

## Inflation Prediction Based on the “Long Memory” Effect: The Case of Russia

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### *Abstract*

The problem of inflation prediction has been in focus of monetary policies of both advanced and emerging economies for several decades. Specifically, this problem is very relevant to the modern monetary policy of the Russian Federation, even after a tremendous success of the Bank of Russia in struggling inflation after the national currency (ruble) crisis in 2014. As of recently, the forecasts of inflation made by the Russian monetary authorities have been showing quite significant discrepancy with the actual figures. This study is aimed at demonstration how the modern approaches of time-series econometrics can be used to significantly improve the quality of inflation prediction. Relevant policy recommendations are discussed.

*Keywords:* inflation prediction, long-memory effects, autoregressive models.

### 1. Introduction

The problem of inflation prediction has been in focus of attention of monetary authorities of both advanced and emerging economies for several decades now. To increase credibility of their policies, over this period central banks of these countries have been setting inflation targets which were comparatively more difficult to reach at times of expansion of economies (for example, before the Global Financial Crisis of 2008-2009, GFC) and were comparatively easier to achieve at times of recession. But in the both cases, a high level of uncertainty associated with the rate of inflation make the problem of its prediction extremely challenging.

In the literature, there is a wide strand of approaches to inflation prediction. For both advanced and emerging economies the authors use different approaches: the traditional multivariate regression approach (Balogun, 2007); the modified Phillips curve approach (Ashiya, 2017); the standard autoregressive models (Arratibel et al., 2009); dynamic stochastic general equilibrium models (DSGE) (Alvarez, 2017); artificial neural network models (Malek et al., 2017).

The focus of this research is on inflation prediction for the Russian economy in the context of its modern monetary policy. After the National Currency Crisis (NCC) of 2014-2015, when the rate of inflation reached 15.5% in 2015, the Bank of Russia conducted a consecutive and consistent monetary policy aimed at lowering the inflation rate in Russia to hit the 4% target level set for December 2017 (Gilenko, 2017, 2018). And the Bank of Russia succeeded. The actual rate

of consumer inflation in December 2017 turned out to be only 2.5%. Since that time, although being quite volatile, the rate of inflation in Russia never exceeded 6% (as of 2019).

- The difficulty of inflation prediction stems from a high level of uncertainty associated with this macroeconomic indicator.
- The traditional approaches to inflation prediction may have limited predictive power.
- Taking the “long memory” effect into account may allow to half the inflation prediction error.

It is well-known that, in particular, based on inflation forecasts the central bank of a country adjusts its monetary policy by changing (if possible) its key interest rate (refinancing rate). In turn, this rate determines the cost of money in the economy, influencing, in particular, the interest rates of different loans for the citizens and the companies in the economy. Thus, more accurate forecasting of inflation will let monetary authorities set the key interest rate adequately, thus, providing a correct price for the monetary resources in the country.

The problem of inflation prediction is very topical in Russia. It is worth noting that inflation forecasts for the Russian economy are made by different organizations, starting from official authorities (the Bank of Russia, the Russian Ministry of Economic Development) and ending with authoritative international organizations (the OECD, the UN, the IMF). The predictions of these institutions are given in Table 1. As it can be seen from the table, the figures are quite different which definitely speaks in favor of the difficulty of inflation forecasting.

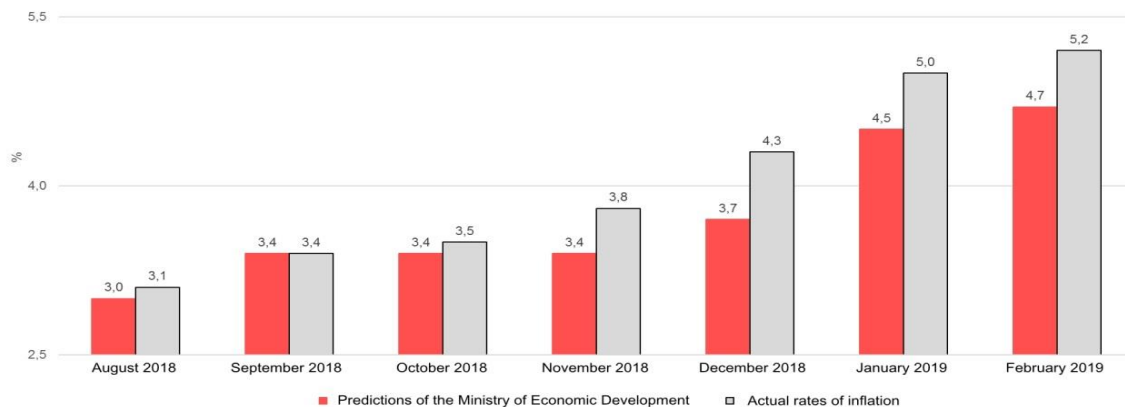
Table 1. Predictions of inflation in Russia for 2019

Institution	Inflation prediction
Bank of Russia	4.7-5.2%
OECD	5.02%
IMF	5.09%
UN	3.9%

Source: Bank of Russia, OECD, IMF, UN.

At the same time, the Russian Ministry of Economic Development (RMED) announces its inflation predictions on the monthly basis. We collected the information on predictions of the RMED and the actual figures of inflation rates and summarized in Fig. 1. As it can be seen from Fig. 1, the predictions of RMED are *systematically inconsistent* with the actual figures of inflation rates.

Figure 1. Predictions by the Ministry of Economic Development and actual rates of inflation in Russia, monthly data



Source: Russian Ministry of Economic Development, Rosstat

This determined the objective of this research. In this paper, using the modern approaches of time-series econometrics we construct an *autoregressive fractionally integrated moving average* (ARFIMA) model (which captures the “long memory” effect in the data) and show that this model outperforms both the model currently used by the RMED and an extended, but still traditionally constructed multivariate regression model.

The rest of the paper is organized as follows. Section 2 gives the methodology and the data collection for the current study. In Section 3 the obtained results are discussed. Section 4 concludes.

## 2. Research methodology

As it was mentioned above, the variety of approaches to inflation prediction is really big. In this research we focus on two of them: a multivariate linear regression model (as a baseline approach) and an ARFIMA-model (as a more advanced approach).

### 2.1 Multivariate linear regression approach

The traditional multivariate linear regression approach to inflation forecasting assumes estimation of the following type of model:

$$\text{Inflation}_t = \beta_0 + \beta_1 \cdot X_{1t} + \beta_2 \cdot X_{2t} + \dots + \beta_k \cdot X_{kt} + \varepsilon_t, \quad (1)$$

where  $X$ s are different economic indicators (and/or their lags);  $\varepsilon_t$  is a non-systematic disturbance term. When building and estimating such types of models, researchers pay close attention both to the economic mechanisms of influence of these economic indicators on the rate of inflation, and to the formal properties of the time-series of these indicators, such as stationarity, seasonality, structural breaks, etc.

The full list of regressors used in this research for multivariate linear regression modeling, as well as their descriptions, expected influences on inflation, and basic summary statistics is given in Table 3.

### 2.2 The ARFIMA modeling

To a major part, time-series analysis is based on studying properties of the underlying time-series, and specifically, how past values of the time-series can be effectively used to predict its future values. From this perspective, different types of “memory effects” have been discussed in the literature.

In econometric modeling, the *autoregressive* approach has been widely used to account for the memory effects in time-series data since the seminal work of G. Box and G. Jenkins (1970). For a non-stationary stochastic process  $Y_t$  with mean  $\mu$ , they introduced an autoregressive integrated moving average model (or ARIMA(p,d,q)) of the following type:

$$\Phi(L)(1 - L)^d(Y_t - \mu) = \Theta(L)\varepsilon_t, \quad (2)$$

where  $\Phi(L)$  and  $\Theta(L)$  are lag polynomials of the corresponding orders  $p$  and  $q$ ;  $L$  is the lag operator ( $L^d Y_t = Y_{t-d}$ );  $d$  denotes the order of integration of  $Y_t$ ;  $\varepsilon_t$  is a white noise process ( $\varepsilon_t \sim iid(0, \sigma_\varepsilon^2)$ ).

Granger and Joyeux (1980) and Hosking (1981) showed that  $(1 - L)^d$  (the differencing operator) can be considered for non-integer values of  $d$  once the following formula is defined:

$$(1 - L)^d = \sum_{k=0}^{\infty} \frac{\Gamma(k-d)L^k}{\Gamma(-d)\Gamma(k+1)}, \quad (3)$$

with  $\Gamma(\cdot)$  denoting the gamma (generalized factorial) function.

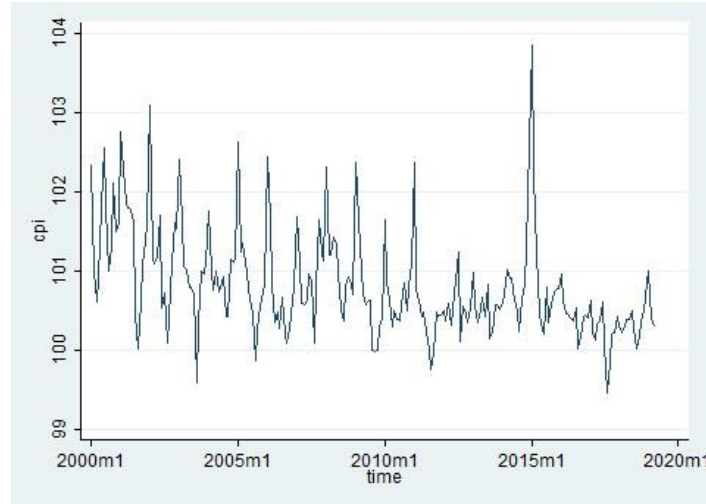
Of specific interest here is the case of  $0 < d < 0.5$ , since, on the one hand, it corresponds to a stationary process, but, on the other hand, the modeled process has a “long memory” in the sense that although individual autocorrelations may be statistically insignificant, their cumulative effect is prominent. Graphically, the “long memory” effect represents the idea that the time-series of a stochastic process resembles itself in its parts.

The importance of long-range dependence in economic time-series was first studied by Mandelbrot (1972), who proposed the R/S (range over standard deviation) statistic, originally developed by Hurst (1951). Lo (1991) modified the R/S statistic to account for the effect of short-range dependence to derive a consistent estimate of the long-range variance of the time series. The Lo test is used in this study to detect the presence of the “long memory” effect in the time-series of inflation.

### 2.3 Data collection

For our empirical analysis we collected information on different relevant macroeconomic indicators. We used the official monthly data for the period from January 2000 to March 2019. For illustrative purposes, Fig. 2 gives the time-series of the CPI index in Russia over that period. As it can be seen from the graph, the dynamic of the CPI index visually has two properties: seasonality and self-resemblance. Preliminarily, this may speak in favor of the presence of the “long memory” effect in the time-series.

Figure 2. Values of the CPI index in Russia, 2000-2019.



Source: Rosstat

To estimate our models, the data were split into a training and a test samples as specified in Table 2. The training samples for the two models were different. For the traditional multivariate regression model we used the training sample from January 2009 to September 2018 to avoid the structural breaks in the variables at the time of the GFC of 2008. But for the ARFIMA-model we used the sample from January 2000 to September 2018 to capture the “long memory” effect as discussed above.

Table 2. Training and test samples for model estimation

Model	Training sample	Test sample
Multivariate linear regression model	January 2009 – September 2018 (117 observations)	October 2018 – March 2019 (6 observations)
ARFIMA-model	January 2000 – September 2018 (225 observations)	October 2018 – March 2019 (6 observations)

Details on the collected macroeconomic variables are provided in Table 3. It gives the names and descriptions of the variables, as well as their measurement units and expected (theoretical) influence on inflation rate (to later compare with the results of estimation of the multivariate linear regression model). Also, basic summary statistics (minimum, mean, and maximum values) are provided.

Table 3. Description of the variables

Variable	Description	Measurement units	Expected influence on inflation rate*	Minimum	Mean	Maximum
CPI	The CPI index	index points	x	99.5	100.6	103.9
keyrate	The key interest rate of the Bank of Russia	%	–	5.5	9.1	17.0
M2	Money supply	bln rubles	+	11431.0	28132.0	44892.0
unemp	Unemployment rate	%	–	104.6	106.0	109.4
GDP	Nominal gross domestic product	bln rubles	+	2862.0	6135.0	10172.0
Brent	Price of oil Brent	USD/barrel	+	35.9	80.2	126.1
exch	Ruble/USD nominal exchange rate	rubles per USD	+	27.91	44.3	77.9
imports	Nominal value of imports	bln rubles	+	9100.0	21425.0	32481.0
tariffs	Index of tariffs of housing and communal services	%	+	92.2	100.8	116.1
capital	Investments in physical capital	bln rubles	–	18224.0	64788.0	310214.0
CPIexp	Index of inflation expectations	%	+	86.0	101.1	118.0

\* Due to the limited space, formally here we do not provide an extended discussion of the expected influence of each of variables on inflation. The directions of these influences (the signs of the variables) follow from a traditional discussion of potential impacts of these variables on inflation.

#### 2.4 Research hypotheses

Based on the previous theoretical discussion and the preliminary analysis of the data, for this research we formulated the following principal working hypotheses:

*Hypothesis 1: The time-series of inflation in Russia has the “long memory” effect.*

*Hypothesis 2: An ARFIMA model outperforms the traditional regression models in the sense of lower prediction error.*

Let us now switch to the discussion of the results of our calculations that were made in Stata 14.0.

### 3. Results and discussion

Below we provide the results of estimation of the two models of this research. We give and discuss the final specifications of the models which were selected based on the Schwarz Bayesian information criterion (SBIC).

#### 3.1 Results of multivariate linear regression estimation

The results of estimation and specification optimization of the adopted multivariate linear regression model are given below:

$$\begin{aligned} \widehat{\Delta CPI}_t = & 24.11 + 0.53^* \cdot \Delta CPI_{t-1} + 0.24^* \cdot \Delta CPI_{t-6} + 0.21^* \cdot \Delta CPI_{exp_t} \\ & - 0.014^* \cdot CPI_{exp_{t-1}} - 0.15^* \cdot keyrate_t + 0.003^* \cdot \log(M2)_{t-1} \\ & - 0.14^* \cdot unemp_{t-6} + 1.99^* \cdot \log(GDP)_t + 0.0003^* \cdot \log(GDP)_{t-12} \\ & + 0.008^* \cdot Brent_{t-1} + 0.026^* \cdot exch_t - 0.027^* \cdot exch_{t-6} \\ & + 0.025^* \cdot exch_{t-12} + 0.02^* \cdot \log(imports)_{t-9} + 0.06^* \cdot \Delta tariffs_{t-9} \\ & - 2.21^* \cdot \log(capital)_t - 0.002^* \cdot \log(capital)_{t-6} \end{aligned} \quad (4)$$

where \* denotes statistical significance of the coefficient at the 5% level of significance.

The necessary tests of model specification adequacy (such as tests for normality, heteroscedasticity, autocorrelation, RESET, multicollinearity, stationarity, overall significance and spurious regression) were run and passed. It should be noted that all the coefficients in model (4) have the expected mathematical signs, and the coefficient of determination of the model is  $R^2 = 0.921$ . Thus, it was decided to use the model for prediction purposes (see subsection 3.3).

#### 3.2 Results of ARFIMA-modeling

In order to address *Hypothesis 1*, we, first, ran the test for the “long memory” effect on the training sample for the CPI time-series. To this end, we applied the Lo test for the “long memory” effect. The results of this test are given in Table 4.

Table 4. Results of the Lo test for the “long memory” effect

Lo Modified R/S test		
Critical values for H0: CPI is not long-range dependent		
90%:	[ 0.861, 1.747 ]	
95%:	[ 0.809, 1.862 ]	
99%:	[ 0.721, 2.098 ]	
Test statistic:	.67	(0 lags via Andrews criterion) N = 230

As it can be seen from the table, the value of the test statistic is 0.67 and is beyond even the 99% confidence interval. Thus, we reject the null hypothesis of no “long memory” effect in the time-series of Russian CPI. Thus, *Hypothesis 1 receives support* and building of an ARFIMA-model for this time-series is appropriate.

The optimized and estimated specification of the obtained ARFIMA(13, 0.39, 12)-model is given below:

$$\Delta^{0.39}\widehat{CPI}_t = 100.81^* + 0.37^* \cdot \Delta^{0.39}CPI_{t-1} + 0.97^* \cdot \Delta^{0.39}CPI_{t-12} - 0.38^* \cdot \Delta^{0.39}CPI_{t-13} - 0.083^* \cdot \varepsilon_{t-2} - 0.082^* \cdot \varepsilon_{t-3} - 0.10^* \cdot \varepsilon_{t-5} + 0.054^* \cdot \varepsilon_{t-7} - 0.78^* \cdot \varepsilon_{t-12} \quad (5)$$

where \* denotes statistical significance of the coefficient at the 5% level of significance. The necessary tests of model specification adequacy (such as tests for normality, heteroscedasticity, autocorrelation, stationarity, overall significance) were run and passed.

Of importance here is the value of  $d = 0.39$  which, again, supports the presence of the “long memory” effect, because this value falls into the range (0, 0.5) as discussed in subsection 2.2.

### 3.3 Predictions of inflation

Since the constructed models successfully passed the specification adequacy tests, we used them to construct predictions for the test sample October 2018 – March 2019. For measuring the accuracy of predictions, we employ the *root mean square error* (RMSE) metric. It is also worth noting that on this test sample we have a chance to compare the accuracy of our predictions with the accuracy of predictions of the Russian Ministry of Economic Development (see Fig. 1).

Table 5. RMSE of inflation predictions (October 2018 – March 2019)

Forecasting Approach	RMSE, %
Predictions of the Russian Ministry of Economic Development	0.42
Multiple linear regression	0.27
<b>ARFIMA (13, 0.39, 12)</b>	<b>0.22</b>

The results of calculation of RMSEs for our predictions are given in Table 5. As it can be clearly seen from the table, the ARFIMA approach outperforms the multiple linear regression model and, what is important, *has approximately twice as better accuracy of inflation prediction as the model currently used by the Russian Ministry of Economic Development.*

This means that our *Hypothesis 2* also received support.

It is worth mentioning that since the ARFIMA approach proved its forecasting efficiency, we applied it to a shorter training sample from January 2000 to December 2013 in order to understand whether the model would be capable of predicting a sharp increase in inflation rate in Russia at the end of 2014 due to the NCC (see Fig. 2). In brief, the model succeeded.

### 4. Conclusions

In this research we focused on the problem of inflation prediction. The problem is very topical for the Russian economy, since, on the one hand, based on inflation expectations the Bank

of Russia conducts its monetary policy; and, on the other hand, as the recent figures show, the inflation predictions by the Russian Ministry of Economic Development sometimes are quite far from the actual values.

In this study we adopted two approaches: an extended multivariate linear regression modeling and the ARFIMA-model approach (to capture the “long memory” effect in the Russian CPI data). It turned out that the both constructed models outperform the current inflation predictions of the Russian Ministry of Economic Development, with the estimated ARFIMA-model indeed capturing the “long memory” effect in the Russian CPI index and being almost twice as more precise as the approach used by the Ministry. Thus, the both hypotheses of this research were supported.

As a result, it can be recommended for the Russian Ministry of Economic Development to use for inflation prediction purposes more advanced models from the time-series econometric analysis.

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The authors declare no competing interests.

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