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DYNAMICS MODELING OF CREDIT INTEREST RATE

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This article provides statistical modeling of the dynamic changes in the interest rate on loans provided by credit institutions to individuals by districts of the Russian Federation from January 2019 to March 2023, using technical analysis tools. A forecast of the credit interest rate for the Ural Federal District until the end of 2023 was constructed. The influence of external factors on the credit interest rate was studied, such external factors include the key rate of the Central Bank, the percentage of inflation, deposits of individuals, the average monthly nominal accrued wages of employees and the consumer price index for goods and services for the period from January 2019 to March 2023 based on data from the Federal Statistics Service.

Keywords: statistics; modeling; credit interest rate; prediction.

Introduction

Loans for individuals are an important financial planning tool. They allow one to receive additional funds to achieve personal goals and objectives. Banks issue loans to individuals to increase their profits by charging interest on the borrowed amount and to provide clients with access to additional financial resources. Credit plays an important role in the economy, providing financing for economic activities, expanding opportunities, and meeting temporary needs [1].

The study of dependencies and correlations among credit interest rates relating to different time periods occupies one of the central places in the theory of finance and investment. Recently, the relevance of this topic has increased significantly due to the influence of crises and epidemics, which entail insufficient solvency and uncertainty about the future [2–6].

Statistical modeling of credit interest rates is a complex task that requires knowledge of mathematics, statistics, and economics. However, a properly constructed model can be a useful decision-making tool in the banking and financial sectors.

1. Time Series Research

For this research, we will analyze the period from January 2019 to March 2023. All data is taken from the official website of the Central Bank of the Russian Federation [7]. Based on monthly data on interest rates on loans provided by credit institutions to individuals in the federal districts of the Russian Federation, we will construct a graph (Fig. 1). The graph shows that the trend towards a decrease and increase in the interest rate is approximately the same in each federal district. The largest jump is noticeable in March-May 2022, but after then it gradually stabilizes. Recently, the maximum credit interest rate has been observed in the North Caucasus Federal District, and the minimum in the Far Eastern Federal District.

The largest jump was in March-May 2022 in the North Caucasus, Siberian, Volga and Ural federal districts. This is explained by the fact that at this time the Russian economy

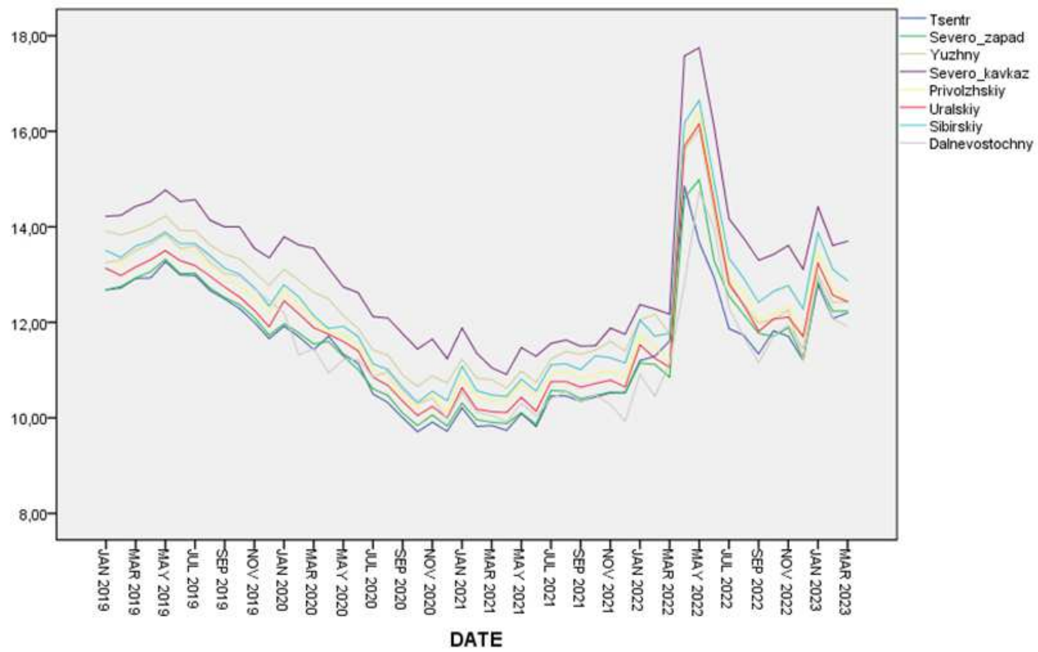

Fig. 1. Graph of changes in interest rates on loans by constituent entities of the Russian Federation over the past 4 years

entered a phase of large-scale structural restructuring. The rise in inflation and the increase in the consumer price index in these districts were most noticeable.

Table 1 presents the result of descriptive statistics carried out in the program Statistical Package for the Social Sciences (SPSS Statistics).

Table 1

Descriptive statistics

Federal District	№	Min.	Max.	Mean	RMS deviation	Coefficient of variation
Central	51	9.71	14.85	11.4822	1.22032	10.63%
Northwestern	51	9.83	14.99	11.5706	1.27158	10.99%
Southern	51	10.62	16.05	12.3729	1.30704	10.56%
North Caucasus	51	10.91	17.75	13.1218	1.54384	11.77%
Volga	51	10.14	16.40	12.0773	1.41356	11.70%
Ural	51	10.00	16.16	11.8755	1.40790	11.86%
Siberian	51	10.32	16.65	12.3016	1.44042	11.71%
Far Eastern	51	9.92	14.74	11.6612	1.32862	11.39%

The average value shows that the least favorable credit interest rate is in the North Caucasus Federal District, but the most favorable is in the Central Federal District.

In the Southern Federal District, the credit interest rate is the least variable, since the coefficient of variation takes the smallest value, and for the Ural Federal District, the coefficient of variation takes the value of 11.86%, therefore, the loan rate is the most variable.

Let us determine the consistency of changes in the credit interest rate in the districts of the Russian Federation by finding pairwise correlations between the districts. All districts are significantly correlated with each other (significance level less than 0.05), so changes in the values of the credit interest rate of one or more federal districts are accompanied by systematic changes in the values of other federal districts.

Cluster analysis is used to group the districts of the Russian Federation into visual classification structures (Fig. 2). On the example of the Central Federal District, it can

	Tsentr	Severo_zapad	Yuzhny	Severo_kavkaz	Privolzhskiy	Uralskiy	Sibirskiy	Dalnevostochny
Tsentr	,000	3,718	46,927	151,727	26,271	15,965	43,215	15,768
Severo_zapad	3,718	,000	37,373	130,411	15,637	7,467	30,856	11,438
Yuzhny	46,927	37,373	,000	39,955	9,791	18,720	8,909	38,358
Severo_kavkaz	151,727	130,411	39,955	,000	58,844	81,931	37,670	130,900
Privolzhskiy	26,271	15,637	9,791	58,844	,000	2,344	3,439	23,735
Uralskiy	15,965	7,467	18,720	81,931	2,344	,000	9,914	18,382
Sibirskiy	43,215	30,856	8,909	37,670	3,439	9,914	,000	38,655
Dalnevostochny	15,768	11,438	38,358	130,900	23,735	18,382	38,655	,000

Fig. 2. Distance matrix

be seen that the North-Western Federal District is closest to it in terms of indicators, and the North Caucasus Federal District is the furthest away.

Belonging to clusters by districts of the Russian Federation: 1 – Central, Northwestern, Southern, Volga, Ural, Siberian, Far Eastern Federal Districts; 2 – North Caucasus Federal District.

Thus, the values of the credit interest rate have similar values and features in the districts of one cluster of the Russian Federation. However, the interest rate is influenced not only by the time factor.

2. Dynamics Modeling of the Credit Interest Rate for the Ural Federal District

Let's study an additive time series model of the credit interest rate for the Ural Federal District; the time series graph is presented in Fig. 3.

Examine the degree of similarity between the time series of the credit interest rate and its lagged version to compare current values with the past ones and identify patterns. Based on the autocorrelation function for the credit interest rate, we can make an assumption about the periodic dependence of the credit interest rate every six months (Fig. 4a). We can exclude the influence of the periodic component of the credit interest rate by calculating the partial autocorrelation, which is also often used to find the order of the autoregressive model for the time series, if its values are significantly different from zero only for the first few lags. Calculation of partial autocorrelation allows us to exclude the influence of the periodic component of the credit interest rate (Fig. 4b).

A time series is considered stable if there is no systematic change in the mean (no trend), no systematic change in the variance, and periodic changes are strictly excluded. In the future, to build a forecast using the ARIMA(p,q,d) model, we need a stationary time series, without trend and seasonality.

The most effective way to convert a non-stationary series to a stationary series is to use a difference transformation (differentiation of a series) [8, 9]. To exclude the formal dependence of consecutive lags between each other in the autocorrelation analysis of time

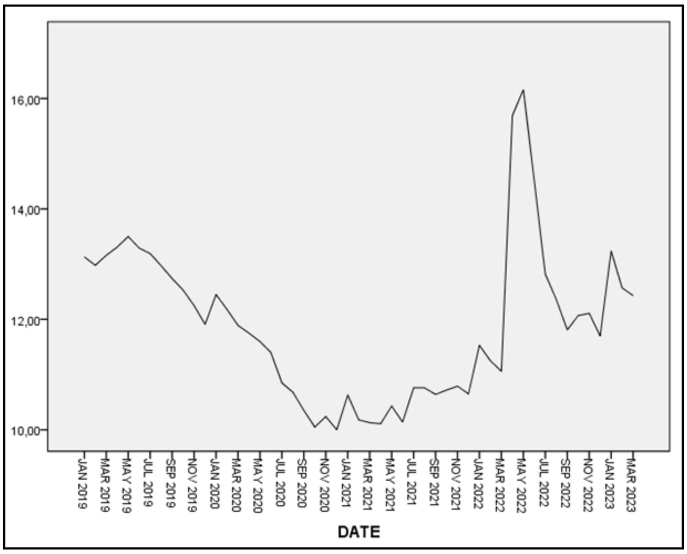

Fig. 3. Graph of the time series under study

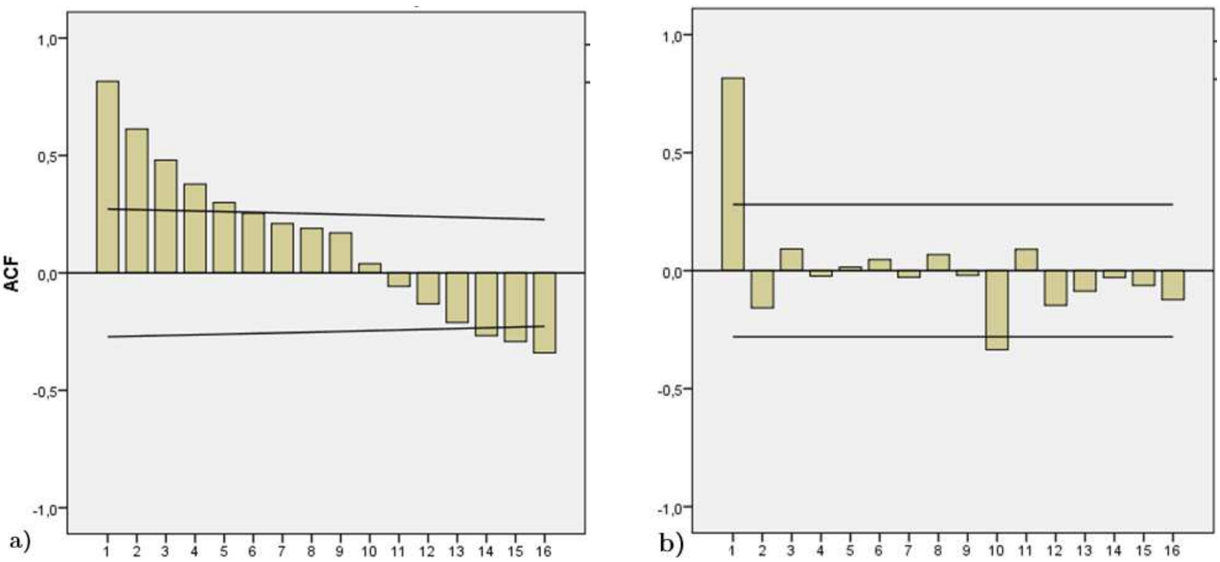

Fig. 4. a) Autocorrelation of the original time series; b) Partial autocorrelation of the original time series

series, it is necessary to subtract the current value of the time series from the previous one, that is, take the difference with lag 1. Differentiation can be done several times until stationary is achieved. As a result, we will get a graph of the first differences for the credit interest rate (Fig. 5).

Thus, the sequence after the difference transformation does not have strongly upward and downward trends and is flat if you do not pay attention to the emission in April 2022. By integrating and subtracting the first differences, the series became stationary. The difference was the first, therefore, the indicator $d = 1$ in the ARIMA(p,q,d) model. The ACF 1 lag is quite significantly above the significance line. Therefore, $p = 1$. There are no PACF lags observed, so $q = 0$. We build an ARIMA(1,0,1) model in SPSS Statistics. In the table containing indicators of the quality of model fit, it is important to note the fairly

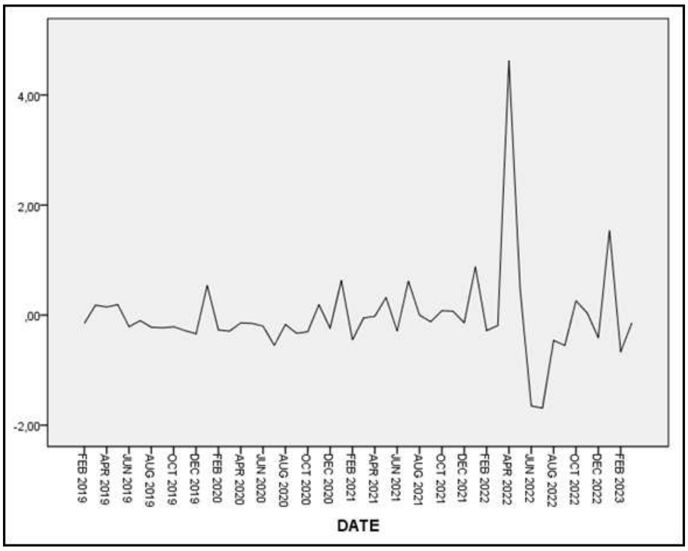

Fig. 5. Graph of the first differences

high coefficient of determination $R^2 = 0.93$ and the negative Bayes information criterion (BIC $= -1.303$), which indicates a fairly high quality of the resulting model. Model of the process under study with confidence intervals is presented in Fig. 6.

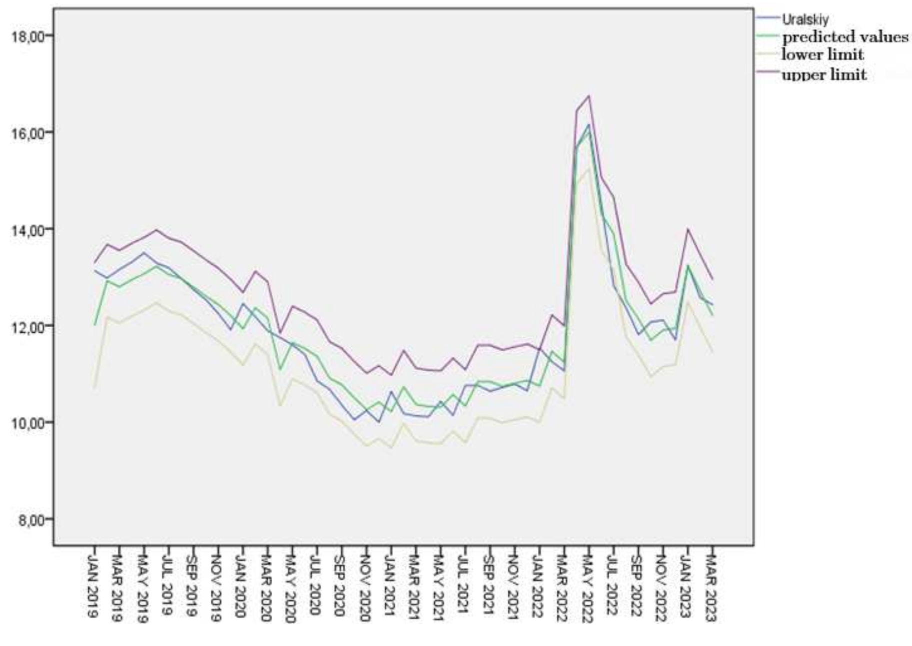

Fig. 6. Predictive model

Using this model, we determine the predicted values of the credit interest rate. Thus, it can be assumed that by the summer of 2023 the credit interest rate in the Ural Federal District will drop to 11.53%. In July 2023 it will increase slightly to 11.77%, and then by the end of the year it will begin to decline again and fall to 11.36% in December. Having analyzed the predicted values, one can notice that in some periods of time the model does not 100% repeat the original time series, but it managed to predict a sharp jump in March-May 2022, and it also almost predicted a fall in the credit interest rate. That is why the forecast values can be used to make management decisions, since the forecast accuracy is good, and it perfectly follows the downward and upward trend of the original time series. For further analysis and modeling of the time series with external factors, we use the Python programming language.

3. Study of the Factor Series

To make an informed management decision, not only data about one variable is important, but also information about its correlation with other variables is of great importance. As a factor series, the following variables can be taken into consideration: credit interest rate, key rate of the Central Bank, inflation rate, deposits and other funds raised by individuals, average monthly nominal accrued wages of employees for a full range of organizations in the economy of the Russian Federation as a whole and consumer price index for goods and services in the Russian Federation for the period from January 2014 to March 2023 (Fig. 7), based on data from the Federal Statistics Service [10].

	stavka	kluch.stavka	infl	vklad	zp	index
0	18.31	5.5	6.07	16938354	29535	100.59
1	18.00	5.5	6.21	16675654	29255	100.70
2	17.78	7.0	6.92	16886666	31486	101.02
3	17.74	7.5	7.33	16554784	32947	100.90
4	17.67	7.5	7.59	16796092	32272	100.90
...	...	...	...	...	...	...
103	12.26	8.0	14.30	37861796	59907	99.48
104	11.80	7.5	13.68	37892490	61879	100.05
105	12.06	7.5	12.63	37330710	62470	100.18
106	12.14	7.5	11.98	37547481	63060	100.37
107	11.56	7.5	11.94	37814021	88468	100.78

108 rows × 6 columns

Fig. 7. Basic data

Having constructed histograms for each indicator in the sample and checked the initial data for normality, we conclude that all indicators are not normally distributed values. Normality should be tested using the Chi-square test and the Shapiro test. Additionally, it is necessary to find the values of skewness and kurtosis to determine the nature of the distribution. Also, using histograms, we can see the frequency of data falling into certain intervals. For example, the key rate is most often found with a value of about 8%. The average salary is most often found in the range from 30000 to 35000 rubles. Descriptive statistics for the original time series are presented in Fig. 8.

Here count is the number of rows in the column; mean – the average value of the column; std – standard deviation; min – sample minimum; max – maximum of the sample; the boundaries of each quartile are 25%, 50% and 75%. Coefficient of variation: for the

	stavka	kluch.stavka	infl	vklad	zp	index
count	108.000000	108.000000	108.000000	1.080000e+02	108.000000	108.000000
mean	14.335185	8.550926	7.256944	2.720204e+07	44998.870370	100.578796
std	3.028850	3.122454	4.516823	6.421738e+06	11351.489978	0.882793
min	10.050000	4.250000	2.200000	1.655478e+07	29255.000000	99.460000
25%	11.995000	7.000000	3.800000	2.298224e+07	35500.000000	100.220000
50%	13.375000	7.750000	5.900000	2.694556e+07	42828.500000	100.425000
75%	17.395000	10.000000	8.482500	3.250286e+07	51205.000000	100.740000
max	21.830000	20.000000	17.830000	3.796366e+07	88468.000000	107.610000

Fig. 8. Descriptive statistics

loan rate – 21.13%, for the key rate – 36.52%, for inflation – 62.24%, for deposits – 23.6%, for the average monthly salary – 25.23% and for the consumer price index – 0.88%. This suggests that the data for the consumer price index is the least variable relative to the average value for the consumer price index. And the most volatile data is for the inflation indicator.

Let us study pairwise correlations between indicators. Since the data is not normally distributed, we use Spearman's rank correlation. Initial independent variables: kluch.stavka, infl, vklad, zp, index. It is necessary to determine the crrelation of each of them with the dependent variable stavka. First, let us study this relation visually using scatter diagrams (Fig. 9)

From the diagrams, one can see a strong correlation between the credit interest rate and the volume of deposits of individuals (vklad) and the average monthly salary (zp), which correspond to the vertical axis. The greater are the volume of deposits of individuals and the average monthly salary, the higher is the credit interest rate. Also, the credit interest rate has correlation with the key rate of the Central Bank (kluch.stavka). To estimate the strength of variable coupling with high accuracy, construct a Spearman correlation matrix for all variables involved in the analysis (Fig. 10).

The greatest correlation is between the volume of deposits of individuals and the average monthly salary. Most likely, this is since the volume of funds raised from individuals and wages are increasing every year. The interest rate on consumer loans also has a strong correlation with these indicators, which was already noticed when analyzing scatter diagrams. The key rate is most interconnected with the indicators of the credit interest rate. And the consumer price index is most correlated with inflation in the country.

Based on these results, it can be assumed that if there is a shortage of money in the country's circulation, credit rates rise, as well as for bank deposits. When the government borrows money from the population, deposit rates increase. That is why it was possible to notice a strong relation in the correlation table between the credit interest rate and the funds raised by individuals.

Next, we express the credit interest rate (stavka) through independent sample variables: key rate (x_1), inflation (x_2), volume of deposits (x_3), average monthly wage (x_4), consumer price index (x_5) (Fig. 11).

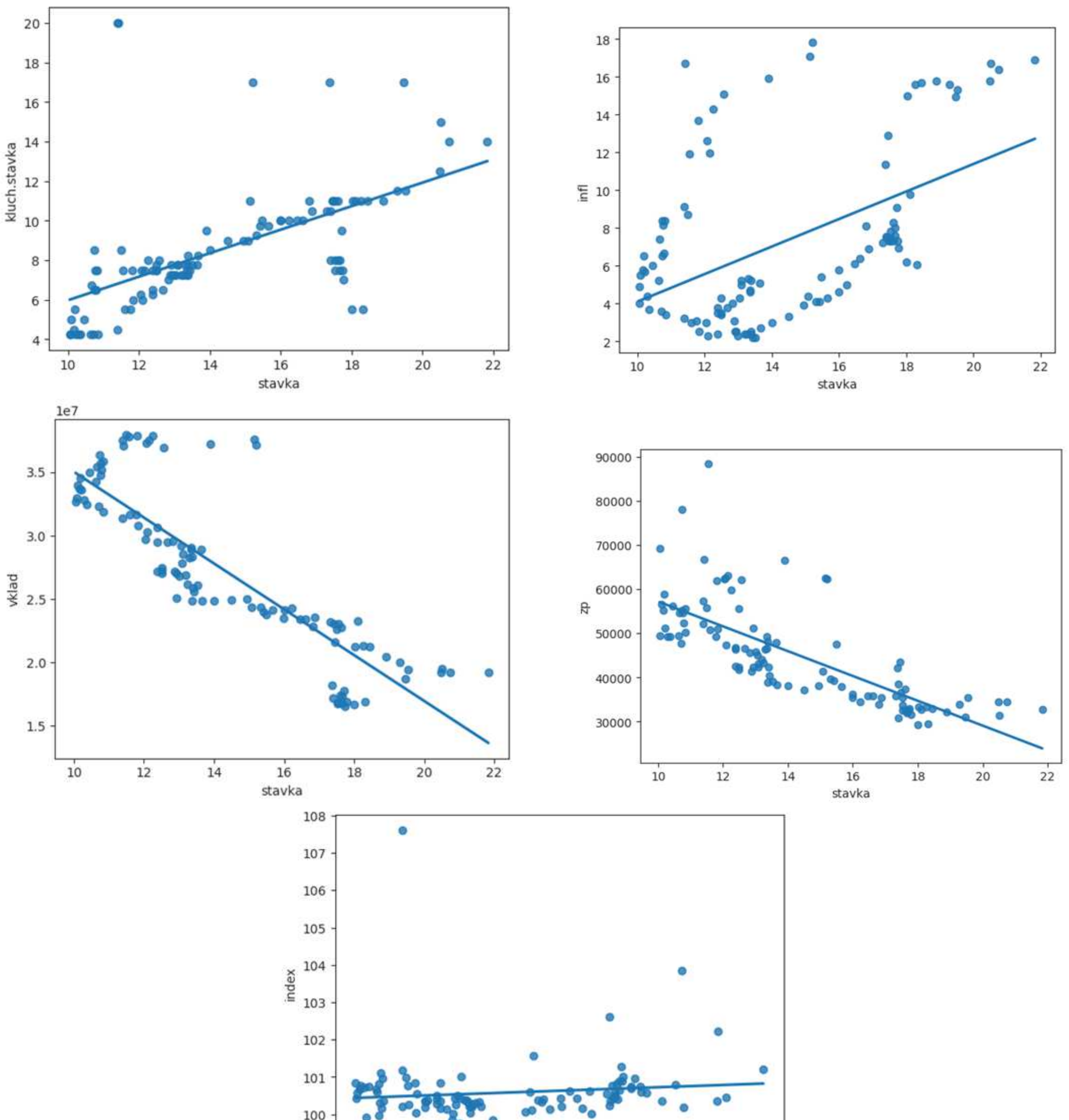

Fig. 9. Scatter diagrams

Thus, let us construct a multiple linear regression equation:

$$y = 77.7190770 + 0.2093745x_1 + 0.2566907x_2 - 0.0000003x_3 - 0.0000254x_4 - 0,5661800x_5.$$

The coefficient of determination $R^2 = 0,959$, means the share of the dispersion of the credit interest rate, i.e. 96% of the data variability is explained by the resulting equation. The Prob (F–statistic) indicator is close to zero, which allows us to conclude that the equation was significant at a significance level of 0.05, therefore, the resulting model is statistically

	stavka	kluch.stavka	infl	vklad	zp	index
stavka	1.000000	0.707063	0.403711	-0.880129	-0.854602	0.128424
kluch.stavka	0.707063	1.000000	0.592611	-0.450082	-0.423096	0.174899
infl	0.403711	0.592611	1.000000	-0.131071	-0.119133	0.394328
vklad	-0.880129	-0.450082	-0.131071	1.000000	0.940381	-0.189749
zp	-0.854602	-0.423096	-0.119133	0.940381	1.000000	-0.120321
index	0.128424	0.174899	0.394328	-0.189749	-0.120321	1.000000

Fig. 10. Spearman correlation matrix

```
                            OLS Regression Results
==============================================================================
Dep. Variable:                 stavka   R-squared:                       0.959
Model:                            OLS   Adj. R-squared:                  0.957
Method:                 Least Squares   F-statistic:                     479.1
Date:                Wed, 17 May 2023   Prob (F-statistic):           3.92e-69
Time:                        10:03:58   Log-Likelihood:                -99.733
No. Observations:                 108   AIC:                             211.5
Df Residuals:                     102   BIC:                             227.6
Df Model:                           5
Covariance Type:            nonrobust
================================================================================
                   coef    std err          t      P>|t|      [0.025      0.975]
--------------------------------------------------------------------------------
const           77.7191      8.388      9.265      0.000      61.081      94.357
kluch.stavka     0.2094      0.030      6.900      0.000       0.149       0.270
infl             0.2567      0.018     14.211      0.000       0.221       0.293
vklad        -3.289e-07   2.15e-08    -15.322      0.000    -3.72e-07   -2.86e-07
zp           -2.542e-05   1.23e-05     -2.061      0.042    -4.99e-05   -9.56e-07
index           -0.5662      0.085     -6.666      0.000      -0.735      -0.398
==============================================================================
Omnibus:                        0.066   Durbin-Watson:                   0.898
Prob(Omnibus):                  0.968   Jarque-Bera (JB):                0.025
Skew:                          -0.031   Prob(JB):                        0.987
Kurtosis:                       2.958   Cond. No.                     3.89e+09
==============================================================================
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Fig. 11. Regression model

significant. In Fig. 11 also shows the values of the regression equation coefficients and their significance.

Using the resulting regression equation, we can calculate the model (predicted) values of the dependent variable (stavka) and the residuals using the function. The graph of model values with a schedule of changes in the credit interest rate superimposed on it is shown in Fig. 12.

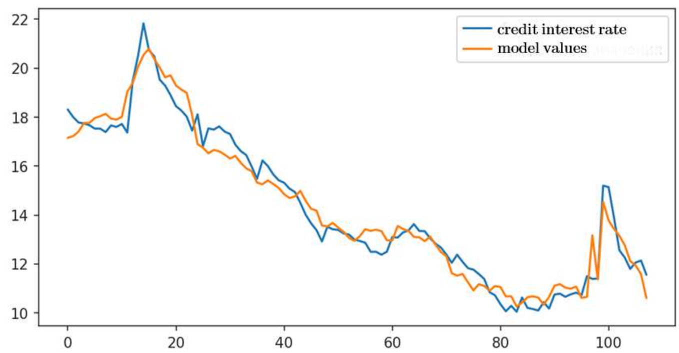

Fig. 12. Predict model

The model values repeat the trends towards a decrease and increase in the interest rate, reflecting its sharp rises and falls.

Let us reduce the complexity of the model. Using the correlation matrix, we will select the most significant indicator for the credit interest rate (Y – variable stavka, X – vklad), construct a paired linear regression equation, evaluate the quality of the equation by the determination index and check for significance the regression equation and coefficients at the significance level of 0.05. The credit interest rate has the greatest correlation relationship with the variable vklad. Let us add another indicator to the equation that does not have a strong connection with the first indicator – vklad, which is the variable infl (Fig. 13).

```
                            OLS Regression Results
==============================================================================
Dep. Variable:                 stavka   R-squared:                       0.928
Model:                            OLS   Adj. R-squared:                  0.927
Method:                 Least Squares   F-statistic:                     679.9
Date:                Wed, 17 May 2023   Prob (F-statistic):           8.11e-61
Time:                        12:31:58   Log-Likelihood:                -130.11
No. Observations:                 108   AIC:                             266.2
Df Residuals:                     105   BIC:                             274.3
Df Model:                           2
Covariance Type:            nonrobust
==============================================================================
                 coef    std err          t      P>|t|      [0.025      0.975]
------------------------------------------------------------------------------
const         22.8113      0.373     61.174      0.000      22.072      23.551
vklad      -3.921e-07   1.23e-08    -31.778      0.000   -4.17e-07   -3.68e-07
infl           0.3016      0.018     17.193      0.000       0.267       0.336
==============================================================================
Omnibus:                        2.659   Durbin-Watson:                   0.664
Prob(Omnibus):                  0.265   Jarque-Bera (JB):                2.178
Skew:                           0.218   Prob(JB):                        0.336
Kurtosis:                       2.458   Cond. No.                     1.32e+08
==============================================================================
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Fig. 13. Regression model

Determination coefficient $R^2 = 0.928$, means the dispersion share of the credit interest rate. Thus, adding the second indicator, the coefficient of determination increased from 0.727 to 0.928. The equation and coefficients turned out to be significant. We will also evaluate how AIC and BIC change; the lower these values are, the better it is. Thus, there is no point in further adding independent variables that do not strongly correlate with those already added and do not violate the significance of the equation and coefficients, since a high-quality equation with a high coefficient of determination has already been obtained. Predict model are presented in Fig. 14.

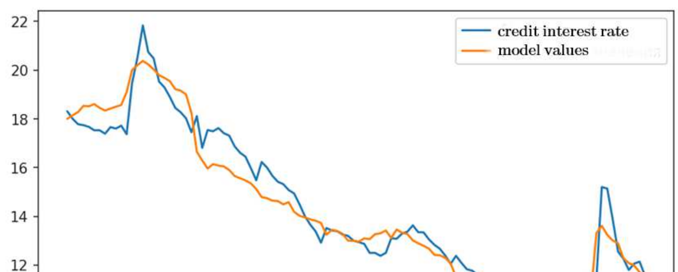

Fig. 14. Predict model

Comparing the values in Fig. 12 and Fig. 14, where a model was built with all the original variables, it can be noted that the equation did not change much, but the complexity of the model was reduced and the overdetermination that can arise because of simple linear regression with a large number of variables was eliminated.

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МОДЕЛИРОВАНИЕ ДИНАМИКИ КРЕДИТНОЙ ПРОЦЕНТНОЙ СТАВКИ

Е. К. Зеркина, Е. И. Назарова

В данной статье осуществлено статистическое моделирование динамики изменения процентной ставки по кредитам, предоставленным кредитными организациями физическим лицам по округам Российской Федерации за период с января 2019 г. по март 2023 г. Построен прогноз кредитной процентной ставки для Уральского федерального округа до конца 2023 года. Изучено влияние внешних факторов на кредитную процентную ставку, рассмотрены такие внешние факторы, как ключевая ставка Центробанка, процент инфляции, вклады (депозиты) физических лиц, среднемесячная номинальная начисленная заработная плата работников и индекс потребительских цен на товары и услуги за период с января 2019 г. по март 2023 г. на основе данных Федеральной службы статистики.

Ключевые слова: статистика; моделирование; кредитная процентная ставка; прогнозирование.

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