

# Sustainable Regional Development based on the Inflation Forecasts: The Adaptive Models Application

I. A. Astrakhantseva<sup>a</sup>, M. D. Ermolaev<sup>b</sup> and A. S. Kutuzova<sup>c</sup>  
*Ivanovo State University of Chemistry and Technology, Sheremetev Avenue, 7, Ivanovo, Russia*

**Keywords:** Sustainable Regional Development, Consumer Price Index, Inflation, Forecasting, Mathematical Models, Neural Networks.

**Abstract:** The article proves the dependence of the regions sustainable development on the inflationary processes dynamics. The practice of using various mathematical models to predict the consumer price index is considered. The experience in the regional inflation forecasting on the basis of a recurrent neural network is presented. The mechanism of forecasting the inflation level on the basis of adaptive models is shown. The algorithm was tested on the basis of indicators for the Ivanovo region. The source of the primary data was the monthly data of the chain consumer price indices (CPI) in the Ivanovo region in 2009-2020. The predictive model was validated on the basis of the consumer price index data for the first three months of 2021. Independently, the issue of assessing the federal-level inflation dynamics impact on the regional-level inflation dynamics is considered.

## 1 INTRODUCTION

The regions sustainable development and the maximum uniformity achievement of such development is a necessary condition for the entire state progressive development. The inflation level has always been one of the key macroeconomic indicators that reflect the current state of economy. The inflation dynamics affects many important areas of public life, i.e. the investment processes flow, the production growth, the population standard of living and the level of social tension, which ultimately contributes to or, on the contrary, restrains the economy progressive development. Therefore, the inflation forecasting (as accurate as possible) is an urgent task for various political, financial and social institutions.

The model and methodological apparatus for inflation forecasting is diverse. The typology and comparative analysis of the predictive qualities of such methods are presented in sufficient detail, for example, in the works of (Faust, 2013; Balackij and YUrevich, 2018; Duncan and Martínez-García, 2018; Gorshkova and Sinel'nikova, 2016)

Among the various approaches to forecasting the price rate dynamics, two areas stand out significantly.

The first direction is based on the assessments of experts in the economic functioning field and on the ordinary economic actors opinions survey (for example, the monthly survey of the University of Michigan (Lahiri and Zhao, 2016)).

The inflation forecasting within the framework of the second direction is carried out on the econometric methods and models basis. At the same time, for short-term forecasting, as a rule, various models of scalar time series (single-factor models) are used. These include:

- Random walk models (RW models). A random walk determines the movement of a random variable (in our case, the inflation rate), the direction of which changes randomly at certain points in time. The change in the inflation rate in this model does not depend on all previous values and does not affect all subsequent changes, while obeying an identical probability distribution with the same parameters, i.e. the average value and the mean square deviation.

<sup>a</sup> <https://orcid.org/0000-0003-2841-8639>

<sup>b</sup> <https://orcid.org/0000-0002-9502-3621>

<sup>c</sup> <https://orcid.org/0000-0002-7511-1667>

- Models of direct and recursive autoregression. The prediction in autoregressive models is based on the analysis of the variable previous values. Within the framework of such a forecast, it is assumed that the inflation rate is in a linear relationship with this indicator in the previous time steps. Statistical indicators are used to calculate the correlation between the output inflation indicator and its values in previous time steps with different lags.
- ARIMA models are created in the autoregressive models development process. They allow to bring the series to a stationary one and implement forecasting by extrapolation, to identify the trend, seasonality in the change in the inflation indicator. Based on these models, for example, monthly forecasts of the main Russian macroeconomic indicators are made, published by the staff of the E.T. Gaidar Institute for Economic Policy.
- For medium-term forecasting, multi-factor models are usually applied. They are expressed as a system of simultaneous equations. The greatest number of different techniques and technical tools for constructing inflation forecasts have been accumulated within the framework of these models.

Among them, first of all, the following models are distinguished:

- Models based on the Phillips curve. These models estimate the inverse relationship between the inflation rate and the unemployment rate. Currently, the modern modification of these models is used in the form of a "triangular model", where the inflation rate is dependent on its past values, the unemployment rate and cost shocks.
- Vector autoregression models (VAR models) study the macroeconomic variable reactions (in our case, the inflation rate) to its previous values and other variables that are responsible, among other things, for regime changes in economic policy or individual shocks in the economy. These models are represented by the independent regression equations systems.
- Dynamic models of general equilibrium. The DSGE models are based on modeling the micro-level economic entities behavior. These models illustrate the dependence of the inflation rate and many other variables: total output, the costs rate, the imports volume, the interest rate, the wages rate, consumption, savings and investments, and the exchange rate.

- Neural networks. We shall emphasise that for the study of such a multi-factorial and complex phenomenon as inflation, this tool can show high efficiency and accuracy of the forecast. The following classes of neural networks are used for time series analysis: multilayer perceptron, deep neural networks, recurrent neural networks, and convolutional neural networks.

We assume the use of a recurrent neural network based on LSTM (Long Short-Term Memory) blocks with a dual attention mechanism (in the encoder and decoder) as the most preferable method. This is a special type of recurrent neural network architecture capable of learning long-term dependencies, which meets the task of the inflation rate forecasting (Astrakhantseva, Kutuzova and Astrakhantsev, 2020).

At the same time, the application of this set of models in practice tends to use a combination of private forecasts made by different methods and instrumental approaches, including the expert ones (Dou, Lo, Muleu and Uhlig, 2017; Andreev, 2016). For example, the Central Bank of the Russian Federation uses the DSGE model of a "small" open economy with the following types of agents: households, firms, the external sector and the central bank. The inflation factors are the interest rates, the exchange rate, the consumption and savings level, wages, the volume of imports, the costs rate, etc. The inflation forecast is constructed by combining the forecasts of different models (Balackij and YUrevich, 2018).

Thus, it is noted that to date, more than 20 types of models for forecasting inflation are used. However, all of them are oriented and used within the national economies framework. The regional specifics of the inflation dynamics within individual countries are not reflected in these models. There are no serious developments related to the modeling of inflationary processes at the regional level. Meanwhile, in the context of regional heterogeneity, significant fluctuations within the national picture of inflation are quite possible. At the same time, in order to apply sound monetary policy measures, the regulator needs to assess the inflationary processes dynamics in regions, since the country sustainable development requires adequate sustainable development of all its parts.

## 2 MATERIALS AND METHODS

We suggest that it is important to consider the specific factors on the meso-level. Traditionally, more attention is paid to the inflation monetary factors, which are directly influenced by regulators (interest rates, exchange rate, lending volumes, consumption volumes, saving volumes). These factors can be accurately quantified and taken into account in mathematical models and machine learning algorithms. However, non-monetary factors also have a significant impact on the consumer price index.

For example, the economic entities and the population inflationary expectations can become a significant factor in the inflationary processes development. This factor is traditionally very significant for Russia. Additionally, non-monetary factors can be the following: the rise in the imports cost, the economy monopolization and, accordingly, the monopolistically set prices "inflating", the shadow sector of the economy presence, the peculiarities in the movement of goods between regions and the system of movement of goods within networks. If, for example, there are no large warehouses in the region, this will lead to an increase in the prices of goods imported into the region for the final consumer. Thus, the Ivanovo Region under study is an outsider region in terms of price attractiveness for short-term loan banks, along with the Kursk and Belgorod regions. The cost of medium-term loans for individuals here is often lower than the market average (Ahmatov, Astrahanceva, Kutuzov, Votchel and Vikulina, 2020). This can provoke an increased demand for credit resources, increasing the money supply in circulation and stimulating the inflationary processes.

Previously, the authors used a recurrent neural network to analyze a number of inflation factors at the regional level, such as: the amount of the population income, the average monthly wages, the population monetary expenditures, the retail turnover, the volume of paid services to the population, the volume of individuals deposits, the amount of citizens debt on loans, the dollar-ruble exchange rate, etc. Having identified potential factors of inflation, the authors conducted a correlation and regression analysis and marked the dollar-ruble exchange rate and the increase in citizens debt, with the exception of currency revaluation, as parameters with a characteristic dependence. Next, all the identified potential inflation factors were taken for forecasting using a neural network.

The results of the forecast are presented in Figure 1. These results indicate that the direction of changes in the actual indicator and the planned indicator coincides almost over the entire time horizon, however, the algorithm could not accurately predict the fluctuations amplitude. We shall note the divergence between the fact and the forecast in the first half of 2019 and in the spring of 2020. The increase in inflation in January-February 2019 and its increased values compared to the forecast in the first half of 2019 is explained by the increase in utility tariffs and the rise in the price of fruit and vegetable products. In addition, the increase in prices at the beginning of 2019 could be due to the factor of high inflation expectations already mentioned above, which, according to the Bank of Russia, were formed under the influence of the dynamics of prices for gasoline, food and fluctuations in the ruble exchange rate. We shall note that the model could not accurately account for these factors (Figure 1).

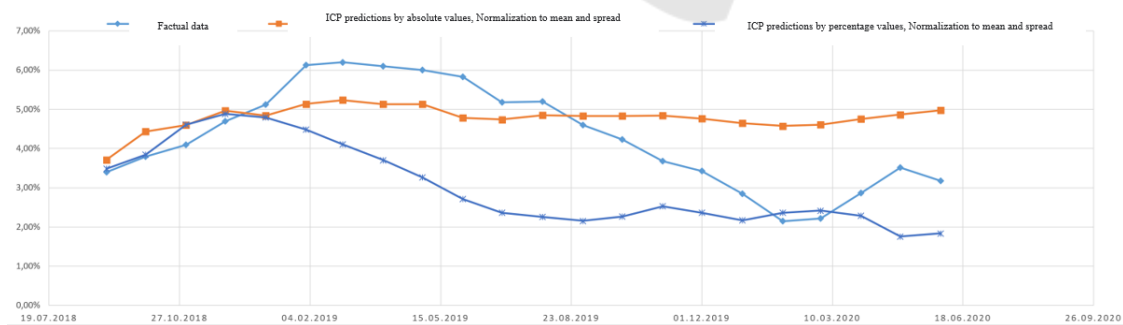


Figure 1: The comparison of predicted data with actual CPI figures.

However, while considering the importance of specific meso-level factors, it seems fair that the processes occurring in lower-level systems are formed and largely reflect the dynamics of processes occurring in higher-level systems. Obviously, the

same applies to inflation. Therefore, at the first stage of the study, it is expected to assess the degree of CPI dynamics correlation at the federal and regional levels over a sufficiently long time interval.

The applied part of the study concerns the actual forecasting of the inflation rate in a particular region (in the Ivanovo region). The initial statistical basis for the predictive models construction was the monthly data of the Ivanovo branch of the Central Bank of the Russian Federation on indicators reflecting the inflation rate in the region (CPI). The period relative to which the models were built, 2009-2020, the period relative to which the quality of the models was checked, the first three months of 2021.

In the first part of the study, we compared the inflation rates dynamics (December to December last year) in the Central Federal District regions with the inflation rate dynamics in Russia as a whole for the period 2000-2020. The comparison was carried out by the methods of correlation and regression analysis. As follows, the linear regression models of the dependence of the regional level of inflation on the federal level were constructed. The quality of models was traditionally evaluated by the value of the determination coefficient. The comparison of the inflation rates dynamics in the Russian Federation and in the Ivanovo Region is shown in Figure 2.

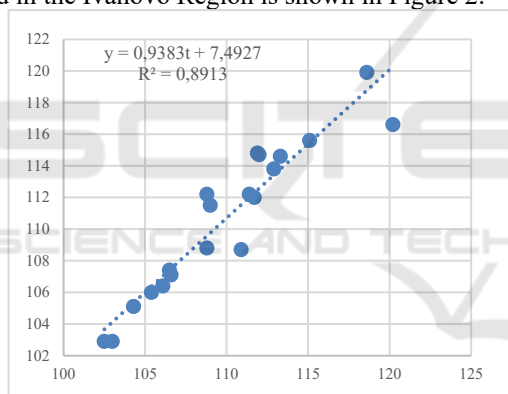


Figure 2: Comparison chart of inflation rates in the Russian Federation and in the Ivanovo region by year in the period 2000-2020.

All constructed models are statistically significant at a significance level of 0.01. The values of the determination coefficient for all regions are within the range of  $0.874 < R^2 < 0.983$ , which indicates the high quality of the constructed models.

For the Ivanovo region,  $R^2 = 0.891$ . It can be interpreted as follows: the price variation in this region is on average 89% due to the impact of inflationary processes at the macro level. It should be noted that in terms of this indicator, the Ivanovo Region occupies the penultimate place among the Central Federal District regions. Taking into account the internal annual dynamics, we can conclude that there are

certain features of the inflationary processes in this region.

In the context of comparing the inflationary processes at the meso-and macro-levels, another important indicator is a matter of concern, in particular, the total price growth in the region over the entire period under review. In contrast to the determination coefficient, which reflects the degree of price dynamics synchronicity at the federal and regional levels, this indicator represents the main inflationary outcome in the region or country under consideration. At the same time, it is obviously equivalent to consider the actual values of consumer price growth in the regions or the ratio of these values at the regional and federal levels. Figure 3 shows the growth of prices in the Central Federal District regions, as well as in Russia as a whole for the period 2000-2020.

In general, in most regions of the Central Federal District, the growth rate exceeds the national level. The leader is the Yaroslavl region (the growth is 771%), the outsider is the Oryol region (the growth is 639%). The growth in Russia is 655%.

Thus, we can talk about a certain differentiation of inflationary processes in the regions. At the same time, it is possible to assume the existence of some typologically similar realizations of price dynamics for certain groups of regions. Therefore, at the next stage of the study, we conducted a cluster analysis of the Central Federal District regions based on the two above-mentioned indicators, i.e. on the determination coefficient of the regional inflation rate dependence on the federal level, as well as the amount of consumer price growth in the regions for the period 2000-2020.

After the necessary data standardization procedure, the clustering itself was carried out using the k-means method. The choice of the optimal number of clusters  $n$  was carried out on the results variance analysis basis, in particular, for the first  $n$ , for which the p-values for both variables were less than the accepted significance rate  $\alpha = 0.01$ . This condition was achieved at  $n = 3$ . Thus, the Central Federal District regions were divided into three groups with typologically similar characteristics of price dynamics. The most interesting cluster is the one containing four regions – Ivanovo, Kursk, Ryazan, and Tula. The distinctive features of the cluster are, first, relatively low determination coefficient values and, on the contrary, a significant increase in consumer prices in the period under review. That is, the inflation rate dynamics in these regions is the most individualized and unstable. We shall also note that the Ivanovo Region is the closest to the center of this cluster.

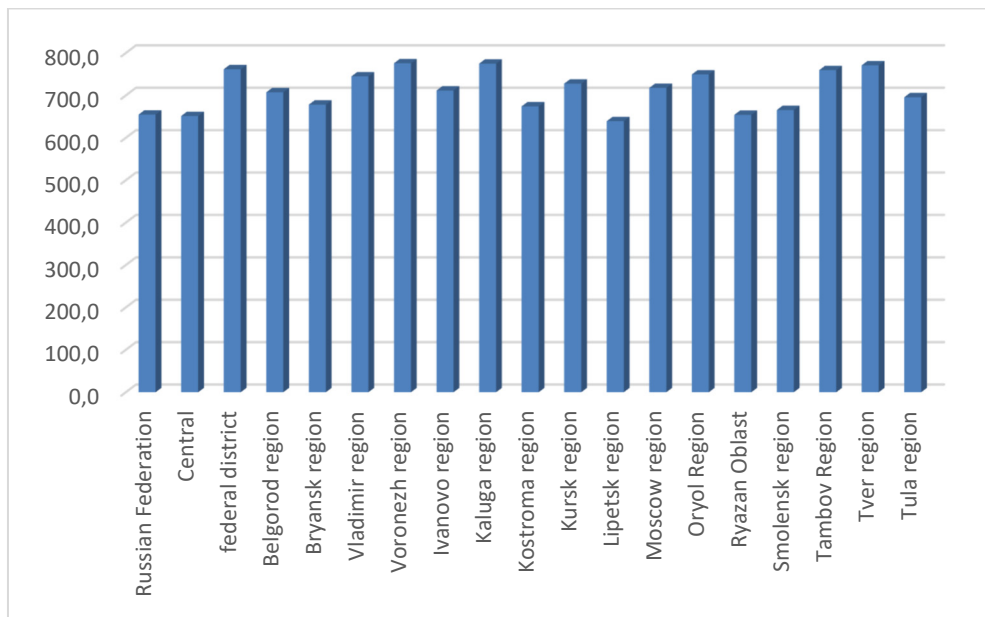


Figure 3: The consumer price growth in the Central Federal District and the Russian Federation as a whole for the period 2000-2020 (in %)

### 3 RESEARCH RESULTS

The forecast of the inflation rate in the Ivanovo region was carried out on the basis of adaptive models (or exponential smoothing models). Methodically, this can be represented as follows.

At first, the initial series of chain consumer price indices is converted into a series of basic indices (the base is December 2008).

The resulting series represents the generalized price level dynamics in the Ivanovo region relative to the prices of December 2008 (Figure 4).

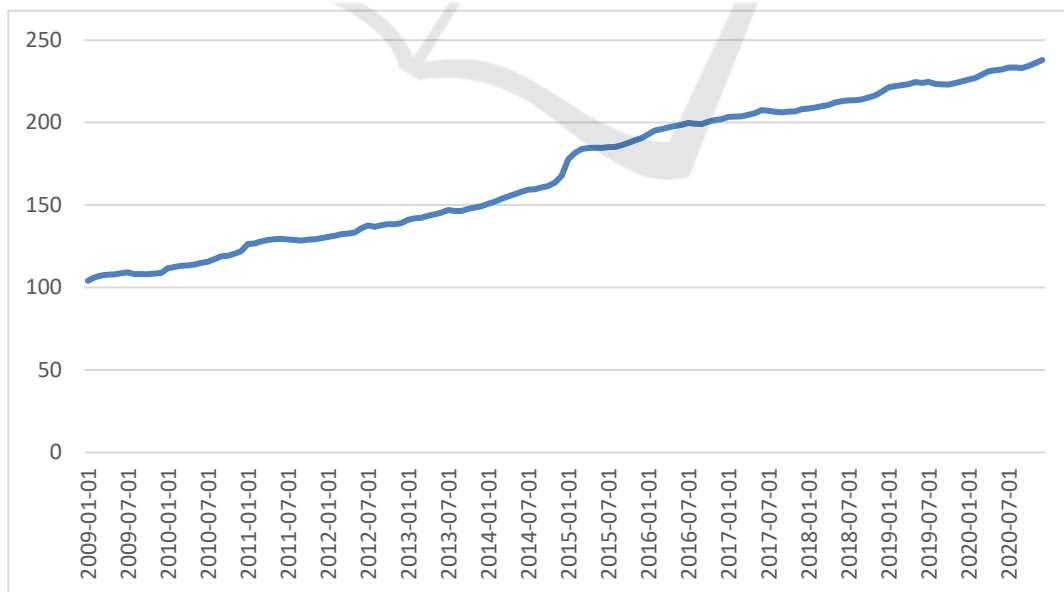


Figure 4: The dynamics of basic consumer price indices in the Ivanovo region in the period 2009-2020 (the basis is 100% – December 2008).

It is easy to see that the dynamics are quite regular and generally close to linear. Notable deviations from the general trend are visible at the end of 2014 (to a greater extent) and at the end of 2010 (to a lesser extent). In addition, at the turn of 2014-2015, there is a certain slowdown in the inflation rate.

The visual analysis of the dynamics allows us to conclude that it is advisable to use the adaptive forecasting methods that take into account the fact that the data obtained chronologically last. These data are considered the most important in forecasting, since they give an idea of the direction in which the development of the current trend will go.

Adaptive models were built using the STATISTICA 10 application software package. At the same time, we proceeded from two premises. Firstly, we proceeded from the existing but changing trend of the dynamics under consideration and, secondly, from the presence of an inflation seasonal factor, although visually it is difficult to grasp, but theoretically it occurs quite reasonable.

The STATISTICA package allows to build several types of adaptive models, differentiated on the basis of the microtrends types (linear, exponential, damped), as well as the seasonal dynamics nature (additive or multiplicative). The selection of adaptive parameters for each model type was carried out according to the criterion of minimizing the mean absolute percentage error (MAPE).

Table 1 shows the results of constructing the optimal adaptive models of each type. In general, the MARE index minimum value corresponds to a model with the damped microtrends and additive seasonality. The optimal adaptation parameters are 0.7, 0.1, and 0.9 (VM model (0.7; 0.1; 0.9)).

The inflation post-forecast for 2021 was carried out precisely on the basis of this model.

Figure 5 shows the results of forecasting based on this model.

Table 2 shows the inflation rate forecast values in the Ivanovo region in 2021.

Table 1: The results of the inflation dynamics adaptive models constructing in the period 2009-2020.

The seasonality nature	The microtrends type	Parameters			MAPE
additive	linear	0.9	0.1	0.6	0.406
additive	exponential	0.9	0.1	0.7	0.416
additive	damped	0.7	0.1	0.9	0.400
multiplicative	linear	0.9	0.1	0.4	0.414
multiplicative	exponential	0.9	0.1	0.3	0.415
multiplicative	damped	0.7	0.1	0.9	0.416

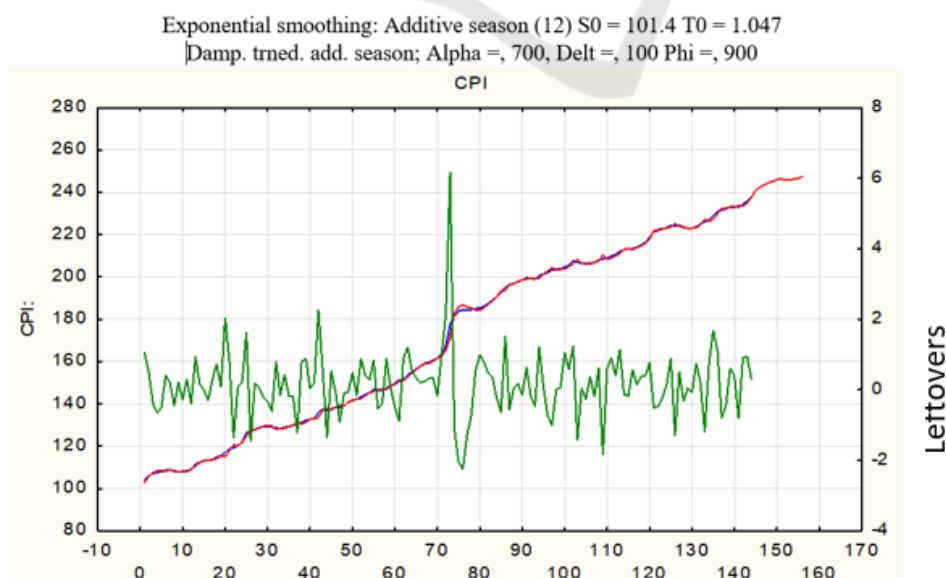


Figure 5: The demonstration of the results of forecasting the basic inflation indices in the Ivanovo region

Table 2: The inflation rate forecast in the Ivanovo region in 2021 (in the YoY - Year over Year format).

Month	Forecast	Fact	Month	Forecast	Fact
January	6.61	6.33	July	5.65	-
February	6.78	6.97	August	5.38	-
March	6.36	6.64	September	5.55	-
April	5.82	-	October	5.10	-
May	5.89	-	November	4.50	-
June	5.94	-	December	4.00	-

Within this format, the average monthly forecast error was 4.4% in January, 2.7% in February, and 4.2% in March. If we consider the inflation growth as a whole for three months, the error will be less than 1%, which indicates the adequacy of the chosen forecasting methods.

## 4 CONCLUSION

Thus, the study revealed differences in the course of inflationary processes in regions. Based on the cluster analysis, three classes of regions with typologically similar dynamics of consumer prices were identified. As a hypothesis, we can assume that each of these typologies determines the choice of a particular model for predicting the regional inflation rate.

For the Ivanovo region (the region of the most "unstable" cluster) an adaptive model for forecasting monthly data on the inflation rate was built. The forecast results in the post-forecast period (the first three months of 2021) showed a fairly high accuracy.

This study complements the domestic and foreign methods of studying the inflation factors and its forecasting, taking into account regional specifics. The identification of these specifics in the inflationary processes formation will allow us to adjust the regulator monetary policy and create conditions for ensuring the progressive development of the regions within the country.

## REFERENCES

- Faust J. (2013). Wright J.H. Forecasting inflation. Handbook of economic forecasting. Vol. 2, pages 2–56.
- Balackij E.V., YUrevich M.A. (2018). Prognozirovanie inflyacii: praktika ispol'zovaniya sinteticheskikh procedur. *Mir novoj ekonomiki*, 4 pages 20–31.
- Duncan R., Martínez-García E. (2018). New Perspectives on Forecasting Inflation in Emerging Market Economies: An Empirical Assessment. *Working paper*. <https://www.dallasfed.org/~media/documents/institute/wpapers/2018/0338.pdf>.
- Gorshkova T., Sinel'nikova E. (2016). Sravnitel'nyj analiz prognoznyh svojstv modelej rossijskoj inflyacii. *Nauchnyj vestnik IEP im. Gajdara*, 6, pages 34–41.
- Lahiri K., Zhao Y. (2016). Determinants of consumer sentiment over business cycles: Evidence from the US surveys of consumers. *Journal of Business Cycle Research*, Vol. 12, 2, pages 187–215
- Astrakhantseva I., Kutuzova A., Astrakhantsev R. (2020). Artificial Neural Networks in Inflation Forecasting at the meso-level. SHS Web of Conferences. 93. 3rd International Scientific Conference on New Industrialization and Digitalization, 2020. 02005. DOI: 10.1051/shsconf/20219302005 [https://www.shs-conferences.org/articles/shsconf/abs/2021/04/shsconf\\_nid2020\\_02005/shsconf\\_nid2020\\_02005.html](https://www.shs-conferences.org/articles/shsconf/abs/2021/04/shsconf_nid2020_02005/shsconf_nid2020_02005.html)
- Dou W., Lo, A., Muley A., Uhlig H. (2017). Macroeconomic models for monetary policy: a critical review from a finance perspective SSRN working paper. <https://ssrn.com/abstract=2899842>.
- Andreev A. (2016). Prognozirovanie inflyacii metodom kombinirovaniya prognozov v Banke Rossii. *Bank Rossii. Seriya dokladov ob ekonomicheskikh issledovaniyah*, 14, pages 2–11.
- Ahmatov K, Astrahanceva I., Kutuzova A., Votchel L., Vikulina V., (2020). Harmonization of banking business models with the needs of the economy by encouraging the exogenous social responsibility. *Journal Quality-Access to Success* Journal, Vol. 21, 174, pages 81-87.
- Inflyacionnye ozhidaniya (2020). [https://cbr.ru/statistics/ddkp/inflationary\\_expectations/](https://cbr.ru/statistics/ddkp/inflationary_expectations/)
- Federal'naya sluzhba gosudarstvennoj statistiki. (2020). <https://rosstat.gov.ru/priceVuiT>, 4(32):. <https://cyberleninka.ru/article/n/ekologicheskaya-sostavlyayuschaya-pri-razrabotke-strategii-ustoychivogo-razvitiya-regionalnogo-apk> (Accepted: 13.04.2021).
- Dudin M.N., Kalendzhyan S.O., Lyasnikov N.V. 2017. Green economy: a practical vector for Russia's economic development. *Ekonomicheskaya politika*, 12(2), pages 86–99.
- Mirzekhanova Z.G. 2018. Ecological aspects of the modern development of remote regions in the format of the "green economy" model. *Regional'naya ekonomika: teoriya i praktika*, 6, pages 1082-1096.