For citation: Ekonomika regiona [Economy of Region]. — 2016. — Vol. 12, Issue 4. — pp. 1040–1049
doi 10.17059/2016–4–6
UDC: 332.1
JEL: C52, C53

G. Y. Gagarina [a)], ***N. A. Moiseev*** [a)], ***A. V. Ryzhakova*** [a)], ***G. V. Ryzhakov*** [a, b)]
[a)] Plekhanov Russian University of Economics (Moscow, Russian Federation)
[b)] Skolkovo Institute of Science and Technology (Skoltech),
(Moscow, Russian Federation; e-mail: mr.nikitamoiseev@gmail.com)

ESTIMATION AND FORECAST OF REGIONAL COMPETITIVENESS LEVEL [1]

The paper is devoted to the development of methods for point and interval forecasting of the integral index of regional competitiveness. We stick to one of the most commonly used approaches to assessing the level of competitiveness based on its advantages over the others. As a result of this approach, the integral competitiveness index appears to be bounded, i.e. has a lower and upper limit. Due to this particular feature, it is proposed to carry out the forecasting of competitiveness index using multivariate logistic regression. The parameters of such model are determined using OLS through an inverse logarithmic transformation of the dependent variable. To calculate interval forecasts for the model, we proposed a new probability distribution for the errors of the nonlinear regression equation in the class of logistic curves. According to the proposed method, we calculated and forecasted the regional competitiveness level for the Russian Federation until 2020. The analysis of the data revealed some features of the regions distribution in terms of competitiveness level and indicated regional development trends. The paper has been prepared within the research project №1675: "Methodological and analytical tools for solving problems of spatial development of Russian economy under conditions of modern reforms" in terms of the basic part of the state order in the field of scientific activity of Russian Ministry of Education.

Keywords: integral index of competitiveness, time series forecasting, prediction of bounded variables, logistic regression, OLS, multifactor linear regression

1. Introduction

Management and evaluation of regional competitiveness is one of the most popular areas of research in economics. Recent literature has presented a number of approaches to assessing the competitiveness level of country's single region. For example, in [1] authors developed various integral indices, reflecting regional competitiveness and social and economic development based on statistical data. These indices include an index of current competitiveness, index of industrial competitiveness, index of infrastructure development and communications, index of innovative regional development and index of foreign economic activities. The same idea of selecting and integrating macroeconomic indicators prevails also in [2, 3, 4]. In [5], the stress is made on including territorial and natural and ecological components in a process of competitiveness evaluation. [6, 7] focus on a clustering approach to grounding the competitive advantages of regional economic subsystems. Some studies, such as [8] elaborate matrix approach to assessing regional competitiveness incorporating Herfindahl-Hirschman Index of market concentration. There is also literature with non-traditional approaches to the discussed problem, for example, refer to [9] where the author regards competitiveness from an evolutionary perspective. The proposed methods differ not only in the methodology of competitiveness computation, but also directly determine its characteristics, such as tolerance region, sensitivity to changes in the total competitiveness, dependence on maximum and minimum values of macroeconomic indicators, etc. Excellent reviews of most popular methods were conducted in [10, 11]. Despite the high interest in the topic of regional competitiveness evaluation, relatively small amount of literature is devoted to the methodology of competitiveness forecasting, however, this is a significant omission, as reliable estimates of the future socio-economic status of a region significantly affect the management policy and attraction of foreign and domestic investments.

Since competitiveness level is a fuzzy term, it is quite hard to verify the superiority of one evaluation method over another. Therefore, the choice of selecting one method or another fully lies at

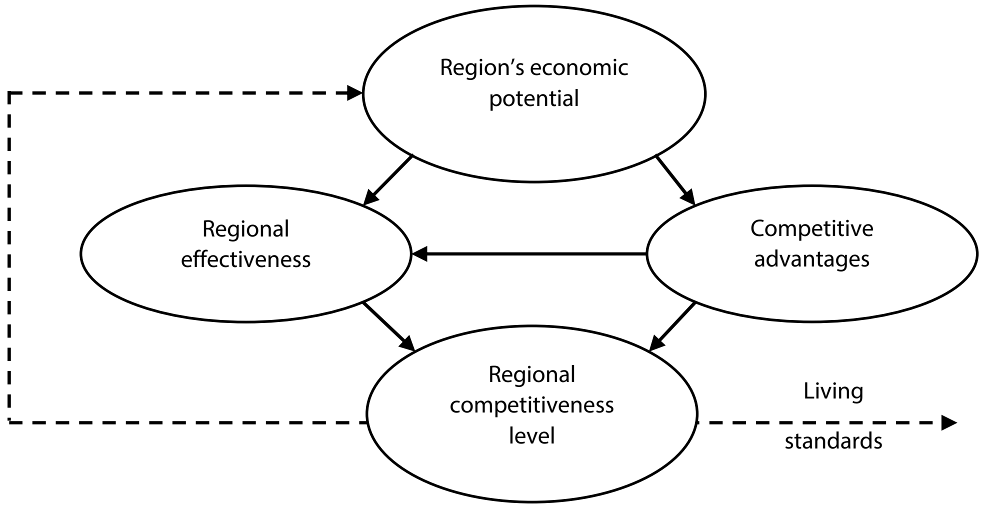

Fig. 1. *Mechanism of regional competitiveness formation*

researcher's discretion, his/her ideas, and purposes of conducted study. In this regard, this paper focuses rather on developing new mathematical tools for modeling and forecasting regional competitiveness index, than creating another approach to its assessment. We considered the main class of integrated indicators — bounded (having upper and lower limit) for which we propose an approach that allows to standardize the procedure of competitiveness index forecasting. Proposed methods can be successfully applied to any other integrated indices of regional competitiveness, constructed according to different approaches.

The paper is organized as follows: section 2 deals with existing methods of estimating the regional competitiveness. Section 3 is devoted to the development of mathematical approaches for predicting the integral index of regional competitiveness. In section 4 we conduct a finite sample investigation of proposed methods on regions of the Russian Federation and section 5 discusses the results and determines directions for further research.

2. Estimation of regional competitiveness index

Competitiveness of a region is its capacity to produce goods that can compete on the market using existing and creating new competitive advantages, incorporating economic potential and maintaining people's quality of living according to international environmental standards, see figure 1.

Here we explain in more detail what is implied by the term "competitiveness level". This term means that integral assessment of a region's capacity to compete should be compared to the same index of the reference region. As the reference region, researchers commonly use the one that actually exists and has a medium or best statistical indicators. Such an assessment may be calculated, based on the identification of the socio-economic level of regional development, as well as the region's ability to attract foreign capital [10, 11].

To calculate the competitiveness of a region, we will use the methods of quantitative analysis, which are based on macro-economic characteristics in order to identify trends in the development of a subject of country's economy and social sphere. Quantitative methods of assessment are an integral type evaluation of performance. Such integrality can be achieved by counting the collective of individual performances, showing the dynamics of regional internal processes, see for example [1, 10–12].

In this paper, we compute the integral index of competitiveness by three systems of macroeconomic indicators, see Table 1.

In order to synthesize all integrated indicators related to economic potential, as well as regional performance, competitive advantages and competitiveness, we should resort to using non-parametric statistical analysis techniques. The main advantage of using the above methods has always been a decrease in the dimension of the original data matrix using the method of shrinkage of the original data. It is worth noticing that non-parametric methods, including multivariate statistical comparisons, do not possess significant sensitivity to changes in statistics. They can be used in small samples and do not require a comparable basis of measurements of individual parameters.

The above-mentioned disadvantages are eliminated by multidimensional non-parametric methods, which are based on the principle of relative valuations. Hence we consider the most relevant of them — the method of relative difference. It stipulates assessments of individual performance with

Table 1

System of regional competitiveness indicators

System of indicators of economic potential of a region	System of indicators of regional efficiency	System of indicators of competitive advantages
Economically active population, ths. people	Production of *GRP* (*GVA*) per 1 employed in the economy of the region, ths. rub./person	Cost of fixed assets per 1 employed in the economy, ths. rub.
Cost of capital assets in all industries, mil. rub.	Production of *GRP* (*GVA*) per 1 ruble of fixed assets value in the region, rub.	Depreciation of fixed assets in the region, %
Gross domestic expenditure on research and development, ths. rub.	Cost of wages per 1 ruble of *GRP* (*GVA*), rub.	Investments in fixed capital per 1 employed in the economy of the region, ths. rub.
Net financial result of the region, mil. rub.	Share of unprofitable organizations, %	Unemployment rate, %
Investments in fixed capital, mil. rub.	Retail trade turnover per 1 employed in the economy, ths. rub.	The number of people with income below the minimum wage, %
Gross regional product, mil. rub.	Population immigration rate per 10 000 people	Innovation activity, %

the help of normalization by formulae (1) and (2). In other words, the excess of the i^{th} value for the j^{th} region over the smallest value that relates to the variance of i^{th} individual index over the entire set of regions. Here we note that formula (1) is used in case when a larger value of the index is a positive characteristic of a region (*GRP*, the value of fixed assets, the financial result of a region, etc.), and formula (2) — when a greater value of the index is a negative characteristic of a region (depreciation of fixed assets, unemployment, wage costs per 1 ruble of *GRP*, etc.).

$$t_i = \frac{P_i - P_{i\min}}{P_{i\max} - P_{i\min}}, \quad (1)$$

$$t_i = \frac{P_{i\max} - P_i}{P_{i\max} - P_{i\min}}, \quad (2)$$

where P_i — actual value of i^{th} individual indicator, $P_{i\min}$ — minimum value of i^{th} individual indicator on all considered regions, $P_{i\max}$ — maximum value of i^{th} individual indicator across all considered regions.

The value of the integral coefficient is obtained by a simple average of the individual factors — formula (3).

$$U = \sum_{i=1}^{n} \frac{t_i}{n}, \quad (3)$$

where n — total number of individual indicators.

Considering that the values of t_i belong to the range [0; 1], then $U = 1$ can be reached only if i^{th} region has the best values across all individual indicators.

In our opinion, this method of construction of integral competitiveness index has the following key benefits. It does not impose restrictions on individual non-negative indices in a region, also no difficulties arise with indicators that take both positive and negative values, for example, with the balance of payments. The resulting index of competitiveness due to its strict positivity is easily translated into continued and reference growth index, which can visually monitor the trends of development of regions. Finally, the relative difference method allows to obtain an informative measure by which it is possible to assess the competitiveness of a region without resorting to a comparison with other regions of a country: the values close to one testify unique superiority of one region over the others and vice versa, the values close to zero — low level of competitiveness.

3. Prediction of regional competitiveness index

Let us have a set of time series $\{y_t, X_t : t = 1, \dots, n\}$, where y_t — competitiveness index at time t, $X_t = (x_{0t}, x_{1t}, x_{2t}, \dots, x_{kt})$ — a set of explanatory variables. Since in this case tolerance range of target variable is bounded from above and below, it is proposed to use a multivariate logistic regression to obtain a point forecast of competitiveness index. The formula of the logistic curve is written as follows:

$$y_t = \frac{1}{1 + e^{-z(t)}}, \quad (4)$$

where $y_t \in (0; 1)$ and represents a scaled index of regional competitiveness, $z(t) \in (-\infty; +\infty)$.

It is worth noticing that $z(t)$ may be either linear or non-linear function of explanatory variables X_t. Parameters of such model are estimated by using OLS for which we previously conduct an inverse logarithmic transformation of the target variable, as shown below:

$$z(t) = -\ln\left(\frac{1}{y_t} - 1\right). \quad (5)$$

Thus linear model can be presented as follows:

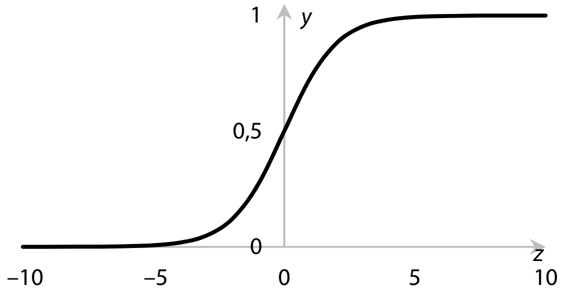

Fig. 2. *Logistic curve*

$$z(t) = X_t B + e_t, \qquad (6)$$

where $B = (b_0, b_1, \ldots, b_k)'$, is a column-vector of estimators for true model's parameters β, which is independent of any realization of vector X_t, e_t—"white" noise, which is assumed to be subject to normal distribution.

Parameters vector for such class of models is then estimated as below:

$$B = \left(X^T X\right)^{-1} X^T Z, \qquad (7)$$

where $X = \begin{pmatrix} X_n \\ X_{(n-1)} \\ \vdots \\ X_1 \end{pmatrix}, Z = \begin{pmatrix} z_n \\ z_{n-1} \\ \vdots \\ z_1 \end{pmatrix}.$

We also suppose that all OLS prerequisites hold, i.e.

$$E\left(e_t \middle| X_t\right) = 0, \qquad (8)$$

$$E\left(e_t^2 \middle| X_t\right) = \sigma^2, \qquad (9)$$

$$\operatorname{cov}\left(e_i; e_j\right) = 0, \forall i \neq j. \qquad (10)$$

In case $z(t)$ is a non-linear function of X_t, then the model will be presented as shown below:

$$z(t) = h\left(X_t, B\right) + e_t, \qquad (11)$$

where h is a continuously differentiable function of its arguments.

If prerequisites (8–10) hold, then the vector of parameter estimators (11) is computed with the help of numerical minimization of the following target function:

$$S(B) = \frac{1}{2}\sum_{t=1}^{n}\left(z(t) - h\left(X_t, B\right)\right)^2 \to \min. \qquad (12)$$

For an illustration of the probability distribution of model's errors we find the probability density function for y_t at the fixed value of variable t. To do this, we carry out the following calculations:

$$y_t = \frac{1}{1+e^{-(\hat{z}(t)+\varepsilon)}} = \frac{1}{1+e^{-\hat{z}(t)}e^{-\varepsilon}} = \frac{1}{1+\alpha e^{-\varepsilon}}.$$

where $\hat{z}(t) = X_t B$, $\alpha = e^{-\hat{z}(t)}$ and $\alpha \in (0; +\infty)$.

Thus the probability distribution of random variable y_t, will depend on parameters α and σ. At the first stage we derive the cumulative distribution function as presented below:

$$cdf_Y(y) = P(Y < y) = P\left(\frac{1}{1+\alpha e^{-x}} < y\right) =$$

$$= P\left(x < -\ln\left(\frac{1-y}{ay}\right)\right) = \frac{1}{\sqrt{2\pi}\sigma}\int_{-\infty}^{-\ln\left(\frac{1-y}{ay}\right)} e^{\frac{-x^2}{2\sigma^2}}dx.$$

Here σ denotes standard deviation of "white" noise ε. In order to derive the probability density function we differentiate the obtained function with respect to y.

$$pdf(y) = cdf_Y(y)' = \left(\frac{1}{\sqrt{2\pi}\sigma}\int_{-\infty}^{-\ln\left(\frac{1-y}{ay}\right)} e^{\frac{-x^2}{2\sigma^2}}dx\right)'_y =$$

$$= \frac{1}{\sqrt{2\pi}\sigma}e^{\frac{-\ln^2\left(\frac{1-y}{ay}\right)}{2\sigma^2}}\left(-\ln\left(\frac{1-y}{ay}\right)\right)'_y.$$

From here we obtain the analytical form of the probability density function for forecasted value of y which is shown below:

$$pdf(y) = \frac{1}{\sqrt{2\pi}\sigma y(1-y)}e^{\frac{-\ln^2\left(\frac{1-y}{ay}\right)}{2\sigma^2}}. \qquad (13)$$

Depending on the parameters, derived probability distribution takes up different shapes (see fig. 3). If parameters $\alpha = 1$, $\sigma = 0.5$ distribution is close to normal, in case when $\alpha = 0.3$, $\sigma = 0.7$ and $\alpha = 3$, $\sigma = 1.3$ distribution is clearly skewed, and it has approximately the shape of α parabola. Note that in the latter case, the model is uninformative because the confidence intervals will cover virtually the entire tolerance range of the target variable. Therefore, during specification of regression equation researchers should pay attention to the standard deviation of model's residuals, as if the value is greater than 2, the constructed model would be uninformative.

To obtain the interval forecast it is necessary to calculate explicitly the expected mean square forecast error (MSFE). MSFE consists of two components: the variance of "white" noise and the variance of the regression line [13]. This can be presented as follows:

$$MSFE_{t+1} = Var\left(\hat{z}_{t+1} - z_{t+1}\right) =$$

$$= \sigma^2 + Var\left(\hat{z}_{t+1} - E\left(\hat{z}_{t+1}\right)\right). \qquad (14)$$

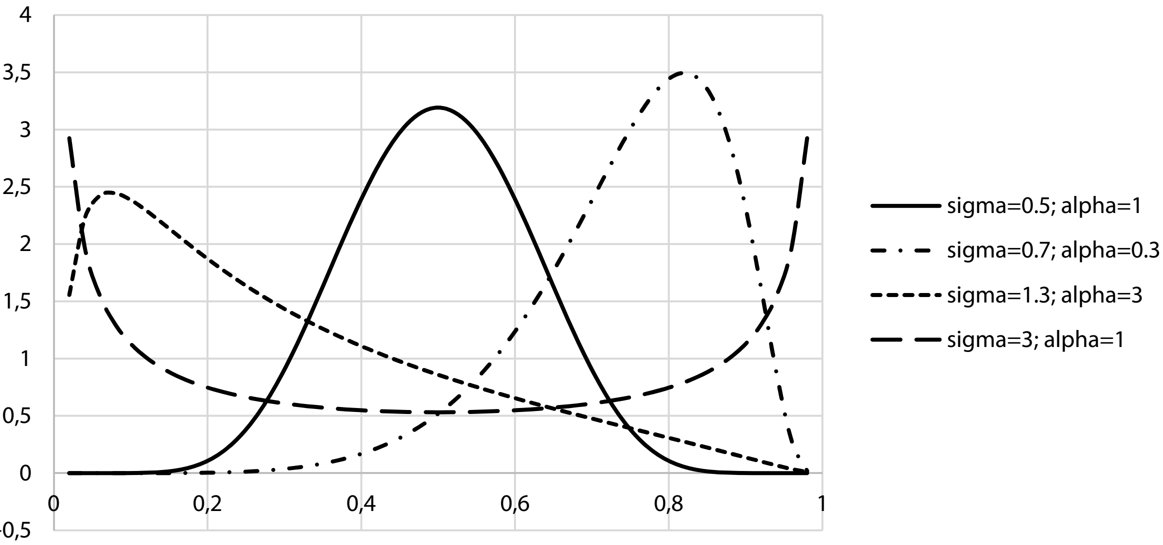

Fig. 3. *Probability density function of y*

Hence we display the derivation of the explicit formula for the regression line variance.

$$Var\left(\hat{z}_{t+1}-E\left(\hat{z}_{t+1}\right)\right)=E\left(\hat{z}_{t+1}-E\left(\hat{z}_{t+1}\right)\right)^2=$$
$$=E\left(X_{t+1}\left(B-\beta\right)\left(B-\beta\right)^T X_{t+1}^T\right)=$$
$$=E\left(X_{t+1}\left(X^TX\right)^{-1}X^T\varepsilon\varepsilon^TX\left(X^TX\right)^{-1}X_{t+1}^T\right)=$$
$$=X_{t+1}\left(X_i^TX_i\right)^{-1}X_i^TE\left(\varepsilon\varepsilon^T\right)X\left(X^TX\right)^{-1}X_{t+1}^T=$$
$$=\sigma^2X_{t+1}\left(X^TX\right)^{-1}X^TX\left(X^TX\right)^{-1}X_{t+1}^T=$$
$$=\sigma^2X_{t+1}\left(X^TX\right)^{-1}X_{t+1}^T.$$

As we don't know the true error variance, we substitute σ^2 with its unbiased estimator s^2, which is computed as follows:

$$s^2=\frac{\sum_{i=1}^{n}e_i^2}{n-k-1}, \qquad (15)$$

where k is a number of explanatory variables in the model.

Thus, mean square forecast error can be presented as below:

$$MSFE_{t+1}=s^2\left(1+X_{t+1}\left(X^TX\right)^{-1}X_{t+1}^T\right). \qquad (16)$$

In case if $z(t)$ is a non-linear regression mean square forecast error is computed as follows:

$$MSFE_{t+1}=s^2\left(1+\frac{\partial h\left(X_{t+1},B\right)}{\partial B^T}\left(Q\right)^{-1}\frac{\partial h\left(X_{t+1},B\right)}{\partial B}\right) \qquad (17)$$

where $Q=\sum_{t=1}^{n}\left(\frac{\partial h\left(X_t,B\right)}{\partial B}\right)\left(\frac{\partial h\left(X_t,B\right)}{\partial B^T}\right)$ and $Var\left(B\right)=s^2Q^{-1}$.

Since the true errors of regression models, which meet the prerequisites (8–10), are subject to normal distribution, confidence intervals for the resulting point forecasts can be determined using t-distribution with significance level α and the number of degrees of freedom equal to $n-k-1$, where k—number of explanatory variables in the model.

$$\hat{z}_{t+1}-t_{\alpha,n-k-1}\sqrt{MSFE_{t+1}}<$$
$$<z_{t+1}<$$
$$<\hat{z}_{t+1}+t_{\alpha,n-k-1}\sqrt{MSFE_{t+1}}. \qquad (18)$$

As we are interested in obtaining the confidence intervals for the integral competitiveness index, we give the formula for calculating them. Since the logistic function is monotonically increasing throughout its tolerance range, we will use the following algorithm for interval estimates. In the first step, we obtain upper and lower bound of the confidence interval for $\hat{z}(t)$:

$$\hat{z}_{low}=\hat{z}\left(t\right)-t_{\alpha,n-m-1}\sqrt{MSFE_{t+1}},$$
$$\hat{z}_{top}=\hat{z}\left(t\right)+t_{\alpha,n-m-1}\sqrt{MSFE_{t+1}}. \qquad (19)$$

where $t_{\alpha,\,n-m-1}$ is a Student's distribution quantile.

Then, based on this interval we obtain the interval for the target variable which is an integral index of regional competitiveness.

$$y_{low}=\frac{1}{1+e^{-\hat{z}_{low}}},\ \ y_{top}=\frac{1}{1+e^{-\hat{z}_{top}}}. \qquad (20)$$

$$y_{low}<y_{t+1}<y_{top}. \qquad (21)$$

Thus, the presented method allows to obtain both point and interval forecast of the integral index of regional competitiveness, varying within a certain range.

4. Application of proposed method of forecasting competitiveness level

To evaluate and predict the level of regional competitiveness we built a statistical database of macroeconomic indicators on the subjects of the Russian Federation from 2002 till 2013. According to indicators specified in table 1, we calculated the level of regional competitiveness and sorted them descending, see table 2. We also conduct the same calculations excluding Moscow city from considered data. This is done in order to avoid false conclusions from obtained results, as the supreme position of the capital of Russia is stipulated rather by political factors than by economic ones. Thus, its inclusion may affect the frequency distribution of competitiveness level for other regions.

As an explanatory variable for building predictive regression models, we select a time factor. This choice is explained by a short data frame, due to which it is extremely difficult to include a larger number of explanatory variables. We tested three regression models:

1) $\hat{z}(t) = b_0 + b_1 t$;
2) $\hat{z}(t) = b_0 + b_1 t + b_2 t^2$;
3) $\hat{z}(t) = e^{b_0 + b_1 t}$.

Based on a comparative analysis of the results, we select the linear model (№ 1) as having the least mean square forecast error. According to the method presented in section 3 of this paper, we built a point and interval forecast of competitiveness of each region for 2016 and 2020 (Table 2).

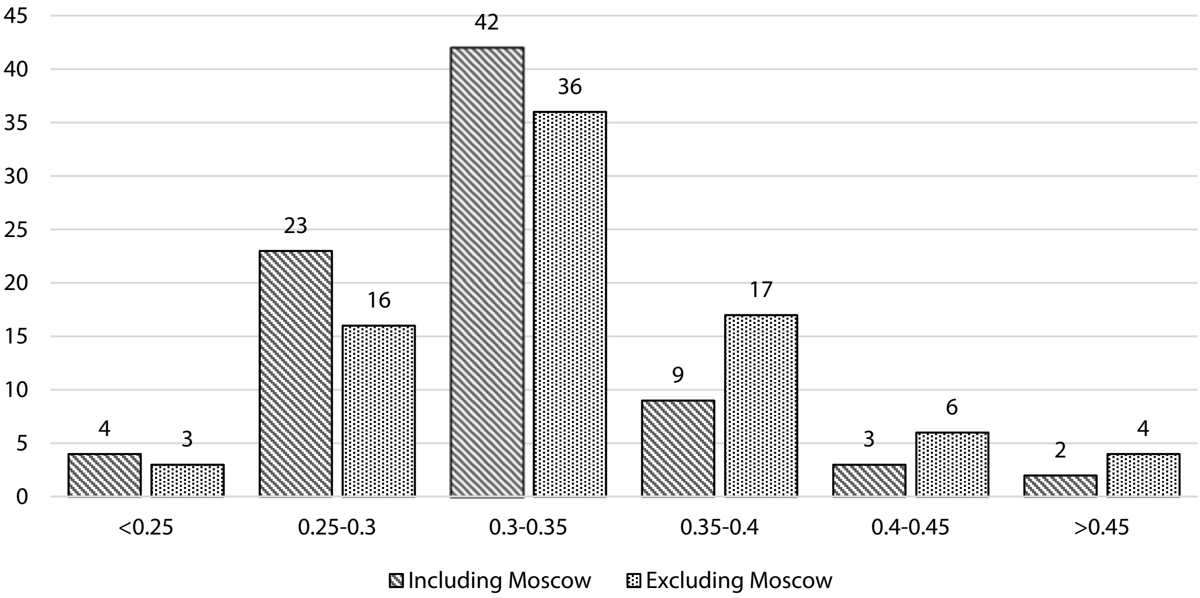

Fig. 4. *Frequency histogram of regions by competitiveness level, 2013*

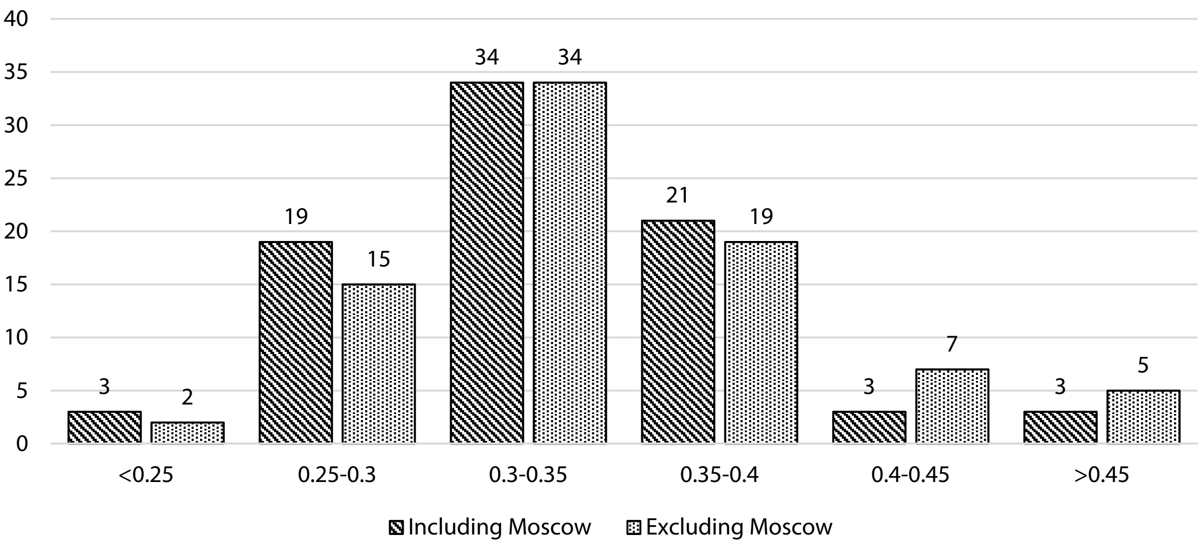

Fig. 5. *Frequency histogram of regions by competitiveness level, 2016*

Table 2

Estimation and forecast of competitiveness level of subjects of the Russian Federation

Region	2013	2016	2016 (lower bound*)	2016 (upper bound*)	2020	2020 (lower bound*)	2020 (upper bound*)
Moscow	0.688	0.676	0.615	0.732	0.664	0.591	0.730
Tyumen region	0.453	0.413	0.361	0.467	0.385	0.327	0.447
Moscow region	0.444	0.457	0.422	0.493	0.469	0.428	0.511
Saint-Petersburg	0.423	0.437	0.388	0.487	0.442	0.385	0.501
Krasnodar region	0.415	0.412	0.386	0.439	0.425	0.393	0.457
Khanty-Mansi Autonomous Okrug	0.388	0.346	0.294	0.402	0.317	0.260	0.380
The Republic of Ingushetia	0.385	0.365	0.278	0.463	0.403	0.297	0.520
Republic Bashkortorstan	0.372	0.373	0.342	0.405	0.378	0.342	0.416
Rostov region	0.366	0.374	0.341	0.408	0.382	0.343	0.422
Krasnoyarsk region	0.362	0.366	0.344	0.389	0.369	0.343	0.395
Omsk region	0.361	0.374	0.328	0.421	0.392	0.338	0.449
Samara Region	0.355	0.354	0.316	0.395	0.371	0.325	0.420
Republic of Tatarstan	0.354	0.368	0.332	0.404	0.374	0.333	0.418
Sverdlovsk region	0.353	0.361	0.327	0.396	0.369	0.329	0.411
Voronezh region	0.350	0.364	0.329	0.401	0.392	0.349	0.436
Novosibirsk region	0.349	0.366	0.319	0.416	0.378	0.323	0.437
Nenets Autonomous Okrug	0.348	0.354	0.294	0.419	0.360	0.290	0.436
Belgorod region	0.348	0.379	0.335	0.425	0.406	0.353	0.461
Sakhalin Region	0.344	0.375	0.313	0.440	0.392	0.319	0.470
Republic of Adygea	0.342	0.346	0.288	0.410	0.368	0.298	0.444
Nizhny Novgorod Region	0.341	0.344	0.312	0.378	0.351	0.313	0.391
The Republic of Dagestan	0.340	0.371	0.329	0.415	0.393	0.343	0.446
The Republic of Buryatia	0.339	0.335	0.290	0.384	0.341	0.288	0.399
Chelyabinsk region	0.339	0.356	0.318	0.396	0.369	0.323	0.416
Irkutsk region	0.337	0.355	0.319	0.391	0.366	0.324	0.409
Stavropol region	0.333	0.352	0.313	0.393	0.369	0.322	0.419
Karachay-Cherkess Republic	0.332	0.340	0.283	0.402	0.360	0.292	0.434
Primorsky Krai	0.331	0.359	0.311	0.411	0.370	0.312	0.431
Kaluga region	0.331	0.354	0.314	0.397	0.373	0.325	0.424
Leningrad region	0.330	0.337	0.303	0.374	0.341	0.301	0.384
Altai region	0.329	0.352	0.310	0.396	0.372	0.322	0.425
Yamalo-Nenets Autonomous Okrug	0.328	0.299	0.255	0.348	0.274	0.226	0.329
Khabarovsk region	0.325	0.324	0.293	0.356	0.327	0.291	0.365
Kemerovo region	0.323	0.352	0.297	0.412	0.358	0.293	0.428
Transbaikal region	0.323	0.327	0.283	0.374	0.336	0.285	0.392
Vladimir region	0.323	0.333	0.296	0.372	0.344	0.300	0.391
Kursk region	0.322	0.344	0.297	0.395	0.369	0.312	0.431
Kaliningrad region	0.318	0.334	0.293	0.378	0.341	0.293	0.393
Oryol Region	0.316	0.319	0.290	0.350	0.335	0.300	0.371
Perm Region	0.315	0.315	0.286	0.346	0.327	0.292	0.364
Tambov Region	0.315	0.333	0.283	0.386	0.359	0.299	0.424
Amur region	0.315	0.321	0.285	0.358	0.323	0.282	0.368
Kabardino-Balkar Republic	0.313	0.320	0.272	0.371	0.323	0.268	0.384
The Republic of Sakha (Yakutia)	0.312	0.312	0.277	0.350	0.312	0.271	0.356
Arhangelsk region	0.311	0.311	0.274	0.350	0.315	0.271	0.362
Tula region	0.308	0.317	0.286	0.351	0.326	0.289	0.366
Tyva Republic	0.308	0.323	0.270	0.380	0.337	0.275	0.405
Ulyanovsk region	0.307	0.326	0.297	0.357	0.344	0.309	0.381
Republic of North Ossetia — Alania	0.306	0.310	0.269	0.354	0.313	0.265	0.364
Saratov region	0.306	0.311	0.277	0.348	0.315	0.275	0.359

Region	2013	2016	2016 (lower bound*)	2016 (upper bound*)	2020	2020 (lower bound*)	2020 (upper bound*)
Ryazan Oblast	0.305	0.309	0.272	0.349	0.314	0.270	0.361
Volgograd region	0.304	0.322	0.281	0.366	0.331	0.283	0.384
Bryansk region	0.303	0.327	0.287	0.369	0.342	0.295	0.393
Ivanovo region	0.303	0.300	0.268	0.335	0.309	0.270	0.351
Novgorod region	0.301	0.312	0.277	0.349	0.322	0.281	0.366
Vologda Region	0.300	0.295	0.252	0.341	0.290	0.241	0.344
Udmurt republic	0.299	0.287	0.247	0.331	0.290	0.243	0.342
Orenburg region	0.299	0.311	0.264	0.363	0.321	0.265	0.384
The Republic of Khakassia	0.297	0.324	0.265	0.389	0.330	0.261	0.408
Lipetsk region	0.296	0.309	0.264	0.357	0.311	0.259	0.368
Tomsk region	0.295	0.285	0.255	0.318	0.280	0.245	0.318
Kirov region	0.294	0.313	0.263	0.367	0.321	0.263	0.386
Pskov region	0.294	0.299	0.258	0.343	0.301	0.253	0.353
Kamchatka Krai	0.293	0.280	0.245	0.318	0.271	0.231	0.315
Altai Republic	0.292	0.319	0.255	0.391	0.332	0.256	0.417
Smolensk region	0.291	0.297	0.265	0.332	0.297	0.259	0.339
Kostroma region	0.288	0.293	0.243	0.348	0.302	0.244	0.368
Tver region	0.287	0.309	0.257	0.366	0.316	0.255	0.383
Komi Republic	0.286	0.276	0.247	0.306	0.266	0.233	0.302
Astrakhan region	0.284	0.268	0.243	0.295	0.259	0.230	0.290
Chechen Republic	0.282	0.770	0.113	0.989	0.943	0.264	0.999
Yaroslavl region	0.279	0.281	0.249	0.315	0.276	0.239	0.316
The Republic of Karelia	0.276	0.264	0.224	0.308	0.247	0.203	0.298
Murmansk region	0.272	0.279	0.243	0.319	0.269	0.228	0.315
Penza region	0.271	0.280	0.230	0.336	0.281	0.223	0.347
Mari El Republic	0.268	0.266	0.232	0.304	0.268	0.228	0.312
Chuvash Republic	0.266	0.262	0.223	0.304	0.254	0.210	0.303
The Republic of Mordovia	0.261	0.270	0.231	0.312	0.272	0.227	0.323
Chukotka Autonomous Okrug	0.261	0.270	0.185	0.375	0.277	0.178	0.404
Kurgan region	0.248	0.249	0.203	0.300	0.248	0.195	0.309
Jewish Autonomous Region	0.247	0.252	0.194	0.320	0.239	0.175	0.317
Republic of Kalmykia	0.221	0.227	0.173	0.292	0.225	0.163	0.301
Magadan Region	0.196	0.191	0.158	0.231	0.170	0.134	0.212

* — calculated 95 % confidence interval.

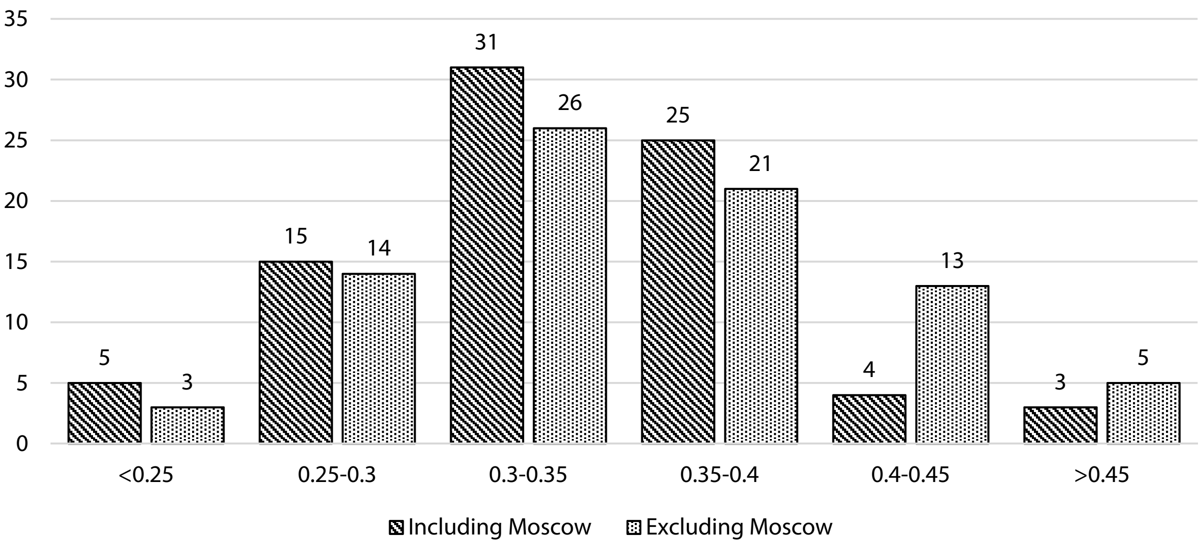

Fig. 6. *Frequency histogram of regions by competitiveness level, 2020*

According to the data from table 2, we built the frequency distribution of the regions in terms of competitiveness level for 2013 and the estimated frequency distribution in 2016 and in 2020 for both cases: with Moscow included and excluded from the calculations. The results are shown in figure 4, figure 5 and figure 6 respectively.

Through the analysis of the statistical data, we can conclude that in 2013 the absolute majority of regions have a very low level of competitiveness, which testifies to their unbalanced development. This inference remains valid even if we exclude Moscow city from our calculations, because as one can see from figure 4 the frequency distribution is not very sensitive to exclusion of the capital. Obtained distribution generally can not be called a competitive economic system in which the distribution of the regions is close to normal. However, if we make a comparison with the expected distribution of the regions in 2016 and 2020, we can hope for some improvement. From figure 5 we see that in comparison with 2013 some part of the regions shifted from the interval within the range 0.25–0.3 to the range 0.3–0.35. The same thing happened with the regions in the range 0.3–0.35: some of them have moved to a higher group of competitiveness. A comparative analysis with 2020 clearly indicates a positive trend: migration of the regions to a group with the higher level of competitiveness.

5. Conclusion

The paper presents a mathematical apparatus that allows to implement the point and interval forecasting of bounded indicators, in particular, the regional competitiveness index. To account for the boundedness of an indicator we propose to use the logistic regression, parameters of which are determined by conventional methods using the inverse logarithmic transformation of the dependent variable. We also derived the distribution of errors for the regression models in its class and an algorithm for computing confidence intervals for point forecasts. It is shown that bounded indicators have a number of advantages, among which are the possibility of translation to chain and reference indices as a result of strict nonnegativity, and informativeness (the region's competitiveness is assessed without comparison with other regions of the state: the values close to one indicate a high level of competitiveness and vice versa, values close to zero indicate a low level). We applied the developed methods of forecasting the competitiveness level to the statistics of the Russian Federation and identified certain trends of regional development. Despite the fact that currently there is a significant imbalance in regional development, by 2020 we can hope for its partial liquidation.

References

1. Kuznetsova, N. V., Vorobeva, N. A. & Koroleva, A. V. (2015). Evaluation of the competitive potential of the economic development of the country: theoretical aspects and Russian practice. *Asian Social Science, 11(14),* 149–160.

2. Benzaquen, J., del Caprio, L. A., Zegarra, L. A. & Valdivia, C. A. (2011). A competitiveness of a region of a country. *Cepal Review, 102,* 67–84.

3. Komarova, V. N., Zjablova, O. V. & Denmukhametov, R. R. (2014). An infrastructure factor in regional competitiveness. *Mediterranean Journal of Social Sciences, 5(18),* 355–360.

4. Martin, R. (2005). *Thinking about Regional Competitiveness: Critical Issue.* Retrieved from: http://www.intelligeneastmidlands.org.uk/uploads/documents/89137/RonMartinpaper1.pdf. (date of access: July 13, 2016).

5. Rubtzov, V. A., Rozhk, M. V., Gabdrakhmanov, N. K., Pratchenko, O. V. & Trofimov, A. M. (2015). Economic-geographical aspects of competitiveness and positioning of countries and regions. *Mediterranean Journal of Social Sciences, 6(3),* 741–745.

6. Porter, M. E. (2003). The Economic Performance of Regions. *Regional Studies, 37(6/7),* 549–578.

7. Voynarenko, M. P. & Bohatchyk, L. A. (2014). Applying cluster tools to develop subregional competitiveness strategy of region's economy. *Actual Problems of Economics, 158(8),* 171–182.

8. Safiullin, M. R., Safiullin, N. Z., Saipullaev, U. A. & Safiullin, L. N. (2013). Estimation of competitiveness of Russian regions by economic activity. *Middle East Journal of Scientific Research, 16(10),* 1413–1418.

9. Boschma, R. A. (2004). Competitiveness of regions from an evolutionary perspective. *Regional Studies, 38(9),* 1001–1014.

10. Kovalska, L. L. (2013). Methodical approaches to analysis and estimation of region's competitiveness. *Actual Problems of Economics, 141(3),* 109–124.

11. Turginbayeva, A. N. & Abildaev, S. T. (2013). Quantitative assessment of regional economy competitiveness (Republic of Kazakhstan case study). *Actual Problems of Economics, 146(8),* 477–485.

12. Nevima, J. & Melecký, L. (2011). Regional Competitiveness Evaluation of Visegrad Four Countries through Econometric Panel Data Model. *Liberec Economic Forum, 10(1),* 348–361.

13. Zubakin, V. A., Kosorukov, O. A. & Moiseev, N. A. (2015). *Improvement of regression forecasting models.* Modern Applied Science. Canada, 9(6), 344–353. DOI: 10.5539/mas.v9n6p344. (date of access: September 25, 2016).

14. Staníčková, M. & Poledníková, E. (2011). The EU Cohesion and Competitiveness in Theory and Practice. *Mezinárodní Baťova konference pro doktorandy a mladé vědecké pracovníky, 7(1),* 1–28.

15. Gagarina, G. Y., & Chainikova, L. N. (2014). Competitiveness of Russia and its regions: organizational aspect of management. *Bulletin of Plekhanov Russian University of Economics, 8(74),* 117–129.

16. Savič, N. (2012). Comparative analysis based on new competitiveness index. *Panoeconomicus, 59(1),* 105–115.

17. Shorokhov, V. P. & Kolkin, D. N. (2007). Assessing the competitive power of a region. *Studies of Russian Economic Development, 18(1),* 62–67.

Authors

Galina Yurievna Gagarina — Doctor of Economics, Associate Professor, Head of the Department of National and Regional Economics, Plekhanov Russian University of Economics (38, Stremanny Per., Moscow, 117997, Russian Federation; e-mail: galina_gagarina@mail.ru).

Nikita Aleksandrovich Moiseev — PhD in Economics, Associate Professor, Plekhanov Russian University of Economics (38, Stremanny Per., Moscow, 117997, Russian Federation; e-mail: mr.nikitamoiseev@gmail.com).

Alla Vladimirovna Ryzhakova — Doctor of Engineering, Professor, Plekhanov Russian University of Economics (38, Stremanny Per., Moscow, 117997, Russian Federation; e-mail: aryzhakova@list.ru).

Gleb Vladimirovich Ryzhakov — PhD in Physics and Mathematics, Associate Professor, Skolkovo Institute of Science and Technology Skoltech, Plekhanov Russian University of Economics (38, Stremanny Per., Moscow, 117997, Russian Federation; e-mail: gryzhakov@mail.ru).