all cases, the main hypotheses were rejected.

5.3.2. Modification of the spatial autoregressive model with the splitting of regions into several groups

Regions of the same country could be divided into more than 2 groups with different economic processes. To model such processes, the spatially autoregressive model can be modified as follows (in this case, 3 groups of regions are considered, but a similar model can be used for a larger number of regions):

For modeling such processes, the spatially autoregressive model can be modified as follows (in this case, 3 groups of regions are considered, but a similar model can be used for a larger number of regions):

$$\begin{pmatrix} Y_t^1 \\ Y_t^2 \\ Y_t^3 \end{pmatrix} = \alpha + \sigma \begin{pmatrix} Y_{t-1}^1 \\ Y_{t-1}^2 \\ Y_{t-1}^3 \end{pmatrix} + \rho_1 \begin{pmatrix} WY_t^1 \\ 0 \\ 0 \end{pmatrix} + \rho_2 \begin{pmatrix} 0 \\ WY_t^2 \\ 0 \end{pmatrix} + \rho_3 \begin{pmatrix} 0 \\ 0 \\ WY_t^3 \end{pmatrix} + \begin{pmatrix} X_t^1 \\ 0 \\ 0 \end{pmatrix} \theta^1 + \begin{pmatrix} 0 \\ X_t^2 \\ 0 \end{pmatrix} \theta^2 + \begin{pmatrix} 0 \\ 0 \\ X_t^3 \end{pmatrix} \theta^3 + \mathrm{c}_t + \varepsilon_t, (6)$$

$$\begin{pmatrix} Y_t^1 \\ Y_t^2 \\ Y_t^3 \end{pmatrix} = \alpha + \sigma \begin{pmatrix} Y_{t-1}^1 \\ Y_{t-1}^2 \\ Y_{t-1}^3 \end{pmatrix} + \rho_1 \begin{pmatrix} WY_t^1 \\ 0 \\ 0 \end{pmatrix} + \rho_2 \begin{pmatrix} 0 \\ WY_t^2 \\ 0 \end{pmatrix} + \rho_3 \begin{pmatrix} 0 \\ 0 \\ WY_t^3 \end{pmatrix} + \begin{pmatrix} X_t^1 \\ 0 \\ 0 \end{pmatrix} \theta^1 + \begin{pmatrix} 0 \\ X_t^2 \\ 0 \end{pmatrix} \theta^2 + \\ + \begin{pmatrix} 0 \\ 0 \\ X_t^3 \end{pmatrix} \theta^3 + \mathrm{c}_t + \varepsilon_t, \qquad (6)$$

where for each year $t = 1, \dots, T$ vector of the dependent variable Y_t was split in three parts, Y_t^1, Y_t^2 и Y_t^3, matrix of explanatory variables X_t for each year $t = 1, \dots, T$ was split in three parts, X^1, X^2, X^3, corresponding to the observations from the 1st, 2nd and 3rd groups of regions, $\alpha = (\alpha_1, \dots, \alpha_n)'$ is the vector of fixed individual effects, c_t – time effect, ε_t is a random error, σ – coefficient of the time lag of the dependent variable, ρ_1, ρ_2, ρ_3 are coefficient of spatial autocorrelation, θ^1, θ^2, θ^3 are vectors of estimated parameters. To estimate models (6), as well as models (5), the generalized method of moments was used.

In the article (Danilenko et al., 2018) devoted to modeling the unemployment rate and in the article (Demidova et al., 2018) devoted to modeling the employment level, Moran's plots were used as the initial division of regions into groups. For each year, this graph is constructed as follows: the modeled variable (for example, the unemployment rate in the region) and its spatial lag are centered and normalized (respectively, $\tilde{Y}$, $\widetilde{WY}$)) and for each *i*-th region (*i = 1, ..., n*) represent the point ($\tilde{Y}_i$, $\widetilde{WY}_i$). Thus, all regions, depending on the location of the corresponding points in one of the four orthants, into which the plane is divided by the coordinate axes, are divided into 4 groups. For example, the regions corresponding to the points that are located the first orthant have an indicator above the average and are surrounded by regions with this indicator also above the average. Moran's plots were created for each of the 2005–2012 years in the article (Danilenko et al., 2018) and for each of 2005–2016 years in the article (Demidova et al., 2018). The region finally belonged to the orthant where it was located most often.

In the article (Danilenko et al., 2018) two groups of regions were identified: High-High group is a group of regions with a high unemployment rate, surrounded by regions with a high unemployment rate, Low-Low group is a group of regions with a low unemployment rate, surrounded by regions also with low unemployment, and the third group of the remaining regions. GRP per capita (PPP), labor productivity, share of urban population, population density, share of population under working age, share of population over working age, share of population with higher education and variables characterizing the structure of the labor market: share employed in agriculture, the share of employed in construction, the share of employed in trade, the share of employed in the public sector, the share of employed in mining, the share of employed in industry were chosen as explanatory variables.

In the article (Demidova et al., 2018), in case of modeling the level of employment in Russian regions, the division of regions into groups was different. A group of High-High regions (with a high level of employment, surrounded by the regions with a high level of employment), and two groups of regions with a low level of unemployment, surrounded by the regions with a low level of unemployment: LL1, which includes regions in southern Russia and LL2, which includes regions in southern Siberia and Trans-Baikal. The GRP per capita (PPP), population density, the share of the urban population, the migration growth of the population, the share of the population under the working age, the share of the population over the working age, the share of the population with higher education among employed and the Herfindahl-Hirschman index, which characterizes the degree of diversification of the region's economy were chosen as explanatory variables.

Hypotheses about the same spatial dependence $H_0: \rho_1 = \rho_2 = \rho_3$ (under the alternative hypothesis $H_1: \rho_1 \neq \rho_2$ or $\rho_1 \neq \rho_3$) and about the same dependence on explanatory variables $H_0: \theta^1 = \theta^2 = \theta^3$ (under the alternative hypothesis $H_1: \theta^1 \neq \theta^2$ or $\theta^1 \neq \theta^3$) were verified by the Wald test and rejected in both articles.

In some cases, the division of regions into groups should be carried out according to expert opinion. In the article (Demidova, 2021), when studying issues related to the beta convergence of Russian regions in terms of GRP, all regions were divided into 3 groups depending on their debt burden and budgetary provision (rich, middle, poor) using the classification of (Zubarevich, Gorina, 2015). The conditional convergence model was estimated:

$$\frac{1}{3} ln \frac{Y_{(t+3)}}{Y_t} = \alpha + \beta^p \begin{pmatrix} ln\, Y_p \\ 0 \\ 0 \end{pmatrix}_t + \beta^m \begin{pmatrix} 0 \\ ln\, Y_m \\ 0 \end{pmatrix}_t + \beta^r \begin{pmatrix} 0 \\ 0 \\ ln\, Y_r \end{pmatrix}_t +$$

$$+\rho^p \begin{pmatrix} W\,ln\,Y_p \\ 0 \\ 0 \end{pmatrix}_t + \rho^m \begin{pmatrix} 0 \\ W\,ln\,Y_m \\ 0 \end{pmatrix}_t + \rho^r \begin{pmatrix} 0 \\ 0 \\ W\,ln\,Y_r \end{pmatrix}_t + \begin{pmatrix} X_p \\ 0 \\ 0 \end{pmatrix}_t \theta^p +$$

$$\begin{pmatrix} 0 \\ X_m \\ 0 \end{pmatrix}_t \theta^m + \begin{pmatrix} 0 \\ 0 \\ X_r \end{pmatrix}_t \theta^r + c_t + \varepsilon_t, \qquad (7)$$

where Y_t t is GRP per capita (in the model it was used in logarithms), $\frac{1}{3} ln \frac{Y_{(t+3)}}{Y_t}$ is the average GRP growth over three years. The share of the urban population, the ratio of investments to the GRP of the region, the share of the population with higher education among the employed, the openness of the regional economy to exports and imports, the density of highways, and the investment risk index were chosen as explanatory factors.

This model was estimated with data for 80 regions for 2000–2017 using standard methods for estimation fixed effect panel data models. As for the previous class of models, the Wald test was used to test (and reject) the hypotheses about the same spatial dependence and the same dependence from all explanatory factors for all selected groups of regions.

5.3.3. Replacing the coefficient of spatial autocorrelation with a linear function of the selected characteristic of the region

In the classical model spatial autoregressive model (3), the parameter ρ characterizes the sensitivity of regions to the impact of other regions and is assumed to be constant. However, we can assume that the large size of the region, low population density, etc. can act as factors that weaken the region's perception of externalities. These regions are likely to be less sensitive to the impact of other regions through passenger flows, migrant flows, etc. On the contrary, a high level of urbanization in a region can intensify externalities. Therefore, in the article (Demidova, Ivanov, 2016) devoted to modeling the rates of economic growth, the coefficient ρ was replaced by a linear function of the variable characterizing the "sensitivity" of the region to external influences Z^j: $\rho_j = \delta_j + \eta_j Z^j, j = 1,2,3$. As such variables, Z^1 – the area of the region, Z^2 – the population density of the region, Z^3 – the share of the urban population of the region were used.

The corresponding modification of the model was as follows:

$$lny_{it} = \alpha_i + \theta\, lny_{it-1} + \gamma lnyY_{it-1} + (\delta_j + \eta_j Z_{it}^j)(\mathrm{W}\, lny)_{it} + (X\beta)_{it-1} + c_t + \varepsilon_{it}, \qquad (8)$$

where i is a region number; t is a year of observation; y_{it} is the rate of economic growth, in percent; Y_{it-1}– gross regional product per capita, in prices of the base year; γ is the convergence coefficientи; X_{it-1} is a matrix of explanatory variables; β is a vector of parameters; W is the boundary weighting matrix; α_i – individual fixed effects; c_t – time effects, ε_{it} are random errors.

GRP per capita (PPP), the share of the urban population, population density, change in the average annual population of the region, the ratio of investments in fixed assets to GRP, the share of the mining sector in GRP, the share of manufacturing in GRP, the share of public sector services of the in the GRP, the share of federal transfers in the budget of the region, the share of employed with higher education, the number of patents per 10,000 inhabitants, the ratio of exports and imports to the region's GRP were chosen as explanatory variables.

This model was estimated by the generalized method of moments in differences (Arellano, Bond, 1991) and the generalized method of moments in systems (Blundel, Bond, 1998; Kukenova, Monteiro, 2009).

5.3.4. Replacing the coefficient of spatial lags in the Durbin model by a linear function of the selected characteristic of the region

The article (Demidova, Kamalova, 2021) also includes the model of economic growth. But in this article, the emphasis was on indicators of the regional institutions quality and measures of the development of business activity. If the quality of regional institutions is high, then the transaction costs for doing business in the region are small, it can be expected that residents of neighboring regions will conduct business in this region and contribute to its growth. And the better the quality of regional institutions, the more active this process will be.

The following indicators of the quality of regional institutions and a measure of the development of business activity in the region were used: $Z^1 = self$ is the number of small enterprises per 10 thousand economically active population, $Z^2 = banks$ is the total index of the region's banking services, $Z^3 = ip$ is the investment potential of the region.

The coefficients ρ and θ in the Durbin model were replaced by linear functions of the variables $Z^j, j = 1,2,3$:

$$\rho_{ij} = \rho_{j0} + \delta_{j0} Z_i^j, j = 1,2,3$$

$$\theta_{ij}^m = \theta_{j0}^m + \eta_{j0}^m Z_i^j, m = 1, \dots, 9; j = 1,2,3.$$

In the article (Demidova, Kamalova, 2021) with modeling the rates of economic growth in Russian regions, an appropriate modification of the SDM model was used:

$$y_{it} = \alpha_i + \varphi y_{it-1} + (\rho_{j0} + \delta_j Z_{it-1}^j) W y_{it} + X_{it-1}\beta +$$
$$+ W X_{it-1}\left(\theta_{j0} + \eta_j Z_{it-1}^j\right) + c_t + \varepsilon_{it}$$

with explanatory variables GRP per capita (in logarithms), share of urban population, share of employed with higher education, ratio of investments in fixed assets to GRP, ratio of exports and imports to GRP of the region, number of patents per 10,000 inhabitants, Herfindahl index - Hirschman as an indicator of diversification of the structure of the regional economy, the share of federal transfers in the budget of the region, the density of highways, which characterizes the development of the region's infrastructure. This model was estimated by the generalized method of moments in differences (Arellano, Bond, 1991).

5.4. Usage of nonparametric spatial models

In some cases, the dependence on explanatory factors in the spatial model is not linear. For example, in the article (Demidova et al., 2020), the dependence of the average change in unemployment for a selected period on the degree of concentration and diversification of the economy is modeled. Due to the overlapping of the effects of Marshall and Jacobs, this dependence may be nonlinear; it is necessary to use more flexible functional form than the linear one. The following model was chosen:

$$Y_i^{[t_1,t_2]} = \beta_0 + \beta_{X_1^*} X_{1i}^{t_1 *} + \beta_{X_2^*} X_{2i}^{t_1 *} + \cdots + f_{X_1}(X_{1i}^{t_1}) + f_{X_2}(X_{2i}^{t_1}) + \cdots + f_{WY}(WY_i^{[t_1,t_2]}) + \varepsilon_i^{t_1},$$

where i is a region number, $[t_1, t_2] \in \{[2007,2016], [2008,2010], [2010,2013], [2013,2016]\}$ are time periods under consideration, $Y_i^{[t_1,t_2]} = \frac{\ln U_i^{t_2} - \ln U_i^{t_1}}{t_2 - t_1}$, U is unemployment level. GRP per capita (PPP), the share of the urban population, the share of the population below working age, the share of the population above working age, migration growth of the population, the share of employed with higher education, population density and indices characterizing the degree of concentration and diversification of the region's economy were explanatory variables. $X_1^*, X_2^*,\ldots$ were variables with linear dependence, and X_1 , X_2 ,…, WY were variables with nonparametric dependence.

This model is estimated using the following procedure:

1) Due to the endogeneity of the spatial lag, it was necessary to estimate an auxiliary nonparametric model:

$$WY_i^{[t_1,t_2]} = \tilde{f}_{X_1^*}^*(X_{1i}^{t_1 *}) + \tilde{f}_{X_2^*}^*(X_{2i}^{t_1 *}) + \cdots + \tilde{f}_{X_1}(X_{1i}^{t_1}) + \tilde{f}_{X_2}(X_{2i}^{t_1}) +$$
$$+\tilde{h}_{WX_1^*}^*(WX_{1i}^{t_1 *}) + \tilde{h}_{WX_2^*}^*(WX_{2i}^{t_1 *}) + \cdots + \tilde{h}_{WX_1}(WX_{1i}^{t_1}) + \tilde{h}_{WX_2}(WX_{2i}^{t_1}) + \cdots + \nu_i$$

with explanatory variables X_1^*, $X_2^*, \ldots, X_1, X_2, \ldots$ and their spatial lags as instruments for WY. $\tilde{f}_{X_1^*}^*, \tilde{f}_{X_2^*}^*, \ldots, \tilde{f}_{X_1}, \tilde{f}_{X_2}, \ldots, \tilde{h}_{WX_1^*}^*, \tilde{h}_{WX_2^*}^*, \ldots, \tilde{h}_{WX_1}, \tilde{h}_{WX_2}$ ... were unknown estimated functions. They were estimated with penalized cubic regression spline using a back-fitting algorithm (Hastie and Tibshirani, 1990).

2) The residuals of the regression estimated at the first step, $\hat{\nu}_i, i = 1, \ldots, n$, were used at the second step when estimating the regression:

$$Y_i^{[t_1,t_2]} = f_{X_1^*}(X_{1i}^{t_1*}) + f_{X_2^*}(X_{2i}^{t_1*}) + \cdots + f_{X_1}(X_{1i}^{t_1}) + f_{X_2}(X_{2i}^{t_1}) + \cdots + f_{WY}(WY_i^{[t_1,t_2]}) + f_v(\hat{v}_i) + \varepsilon_i^{t_1}$$

3) For each explanatory variable linear and nonparametric functional forms were compared. If there was no statistical difference between them, then a linear relationship was used, otherwise, a nonparametric one.

5.5. Interpreting the results of estimation spatial-econometric models

As shown in Elhorst (2014), the marginal effects of the variable X_m for the SDM model (formula 2) are calculated using the formula:

$$\begin{pmatrix} \frac{\partial E(Y)}{\partial X_{m1}} & \cdots & \frac{\partial E(Y)}{\partial X_{mn}} \end{pmatrix} = \begin{pmatrix} \frac{\partial E(Y_1)}{\partial X_{m1}} & \cdots & \frac{\partial E(Y_1)}{\partial X_{mn}} \\ \vdots & \ddots & \vdots \\ \frac{\partial E(Y_n)}{\partial X_{m1}} & \cdots & \frac{\partial E(Y_n)}{\partial X_{mn}} \end{pmatrix} =$$

$$= (I - \rho W)^{-1} \begin{pmatrix} \beta_m & w_{12}\theta_m & \cdots & w_{1n}\theta_m \\ w_{21}\theta_m & \beta_m & \cdots & w_{2n}\theta_m \\ \vdots & \vdots & \ddots & \vdots \\ w_{n1}\theta_m & w_{n2}\theta_m & \cdots & \beta_m \end{pmatrix} = \pi(X_m)$$

Note that $\frac{\partial E(Y_i)}{\partial X_{mj}}$ shows how a change in the variable X_m (for example, the unemployment rate) in region j affects the dependent variable (for example, wage) in region i, $i, j = 1, \dots, n$.

There are

- direct effects if $i = j$, for example, how a change in the unemployment rate in region i will affect wages in this region,
- indirect effects if $i \neq j$, for example, how a change in the unemployment rate in region j will affect wages in region i.

Since there are n direct effects for each variable, and $n^2 - n$ indirect effects for each variable, then, according to the proposal of (LeSage, Pace, 2009), average direct (the sum of all direct effects divided by n) and average indirect effects are usually calculated (the sum of all indirect effects divided by n, not $n^2 - n$) for each variable.

Possibly for large and heterogeneous countries like Russia, the partial marginal effects $\frac{\partial E(Y_i)}{\partial X_{mj}} = \pi_{ij}(X_m)$ are quite different than the average marginal effects.

Therefore, it is interesting to compare partial and average marginal effects. This was done in the article (Demidova, Timofeeva, 2021) devoted to the estimation of the wage curve in Russia based on the data for 2005−2018 using SDM model with the dependent variable real wages (in logarithms). Unemployment rate, share of employees under 20, share of employees over 60, share of urban population, share of employed with higher education, number of small businesses per 10,000 population, average number of employees in small businesses, share of employees in agriculture, construction, mining , manufacturing, trade, the Hirfindahl-Hirschman index, which characterizes the degree of diversification of the region's economy were used as explanatory variables.

To calculate the confidence intervals of direct and indirect partial marginal effects, we used the property of asymptotic joint normality of the parameters ρ, β_1, ..., β_k, θ_1, ..., θ_k estimates with a covariance matrix proportional to the inverted Fisher information matrix, for whose elements consistent estimates are known.

However, it is rather difficult to find the distribution of estimates $\hat{\pi}_{ii}$, $\hat{\pi}_{ij}$.

Therefore, to obtain confidence intervals for direct and indirect partial marginal effects for the variable X_m, the algorithm proposed by LeSage, Pace (2009) is usually used. It is based on the simulations and consists of the following.

1) Find the maximum likelihood estimates of the parameters $\hat{\rho}$, $\hat{\beta}_m$, $\hat{\theta}_m$, and also the estimate of the covariance matrix of these estimates.
2) Generate a random sample of size Ñ: $(\rho^1, \beta_m^1, \theta_m^1)$, …, $(\rho^{\tilde{N}}, \beta_m^{\tilde{N}}, \theta_m^{\tilde{N}})$ from multivariate normal distribution N($(\hat{\rho}, \hat{\beta}_m, \hat{\theta}_m)$, $\widehat{Var}(\hat{\rho}, \hat{\beta}_m, \hat{\theta}_m)$).
3) For each element of this sample, all direct effects are calculated by the formula

$$\frac{\partial \widehat{E(Y_i)}}{\partial X_{mi}} = \hat{\pi}_{ii}(X_m), i = 1, \dots, n,$$

and all indirect effects are calculated by the formula

$$\frac{\partial \widehat{E(Y_i)}}{\partial X_{mj}} = \hat{\pi}_{ij}(X_m), i, j = 1, \dots, n, i \neq j,$$

replacing in the formula

$$\hat{\pi}(X_m) = (I - \hat{\rho}W)^{-1} \begin{pmatrix} \hat{\beta}_m & w_{12}\hat{\theta}_m & \cdots & w_{1n}\hat{\theta}_m \\ w_{21}\hat{\theta}_m & \hat{\beta}_m & \cdots & w_{2n}\hat{\theta}_m \\ \vdots & \vdots & \ddots & \vdots \\ w_{n1}\hat{\theta}_m & w_{n2}\hat{\theta}_m & \cdots & \hat{\beta}_m \end{pmatrix}$$

estimates of the parameters ρ, β_m, θ_m to the corresponding element from the sample (ρ^1, β_m^1, θ_m^1), …, ($\rho^{\tilde{N}}$, $\beta_m^{\tilde{N}}$, $\theta_m^{\tilde{N}}$).
4) The sequence of Ñ elements for each of n direct and $n^2 - n$ indirect partial marginal effects is sorted in ascending order and $\frac{\alpha \tilde{N}}{2}$ of the smallest and $\frac{\alpha \tilde{N}}{2}$ of the largest elements of each sequence are removed.

The lowest and highest remaining elements will be the boundaries of the *(1-α)100%* confidence interval for the corresponding direct or indirect partial marginal effect.

5) If 0 is not included in the calculated confidence interval for the direct or indirect partial marginal effect, then the corresponding marginal effect is significant.

5.6. Spatial factors in models for the level of trust in the main social-political institutions

Regional (in this context, country) differences should be taken into account when using data at the individual level, in particular, when modeling the level of trust in the main political institutions of residents from different countries. It is necessary to take into account not only the individual characteristics of the respondents, but also the economic situation in the country in which these respondents live. In the article (Demidova, 2011), for modeling the level of citizens' trust in the main social and political institutions according to the fifth wave of the WVS, two possible approaches were proposed.

The first approach was to use hierarchical models. To model the level of citizens' trust in the main social and political institutions, we used logit models with random coefficients:

$$P\left(Y_{ij}=1\right)=F\left(\beta_0+u_{0j}+\beta_1 X_{1ij}+\beta_2 X_{2ij}+\cdots+\beta_k X_{kij}+\left(\gamma_j+u_j\right)Z_j\right),$$

$$\begin{pmatrix} u_{0j} \\ u_j \end{pmatrix} \sim N\left(0;\begin{pmatrix} \sigma_0^2 & \rho \\ \rho & \sigma_1^2 \end{pmatrix}\right)$$

where $X_1,\ldots,X_k$ are individual characteristics of respondents (gender, age, educational level, etc.), and Z_j are country-level variables (GDP per capita (PPP) and the corruption perception index).

The second approach was to pre-cluster countries using a dendrogram and use ordered multiple choice models for observations from each cluster:

$$P(Y_i=k|x_i)=F(c_k-x_i'\beta), k=1,\ldots,m,$$

where F is the logistic distribution function.

5.7. Spatial factors consideration in case of a comparative analysis of the attitude towards migrants of different countries and regions residents

Modeling the attitude of residents of different countries to immigrants, as in the previous case, it is necessary to take into account the regional (country) specifics. However, in this case, the countries were divided into groups in a natural way: in the articles (Demidova, 2012; Demidova, 2014) residents of Russia and Ukraine with residents of “old” European countries (included in the EC before 2004) and “new” European countries (entered the EU not earlier than 2004) are compared. In the article (Paas, Demidova, 2014) the residents of Russia and Estonia are compared.

In articles (Demidova, 2012; Demidova, 2014), the following functional form of the model was used:

$$Y_{ij} = \beta_0 + \delta_{NE} \cdot NE + \delta_{RU} \cdot RU$$
$$+ \sum_{k=1}^{K_n} (\beta_k + \delta_{NEk} \cdot NE + \delta_{RUk} \cdot RU) \cdot X_{ki}$$
$$+ \sum_{m \in M_n} (\beta_m + \delta_{NEm} \cdot NE + \delta_{RUm} \cdot RU) \cdot Z_{mj} + \varepsilon_{ij}$$

where i is the number of the individual, j is the number of the country, n is the model number, Y is the variable characterizing the attitude towards immigrants, $X_1, \dots, X_k$ are the individual characteristics of the respondents (gender, age, educational level, etc.), and Z_j are country-level variables (GDP per capita (PPP), unemployment rate, corruption perception index, migration population growth).

To identify which factors, individual or country level, have a stronger influence on the attitude of individuals towards immigrants, the factor decomposition of R^2 was used in each of the estimated models:

$$R_Y^2 = \sum_{i=1}^{k} \hat{\beta}_i \frac{\widehat{\mathrm{Cov}}(X_i, Y)}{\widehat{\mathrm{Var}}(Y)}$$

The ordered multiple choice logit models with the same dependent and explanatory variables were estimated separately for observations for Russia and for Estonia in the article (Paas, Demidova, 2014).

To identify factors influencing the attitude of residents of 61 Russian regions to immigrants, linear models with a dependent variable Y characterizing the attitude of respondents to immigrants and explaining variables age, gender, indicator of higher education, indicator of having a spouse, indicator of the respondent's lack of work, indicator of retirement status, as well as variables characterizing the individual's income were used in the article (Demidova, 2021b).

Regional differences were taken into account by adding a set of dummy variables characterizing the region or type of settlement or the number of inhabitants of the settlement where the individual lives. In all cases, the coefficients for the sets of dummy variables were significant.

The influence of spatial factors on the attitude of respondents to immigrants was also estimated by introducing variables of the regional level (GRP per capita (PPP), the level of regional unemployment, the share of immigrants who came from abroad, the share of construction, the share of wholesale and retail trade, repair of motor vehicles and motorcycles (the main industries where immigrants work) in the region's gross value added).

In addition, a geographically weighted regression model was estimated:

$$Y_i = \beta_0(u_i, v_i) + \sum_{j=1}^{k} \beta_j(u_i, v_i) X_{ij} + \varepsilon_i$$

where i is the number of the individual, $i = 1, \ldots, n$ (in our case $n = 1810$), Y_i is the i-th value of the dependent variable, $X_1, \ldots, X_k$ are explanatory variables. Unlike the classical linear regression model, where the coefficients $\beta_1, \ldots, \beta_k$ are constants, in geographically weighted regression these coefficients are functions of the geographical coordinates of the respondent's settlement (latitude u and longitude v).

6. Contribution

The scientific novelty of the work lies in the development of a spatial-econometric methodology according to the points listed below.

1) A modification of spatial regression models for two interrelated groups of regions has been developed,

2) A modification of the spatially autoregressive model for the regions of one country, divided into several groups, was proposed,

3) A modification of the spatially autoregressive model, associated with replacing the spatial correlation coefficient with a linear function of the selected characteristic of the region (area of the region, population density of the region, share of the urban population of the region), was proposed,

4) A modification of the spatial Durbin model, associated with the replacement of coefficients at spatial lags of the dependent and independent variables by a linear function on the selected characteristic of the region (the number of small enterprises per 10 thousand economically active population, the aggregate index of the region's provision of banking services, the investment potential of the region), was proposed,

5) To determine the influence of the degree of diversification and the degree of concentration of the regional economy on unemployment, a new approach was proposed. This approach included a) the use of several indicators characterizing the degree of concentration and diversification of the regional economy (with data from the level of firms and the level of regions), b) the use of nonparametric spatial-econometric models that were not previously used in the analysis of the Russian labor market, c) comparison of the results of evaluating nonparametric models during periods of crisis and during periods of economic recovery,

6) A new interpretation of the results of spatial-econometric models estimation (using partial marginal effects) and an algorithm for testing the significance of these effects were proposed,

7) A new algorithm based on partial indirect marginal effects was proposed. It allows for each region a) to identify the regions that it affects the most and 2) the regions that most strongly affect this selected region,

8) To identify the factors affecting the attitude of individuals from different countries to immigrants, 1) a new class of models with varying slope coefficients for different groups of countries and 2) a new algorithm that allows to establish the importance of taking into account the economic and institutional indicators of the countries of individuals' residence were proposed,

9) A new algorithm (including geographically weighted regression), which take into account the difference in the influence of the individual characteristics of respondents living in different regions on their attitude towards immigrants was proposed.

7. Main findings[2]

1) There is asymmetry in the influence of the western and eastern regions of Russia on each other, if some changes occur in the western regions (growth of GRP, changes in the unemployment rate, wages, etc.), then this is reflected in both other western and eastern regions. At the same time, the changes taking place in the eastern regions affect only other eastern regions, but not the western ones. The factors affecting the growth of GRP, unemployment, and relative wages in the western and eastern regions differ significantly[3]. (Demidova, 2014).

2) The situation with youth unemployment in Russia in 2000-2009 was more serious than with the total unemployment. Crisis 2008-2009 affected harder the youth than the "adult" population. The factors that influenced youth unemployment in 2000-2009 were different in the western and eastern regions. In particular, the increase in migration flows did not affect youth unemployment in the western regions, but increased in the eastern ones. These results were obtained using spatial regression models for two interrelated groups of regions. (Demidova et al., 2013).

3) The situation with youth unemployment (compared to the total) in Russia in 2000-2009 was better than in Italy. For Russia, there is an asymmetric influence of the northern and southern regions (with an increase in the level of youth unemployment in the northern region, the situation will worsen in the neighboring northern and southern regions, and a change in the situation in the southern region will not affect other regions). In Italy, on the contrary, an

[2] The articles in which these results were published are indicated in brackets
[3] These results were obtained using spatial regression models for two interrelated groups of regions

increase in the level of youth unemployment in the southern region will worsen the situation both in the north and in the south. These results were obtained using spatial regression models for two interrelated groups of regions. (Demidova et al., 2015).

4) We can divide Russian regions into 3 groups according to the level of unemployment: group L - regions with low unemployment, surrounded by regions with low unemployment, group H - regions with high unemployment, surrounded by regions with high unemployment, group LH - all other regions. The unemployment rate in all regions can be reduced by increasing the share of employed in the manufacturing industry and by decreasing the share of employed in public sector. In the group of regions H, the unemployment rate can be reduced by increasing the labor productivity and by increasing the share of people employed in agriculture. These results were obtained by modifying the spatially autoregressive model for regions of one country, divided into several groups. (Danilenko et al., 2018).

5) We can divide Russian regions into 3 groups according to the level of employment (not identical to the groups from item 6)): group H - regions with a high level of employment, surrounded by regions with a high level of employment, two groups of regions with a low level of employment, surrounded by regions with a low level of employment, one located in the south of Russia (group LL1), the second - in southern Siberia and Trans-Baikal (group LL2). The employment rate in all groups can be increased by increasing the degree of specialization of the economy, in the group of regions H by reducing the flow of immigrants, and in the group LL1, on the contrary, by increasing the flow of immigrants, as well as increasing the share of the rural population. In the LL2 group of regions, employment can be increased by increasing the proportion of labor force with higher education. These results were obtained by modifying the spatially autoregressive model for regions of one country, divided into several groups. (Demidova et al., 2018).

6) Beta convergence in GRP takes place only for medium and rich Russian regions, and its rate is significantly higher in the group of rich regions; only middle and poor regions benefit from the growth of neighboring regions, while the opposite trend is observed for rich regions. Investments only contribute to the growth of rich regions, and they are not effective for poor and middle regions. These results were obtained by modifying the spatially autoregressive model for regions of one country, divided into several groups. (Demidova, 2021a).

7) Densely populated and urbanized regions have a higher sensitivity to spatial externalities, i.e. a region surrounded by fast-growing territories will grow the more intensively, the higher its population density and the higher the level of urbanization. These results were obtained using a modification of the spatially autoregressive model associated with replacing the spatial

correlation coefficient with a linear function of the selected characteristic of the region. (Demidova, Ivanov, 2016).

8) The better the institutional environment and the higher the degree of business activity in the region, the more intense the influence of neighboring economies on the rates of economic growth of the region under consideration. These results were obtained using a modification of the spatial Durbin model associated with the replacement of coefficients at spatial lags of the dependent and independent variables by a linear function on the selected characteristic of the region. (Demidova, Kamalova, 2021).

9) The dependence of the change in the unemployment rate on the degree of diversification and the degree of concentration of the regional economy has a nonlinear character, and during times of crises the Marshall effects prevail (unemployment is lower in regions with a high level of concentration of the economy), and during periods of recovery, the Jacobs effects prevail (unemployment below in economically diversified regions). Therefore, in a crisis period, it makes sense for the state to support enterprises whose specialization does not coincide with the main specialization of the region with the help of tax incentives and special subsidies, and to develop the most promising industries in each region during a period of growth. The specifications of the models were determined using the algorithm described in paragraph 6 of the section "Main findings". (Demidova et al., 2020).

10) The sensitivity of wages to changes in the unemployment rate is not the same for Russian regions; it is higher in agricultural and isolated regions. This result was obtained by testing the significance of partial marginal effects in spatial-econometric models. (Demidova, Timofeeva, 2021).

11) The Krasnoyarsk Territory and the Moscow Region are the regions where changes in the unemployment rate have the greatest impact on the level of wages in other regions. This result was obtained using a new algorithm based on testing the significance of partial indirect marginal effects. (Demidova, Timofeeva, 2021).

12) The stronger the strength of spatial interaction between regions, the more serious errors can be caused by neglect of spatial effects (Semerikova, Demidova, 2015). In particular, the sensitivity of wages to changes in unemployment will be overestimated almost twice (Demidova, Timofeeva, 2021), the rate of beta convergence of GRP will be overestimated, for a group of "rich" regions almost twice. (Demidova, 2021a).

13) The degree of trust of the population of different countries in the main social and political institutions depends not only on the individual characteristics of the respondents, but also on

the macroeconomic situation in their country of residence. It is impossible to transfer the experience of economically developed countries to all others. Russia is included in the same cluster with the former republics of the USSR, Eastern European countries, and Latin American countries. Most of all in Russia the respondents trust the army, then, in descending order, the institutions are located as follows: television, government, justice system, press, police, parliament, political party. In these countries, raising the educational level of the population without simultaneously improving its financial situation will not help raise the level of trust in basic institutions, but will lead to the opposite effect. (Demidova, 2011).

14) The influence of respondents' individual characteristics on their attitude towards immigrants differs significantly for residents of Russia and Ukraine compared to the residents of European countries. In Russia and Ukraine, migrants are better treated by those with higher education (in European countries this tendency is even more strong), and by religious respondents (in Eastern European countries, the same is true, and in countries that joined the EU after 2004, there is the opposite tendency), while unemployed respondents treat them worse (in European countries this is not the case). However, when explaining the general attitude towards immigrants, the economic and institutional indicators of the countries of residence of individuals prevail. These results were obtained using a new class of models with slope coefficients varying for different groups of countries and a new algorithm that allows to establish the importance of taking into account the economic and institutional indicators of the countries of individuals' residence. (Demidova, 2012), (Paas, Demidova, 2014), (Demidova, 2014).

15) On average, in the Russian regions, the best attitude toward immigrants is demonstrated by young people and older generation, respondents with higher education and having mean or high income level. However, attitudes towards immigrants and the influence of the chosen factors vary sufficiently and depend on the place of the respondents' residence. The most positive attitudes towards immigrants demonstrate residents of small, non-capital cities, as well as residents of the Samara and Sverdlovsk regions, and most negative of all - residents of the poorest and richest regions. Attitudes towards immigrants are also improving with an increase in the share of construction and trade in the economy of the region (these are industries where a lot of immigrants employed). Local residents gradually get used to immigrants, the higher the proportion of migrants in the region who came from abroad, the better the residents of the respective region relate to immigrants. (Demidova, 2021b).

8. Theoretical significance and practical implications of the dissertation research

The theoretical significance of the dissertation research is the development of the spatial-econometric tools described in Section 6 "Contribution".

Practical implications of the research

The results of the dissertation research were used in the following projects:

1) "The Political Economy of Youth Unemployment", FP7-PEOPLE, Grant agreement ID: 269134, 2012–2015, 7th Framework Program of the European Union,
2) SEARCH (Sharing KnowledgE Assets: InteRregionally Cohesive NeigHbohoods), the 7th Framework Programme for Research and Technological Development in the 'Socio-economic sciences and the humanities' area (FP7-SSH-SSH-2010.2.2.1-266834), 2012–2013, 7th Framework Program of the European Union,
3) IUT20-49 "Structural Change as the Factor of Productivity Growth in the Case of Catching up Economies", 2013–2014, a project of the Estonian Ministry of Education and Research,
4) Project "Spatial effects for eastern and western regions of Russia: comparative econometric analysis" supported by the HSE Research Fund, № 12-01-0057, 2013–2014,
5) Project "Elites, institutions and culture as factors of economic development", supported by the HSE Research Fund, 2016,
6) "Modeling the mutual influence of Russian regions and assessing the effectiveness of state programs using spatial econometric methods", project No. 20-110-50398 within the framework of the RFBR project "Expansion", 2020.

The results of the dissertation research were also used

1) for the preparation of teaching materials for lectures and seminars for the course of econometrics for third-year students of the Faculty of Economics of the National Research University Higher School of Economics and for the course of econometrics for PhD students of the Doctoral School of Economics,

2) in research project seminars for students of the FES NRU HSE,

3) for lectures and seminars of the program of the Higher School of Economics and the Yegor Gaidar Foundation for advanced training "Applied Econometric Methods", cycle 3 "Spatial Econometrics and Methods of Regional Analysis" for teachers-researchers of regional universities.

The results of the dissertation work were used in the scientific reports of the research working group "Center for Spatial Econometrics in Applied Macroeconomic Research" FES.

9. Approbation of research results

The results of the dissertation research were presented in reports at more than 60 conferences, including:

1) April International Scientific Conference "Modernization of Economy and Society", 2012–2020
2) International Conference “Modern Econometrics Tools and Applications” (META), 2014–2020
3) Russian Economic Congress 2013, 2016, 2020
4) International scientific school-seminar named after academician S.S. Shatalin, 2011, 2012, 2013, 2015, 2020
5) North American Regional Science Association (NARSC) Meeting, 2013, 2014, 2020
6) Western Regional Science Association 53rd Annual Meeting, San Diego,16–19 февраля 2014
7) European Regional Science Association (ERSA) Congress, 2013, 2014, 2016, 2019
8) Scientific Conference "Spatial Econometrics and Regional Economic Analysis", University of Lodz, Poland, 2014, 2018
9) World Conference of Spatial Econometric Association (SEA) 2016, 2018,
10) International Workshop "Spatial Econometrics and Statistics”, France, 2014, 2019
11) World Congress of Comparative Economics, August 2015 (Rome), 2017 (St. Petersburg)
12) Annual Conference of the International Society for New Institutional Economics, USA, 2011 (Stanford University), 2012 (Los Angeles)
13) European Association for Comparative Economic Studies (EACES) Conference, 2012, 2014
14) International Economic Association 16th World Congress, Tsinghua University, Beijing, China, July 2011

List of author’s original articles

1) Demidova O.A. (2011). Modeling public confidence in the main social and political institutions: a comparative econometric analysis. *Applied Econometrics*, 114–132. (In Russian).

2) Demidova O.A. (2012). The attitude of residents of European countries to immigrants: a comparative econometric analysis based on the data of European social research. *Applied Econometrics*, 28, 23–34. (In Russian).

3) Demidova O., Marelli E., Signorelli M. (2013). Spatial Effects on Youth Unemployment Rate: The Case of Eastern and Western Russian Regions. *Eastern European Economics*, 51(5), 94–124.

4) Demidova O.A. (2014). Spatial autoregressive model for two groups of interconnected regions (on the example of the eastern and western parts of Russia). *Applied Econometrics*, 34(2), 19–35. (In Russian).

5) Paas T., Demidova O. (2014). How people perceive immigrants' role in their country's life: a comparative study of Estonia and Russia. *Eastern Journal of European Studies*, 5(2), 117–138.

6) Demidova O. (2014). How Russian and Ukrainian citizens perceive the role of immigrants in their country: a comparison with European residents. *International Journal of Computational Economics and Econometrics*, 4(1/2), 181–206.

7) Demidova O., Marelli E., Signorelli M. (2015). Youth labour market performances in the Russian and Italian regions. *Economic Systems*, 39(1), 43–58.

8) Semerikova E.V., Demidova O.A. (2015). Analysis of regional unemployment in Russia and Germany: a spatial-econometric approach. *Spatial Economics*, 2, 64–85. (In Russian).

9) Demidova O.A., Ivanov D.S. (2016). Models of economic growth with heterogeneous spatial effects (on the example of Russian regions). *Economic Journal of the Higher School of Economics*, 20(1), 52–75. (In Russian).

10) Danilenko T., Demidova O., Signorelli M. (2018). Unemployment Clubs in Russian Regions. *Emerging Markets Finance and Trade*, 54(6), 1337–1357.

11) Demidova O., Daddi P., Medvedeva E., Signorelli M. (2018). Modeling the Employment Rate in Russia: a Spatial-Econometric Approach. *Economy of Region*, 14(4), 1383–1398.

12) Demidova O. Convergence of Russian regions: different patterns for poor, middle and rich (2021a). *Economy of Region*, 17(4), 1151–1165.

13) Demidova O., Kolyagina A., Pastore F. (2020). Marshallian vs Jacobs effects: Which is stronger? Evidence for Russia unemployment dynamics. *Structural Change and Economic Dynamics*, 55, 244–258.

14) Demidova O.A., Kamalova E. (2021). Spatial Econometric Modeling of Economic Growth in Russian Regions: Do Institutions Matter? *Economic Policy*, 16(2), 34-59. (In Russian).

15) Demidova O.A., Timofeeva E.A. (2021). Spatial aspects of assessing the wage curve in Russia. *Journal of the New Economic Association*, 3 (51), 51–84. (In Russian).

16) Demidova O.A. (2021) Attitude towards immigrants in Russia: a regional aspect. *Spatial Economics*, 17(3), 103–125. (In Russian).

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