Using the Orange Software Package to Assess the Accuracy of ARIMA and VAR Models for Predicting Stock Prices on the Securities Market*

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Abstract. To maintain and stimulate economic growth in Russia, it is necessary to ensure the development of the financial center. The Russian stock market is not sufficiently developed today. At the same time, the development of the Russian stock market is necessary to ensure balanced, innovative, and stable economic growth in Russia in the long term. The purpose of this article is to improve the accuracy of forecasting the dynamics of stock prices, which contributes to increasing the competitiveness of the domestic market and its attractiveness to investors. The paper examines the functioning of the stock market, identifies current trends in its development and evaluation features. The paper defines the concept of the securities market, examines its participants and types of securities; examines the economic essence of shares and their classification; studies methods for analyzing and evaluating shares; analyzes the current state of the Russian stock market; analyzes shares of a Russian issuer; identifies problems of the modern Russian stock market; develops proposals for improving the Russian stock market. The novelty of this study is a combination of traditional and statistical forecasting methods, which make it possible to obtain a risk assessment simultaneously with the stock price forecast. Also, in the course of the work, conclusions were obtained that deepen knowledge about stock price forecasting.

Keywords: Stock Market, Stock Price Forecasting, ARIMA Model, Var Model.

1 Introduction

Over the past decade, the development of the Russian stock market has taken place in the context of globalization, increased internationalization of securities markets, and increased competition in international financial markets. However, the Russian financial market remains uncompetitive in the global market. Today, the Russian stock market has a limited capacity, insufficient to meet the investment needs of Russian companies, and lags behind the largest and most developed stock markets in the world.

Stock market participants include joint-stock companies that issue shares, professional stock market participants, and investors.

The stock market in Russia began its formation only in the process of privatization when many securities were simultaneously issued on the market. At the moment, this market is organized and controlled by a special state regulatory body — the Bank of Russia.

Russia is one of 16 countries with a stock market capitalization exceeding $ 1 billion. This means that the Russian Federation has favorable conditions for further development of the stock market, in general, and the stock market in particular. The key issue is a dramatic increase in the inflow of funds to the stock market from Russian investors. However, under Russian conditions, citizens' distrust of financial markets will continue for a long time. The only real source of increased Russian investment in the equity market could be state or semi-state institutional investors. But and such budget investments are not an effective solution, as they are associated with some negative aspects.

According to many analysts, the Russian stock market is expected to fall further. The almost complete absence of collective investment schemes, as well as low investment attractiveness in general, are among the factors of weakness in the Russian equity capital market. In this regard, the question of a suitable method for forecasting prices in the Russian stock market is really important, since it will allow both small and large investors to predict the movement of the Russian stock market, make a profit and increase activity in the Russian stock market as a whole.

Predicting stock market dynamics is very important for solving many economic problems. A successful forecast of the future stock premium can result in significant returns. Investors always take into account historical price dynamics to form a forecast of future market movements and make an investment decision.

The predictability of stock returns is a widely studied subject in the economic literature. There are different points of view on forecasts in the field of stock market dynamics. For example, the efficient market hypothesis assumes that stock prices reflect all currently available information and that all price changes are independent of newly discovered information, so that overall market price movements cannot be predicted. The opposite view suggests that there are different methods for generating information about future market prices. Problem The predictability of the stock premium and methods for predicting stock market movements remain open and controversial.

At the moment, research in this area has been conducted by many authors. S. I. Jabbouri [1] attempts to identify the main factors influencing the dividend policy in MENA's emerging markets in the period from 2004 to 2013. The study shows that a dividend policy is positively related to size, current earnings, and liquidity, and negatively related to leverage, free cash flow growth, and the state of the economy. The author notes that understanding the dividend policy improves the forecast of dividend payments and the selection of appropriate valuation models that increase investor confidence and stimulate market activity and economic growth.

Goel, A., Tripathi, V., and Agarwal, M. [2] attempt to study the relationship between information asymmetry and the expected return of shares on the National Stock Exchange (NSE) of India with a sample of NIFTY 500 shares for the period from April

1, 2000, to March 31, 2018, using three different indicators of information asymmetry: number of transactions, institutional ownership, and idiosyncratic instability. Empirical evidence has shown that as the asymmetry of portfolio-related information increases, returns also increase to compensate investors for the risk associated with the information, which confirms the presence of a significant positive relationship between the information asymmetry and the expected return of shares on the NSE. Among the various asset pricing models used in this study, Fama and French's three-factor model with extended information proved to be the best for explaining cross-sector variations in portfolio returns. Similar is the study Esen, M.F., Singal, M., Kot, H.W., Chen, M.-H. [3], in which the authors use the event research methodology to study 21,785 transactions from 165 hotel and travel companies in 2010-2016. Empirical tests show that insider transactions generate abnormal returns on stocks, suggesting that outside investors can succeed by mimicking insider trades.

Biggerstaff, L., Cicero, D., Wintoki, M.B. in progress «Insider trading patterns"[4] consider the informational content of stock trading by corporate insiders. As a result, it is proved that insiders try to maintain their information advantages and increase the profit from trading by disclosing information about transactions after the market closes.

A progressive approach to analyzing data on price movements in the stock market is used by Feuerriegel S., and Prollochs N. [5]. They investigate how stock prices change depending on their response to financial disclosures on various topics. For this purpose, the authors used the Data Mining approach (LDA). Bi Q., Yan H., Chen C., and Su Q. are also devoted to the development of approaches based on artificial intelligence [6].

The imperfection of statistical methods for predicting stock prices is emphasized in their study by Ding G., Qin L.[7]. The authors propose a related model of a deep recurrent neural network with multiple inputs and multiple outputs, based on a long-term short-term memory network. A linked network model can simultaneously predict the opening price, the lowest price, and the highest price of a stock. The corresponding network model was compared with the LSTM network model and the deep recurrent neural network model.

The advantages of the Bayesian method for predicting stock prices are described in the works of Ciapanna E., and Taboga M. [8], as well as Maguluri L. P., Ragupathy R. A. [9]. The authors propose a Bayesian regression model with time-varying coefficients (TVC), which allows us to jointly estimate the degree of instability and the time path of the coefficients, and a hybrid probabilistic model for predicting stock market sentiment based on real-time market data. Both models allow you to predict the risks associated with changes in stocks over time and under the influence of information.

As can be seen, the study of these approaches is widespread among foreign authors but has not yet been evaluated in Russia. Thus, the aim is to improve the accuracy of forecasting the dynamics of stock prices based on a combination of the most common statistical methods and special programs.

2 Materials and Methods

Often, when analyzing economic data, it becomes necessary to assess the dynamics of changes in a certain value or to form a forecast of future values. However, the parameter under study may not necessarily be related to the values of other variables, as in classical regression models. In this case, the models appear time series.

The time series is a series of observed values of the studied quantity, ordered in time. The time series differs significantly from the sample: the values are not equally distributed and they are not independent, i.e. it is unacceptable to place the studied values in any order.

In general, we consider a time series of observations of some magnitude:

$$Y_1, Y_2, \dots, Y_n. \tag{1}$$

These observations are considered as realizations of some arbitrary variable that is described by some stochastic process. One of the main assumptions of time series analysis suggests that the values are observed at the same time intervals.

Identifying the structure of the time series is necessary to correctly identify the model used.

It is assumed that the time series contains two main components:

- systematic component
- error (white noise).

The systematic (regular) component, in turn, can represent It is either a seasonal component or a trend. A trend is a general systematic linear or linear trend. a non-linear component that can change over time.

A seasonal component is a component that repeats itself periodically. A periodic relationship can be formally defined as a correlation relationship of order k between each i-m element of the row and (i-k)-m element. This relationship can be measured using autocorrelation. The parameter k is called lag, lag, or shift.

In practice, seasonal components are determined using correlograms. The correlogram shows the autocorrelation function expressed numerically and graphically. Another useful technique for studying seasonality is to analyze the partial autocorrelation function, which is a deepening of the concept of the above-considered autocorrelation function. Namely, in the partial autocorrelation function, the relationship between observations within the lag is eliminated. Partial autocorrelation describes periodic dependencies more precisely.

White noise is a stationary series that consists of a set of random variables. values that are independent of each other, with a zero mathematical expectation and a constant by variance.

2.1 Moving Average Processes

Moving average order process q - MA(q). General view of the process (2):

$$Y_t = \delta + \varepsilon_t - \theta_1 \varepsilon_{t-1} - \dots - \theta_q \varepsilon_{t-q} \tag{2}$$

where is white noise. Therefore, it represents a certain constant the average and sum of a random variable that is delayed by a certain number of periods, with a coefficient.

The autocorrelation function of these processes abruptly ends at a step, i.e. moving average processes only have "memory" for steps. Moving average processes are stationary for any coefficients.

The moving average equation can be written as an infinite-order autoregression equation, and vice versa. This is the so-called invertibility property, and it affects the choice of estimation methods since the least-squares estimation of moving average processes is possible only if the shift operator polynomial is invertible. A polynomial is invertible if all roots of the characteristic polynomial lie outside the unit circle.

Autoregressive models - AR(p). General view (3):

$$Y_t = \delta + \varphi_1 Y_{t-1} + \varphi_2 Y_{t-2} + \cdots + \varphi_p Y_{t-p} + \varepsilon_t \qquad (3)$$

Therefore, the current value of a process depends on its past values and the implementation of some random component εt which is white noise.

The autocorrelation function of processes AR i_t decreases infinitely, and the partial autocorrelation function ends at step p.

An important part of the autoregression process is the requirement for stationarity. The autoregression process is sometimes stationary, so, for example, if the equation contains only one parameter that exceeds modulo 1, then with each subsequent step, the value of the function will accumulate, that is, the subsequent ones x_t they will constantly grow, so the row will not be stationary. Similarly, there are conditions, which ensure the stationarity of processes in the presence of several parameters.

For autoregressive models, it is particularly easy to use the least-squares method. The estimation does not differ from the estimation of a linear regression model with a lagged dependent variable [10].

2.2 Moving Average Autoregression Processes

Common moving average autoregression processes (ARMA). Process ARMA - there is a combination of the previously named autoregression and moving average processes. General view (4):

$$Y_t \varphi(L) = \delta + \theta(L)\varepsilon_t \qquad (4)$$

where L - the shift operator, which is defined as (5):

$$L^k Y_t = Y_{t-k} \qquad (5)$$

The constant in model (4) has a different interpretation, depending on the applied model. The following two cases are possible:

1) average value of the series (if there are no autoregression parameters),

2) a free member (otherwise).

If during the construction of the model, the procedure for differentiating a series was carried out, then the constant represents the properties of the transformed series, not the original one.

An important problem is the problem of stationarity of the process. It is the stationarity of time series that makes it possible to use standard methods and models that are used to analyze spatial data. Stationarity assumes that the distribution of the variable under study is independent of time.

Stationarity in a broad sense means that the mathematical expectation and variance of a stochastic process are constant and finite, and the covariance between two adjacent values is constant and does not depend on time.

The invertibility property significantly facilitates the task of constructing a series forecast.

2.3 Forecasting

As a rule, the main goal of building a time series model is to obtain predicted values of a variable at some future point in time.

Assume that at time T you need to get a forecast, i.e. the value of the variable in time cycles. At the time of forecasting, when modeling a one-dimensional time series, the information set on which the forecast is based contains the value of the variable and all its lags. In general, In this case, the forecast is a function of the variables of this set.

For the selection process optimal predictors need to minimize mathematical expectation of the square of the prediction error (6):

$$\mathrm{E}\left\{\left(\mathrm{Y}_{\mathrm{T+h}} - \widehat{\mathrm{Y}}_{\mathrm{T+h|T}}\right)^2 | \mathrm{I}_{\mathrm{t}}\right\} \rightarrow \min \tag{6}$$

Based on this, we can say that the best forecast is the conditional mathematical expectation for the given information (7):

$$Y_{T+h|T} = E\{Y_{T+h}|I_t\} \tag{7}$$

Therefore, the optimal prediction satisfies all the usual properties of expectation operators. In particular, the conditional mathematical expectation of the sum is the sum of conditional mathematical expectations.

In all cases, the conditional point forecast asymptotically approaches the average value of the series, and the variance of the forecast error approaches the variance of the series. This means that for a stationary process, the influence of available information on the forecast and its accuracy decreases asymptotically to zero.

When analyzing time series in practice, the theoretical construction by which the series develops is initially unknown. It is necessary based on the source data using empirical data to form a more appropriate model of the economic process.

The task of building a model of the type ARIMA according to the well-known implementation of the time series, Box and Jenkins proposed to divide it into several stages.

Step 1: determine the order of integrability of the series and achieve its stationarity. This is how the order is determined d. After that, based on the analysis of the autocorrelation and partial autocorrelation functions, the parameters are determined p and q. The model can also be selected based on information criteria. This completes the identification of the model.

Step 2: evaluating the model parameters

Step 3: model adequacy assessment (assessment of the significance of the model as a whole and individual coefficient, determination of the stationarity of reversibility, checking the correspondence of model residues to white noise).

Step 4: applying the model. As a rule, the main goal of construction is to estimate the predicted future values of the time series [11].

The model for a non-stationary time series has the form:

$$\Delta^d X_t = c + \sum_{i=1}^{p} a_i \, \Delta^d X_{t-i} + \sum_{j=1}^{q} b_j \, \varepsilon_{t-j} + \varepsilon_t \qquad (8)$$

where εt - stationary time series;

c, ai, bj – model parameters.

Δd – operator of the difference of a time series of order d (sequential taking of d times of first-order differences-first from the time series, then from the obtained first-order differences, then from the second-order differences, etc.).

VAR models (Vector autoregression models) are used for multidimensional time series. The structure is such that each variable is a linear function of past lags of itself and past lags of other variables.

As an example, suppose we measure three different time series variables, denoted by $x_{t,1}$, $x_{t,2}$, and $x_{t,3}$.

The first-order vector autoregression model, denoted as VAR (1), looks like this (9):

$$\begin{aligned} \mathrm{x}_{t,1} &= \alpha_1 + \varphi_{11}\mathrm{x}_{t,1,1} + \varphi_{12}\mathrm{x}_{t,1,2} + \varphi_{13}\mathrm{x}_{t,1,3} + \omega_{t,1} \\ \mathrm{x}_{t,2} &= \alpha_2 + \varphi_{21}\mathrm{x}_{t,1,1} + \varphi_{22}\mathrm{x}_{t,1,2} + \varphi_{23}\mathrm{x}_{t,1,3} + \omega_{t,2} \\ \mathrm{x}_{t,3} &= \alpha_3 + \varphi_{31}\mathrm{x}_{t,1,1} + \varphi_{32}\mathrm{x}_{t,1,2} + \varphi_{33}\mathrm{x}_{t,1,3} + \omega_{t,3} \end{aligned} \qquad (9)$$

Each variable is a linear function of the values of lag 1 for all variables in the set. In the VAR (2) model, the values of lag 2 for all variables are added to the right-hand side of the equations. In the case of three variables x (or time series), there will be six predictors on the right side of each equation, three terms with a lag of 1 and three terms with a lag of 2. In general, for a VAR (p) model, the first p lags of each variable in the system will be used as regression predictors for each variable.

VAR models are a special case of more general VARMA models. VARMA models for multivariate time series include the VAR structure shown above, along with the moving average terms for each variable. More generally, these are special cases of ARMAX models that allow you to add other predictors that are outside the multidimensional set of primary interest.

3 Results

The predictability. of stock returns is extremely important for solving many fundamental questions of economics and finance. There are various methods for performing this analysis. The most common approach is predictive linear regression, which reveals the relationship between stock market returns and certain market indicators, such as inflation, dividend yield, or default spread. Most of the existing literature on predicting stock returns assumes that there is a linear relationship between market indices and stock returns. In other ways to other words, it is possible to predict future stock market movements using econometric approaches [12].

From March 2014 to the present, the economy of the Russian Federation has been operating in a new and extremely difficult environment. The reason for this functioning should be considered the introduction of anti-Russian sanctions by the United States and the European Union. One of the main reasons for their occurrence is the annexation of Crimea to the Russian Federation following a referendum. The main purpose of launching anti-Russian sanctions was to put pressure on Russia to change its position on world issues and the course of further development, as well as damage its economy. Every year the situation in this issue is gaining momentum. Thus, the analysis of the impact of anti-Russian sanctions on economic processes is still relevant today. They have had and continue to have a significant impact on the economy of our country and, of course, have some negative consequences for the Russian Federation, as well as some negative outcomes for the West [13].

Delphshirre Holdings Limited data is used as the research base. To predict the dynamics of the stock price, we will use two methods (models), namely: ARIMA and VAR.

The entire forecasting process is carried out in several stages:

1. Let's make a selection of data for forecasting;
2. Transform it into a convenient file for processing (file type *.csfto a file *.exel);
3. Convert a non-stationary series to a stationary one;
4. Define the target variables (exchange rate dynamics parameters, opening and closing prices, maximum and minimum prices per session, and specify the date as metadata);
5. Let's perform forecasting using two models;
6. Plot the obtained values (based on VAR for all target variables and ARIMA by any one variable);
7. Generate the received data in tabular form and save it in an external application (Excel).

The entire process ("Workflow" in a software package “Orange”) of forecasting is shown in Fig. 1:

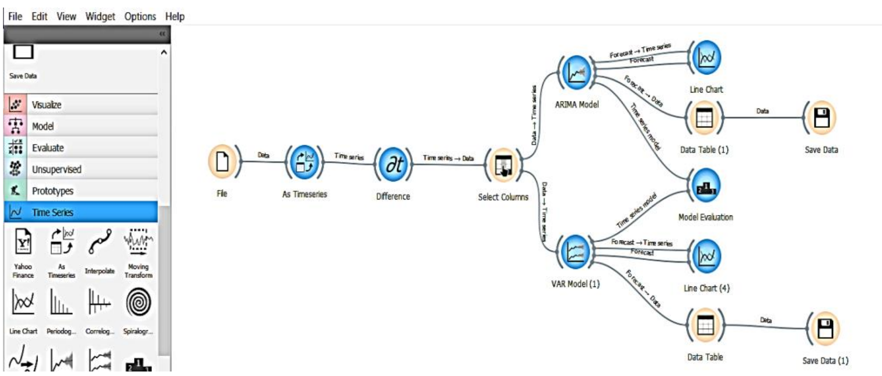


Fig. 1. "Workflow" of the time series forecasting process.

Stage 1. Creating a sample of data for forecasting. At this stage, you need to determine the parameters of the time series. We will perform the analysis based on the following characteristics:

- opening price (Open);
- closing price (ClosingPrice);
- the maximum price per session (DailyHigh);
- minimum price per session (DailyLow);
- quote date (Date).

In addition, we will determine the time series horizon, namely all quotes for the period from April 1, 2019, to April 1, 2021. In other words, the range is 3 years.

Step 2. Transform the initial file into a new file (file of type .csfto a file .exel), see Fig. 2:

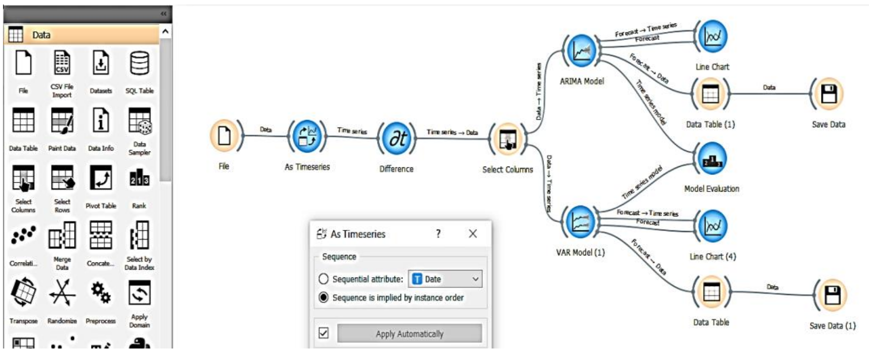


Fig. 2. Converting quotes to a convenient file for processing.

Step 3. Convert a non-stationary series to a stationary one. The transformation makes it possible to make forecasts based on the selected models (high volatility can significantly affect the variance and the quality of the forecast as a whole) (see Fig. 3).

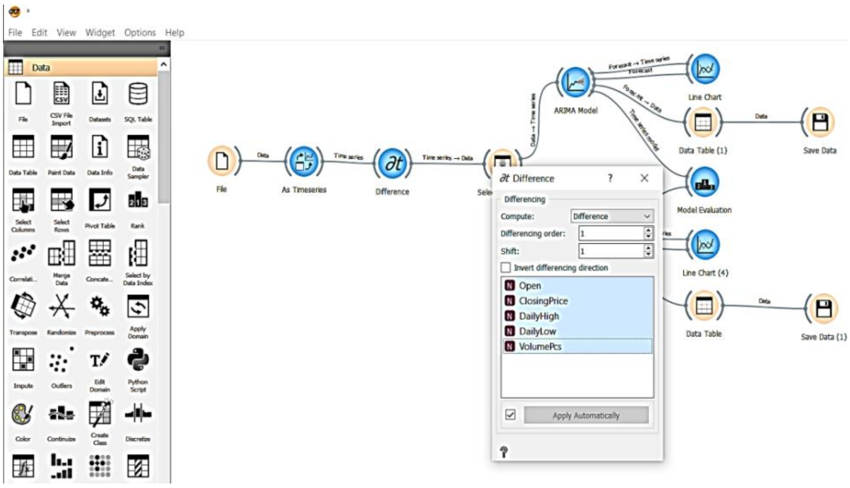


Fig. 3. Converting a time series to a stationary one.

Step 4. Define the target variables. The target variables will be the parameters of the exchange rate dynamics: the opening and closing price, the maximum and minimum price per session. Enter the date as metadata. These parameters must be specified with the assigned status since the program must understand what data the forecast will be based on.

Here you need to consider that ARIMA processes only one target variable, so each time series parameter must be entered separately. When calculating by model VAR there is no such restriction, so all variables can be immediately designated as target variables and the calculation can be started immediately (see Fig. 4).

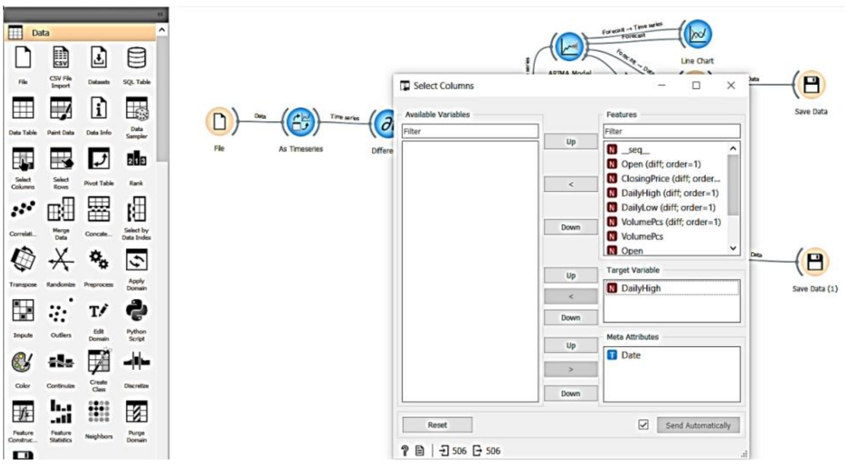


Fig. 4. Defining target variables.

Step 5. Let's make a prediction using two models. At this stage, you need to determine the calculation parameters for each model. In the pop-up window. By model VAR the approach is similar to the Box-Jenkins methodology, with choosing the type of optimization and forming a trend (we choose "None", that is, we leave the basic settings), (see Fig. 5 and 6).

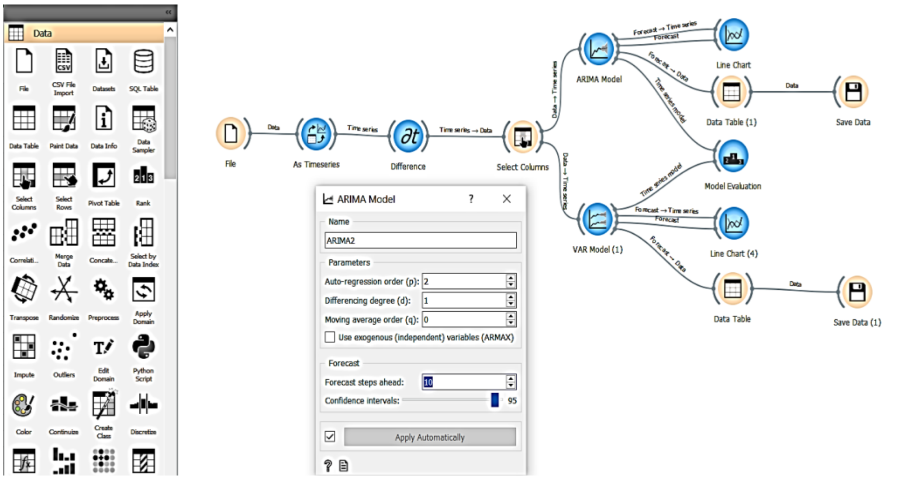


Fig. 5. Forecasting the dynamics of the exchange rate using two models (the figure shows ARIMA).

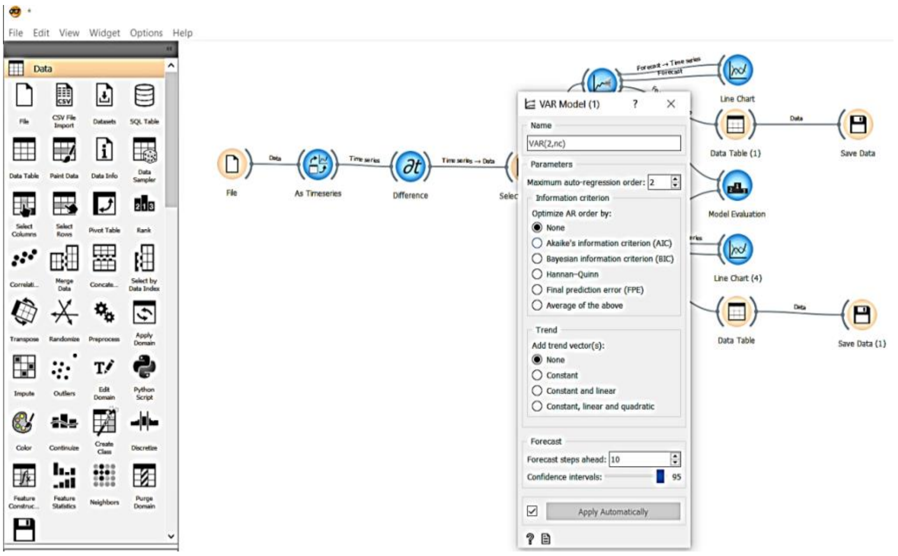


Fig. 6. Forecasting the dynamics of the exchange rate using two models (the figure shows VAR).

Step 6. Plot a graph of the obtained values (based on VAR for all target variables and ARIMA for any one variable) (see Fig.7 and 8).

As you can see from the graphs below, the forecast depends on the number of calculation steps, and with each step, the forecast shows a positive trend.

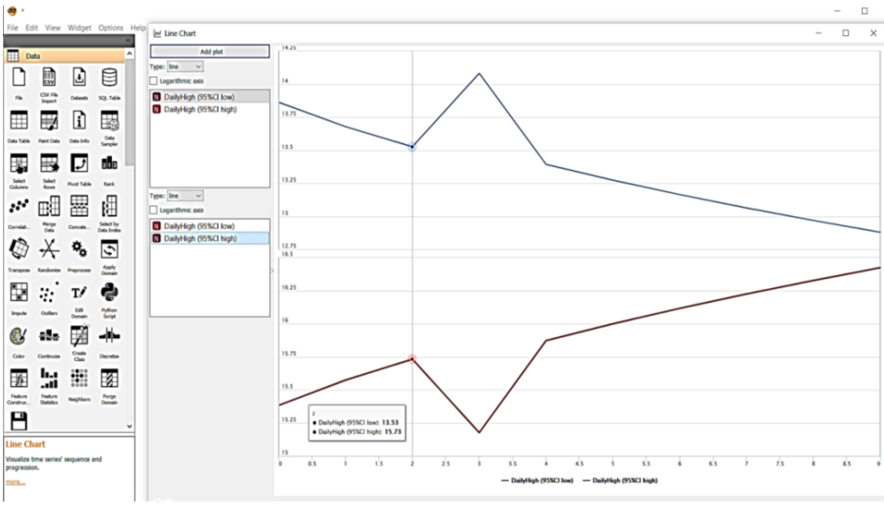


Fig. 7. Graph of the forecast of the main parameters of the stock price using ARIMA models.

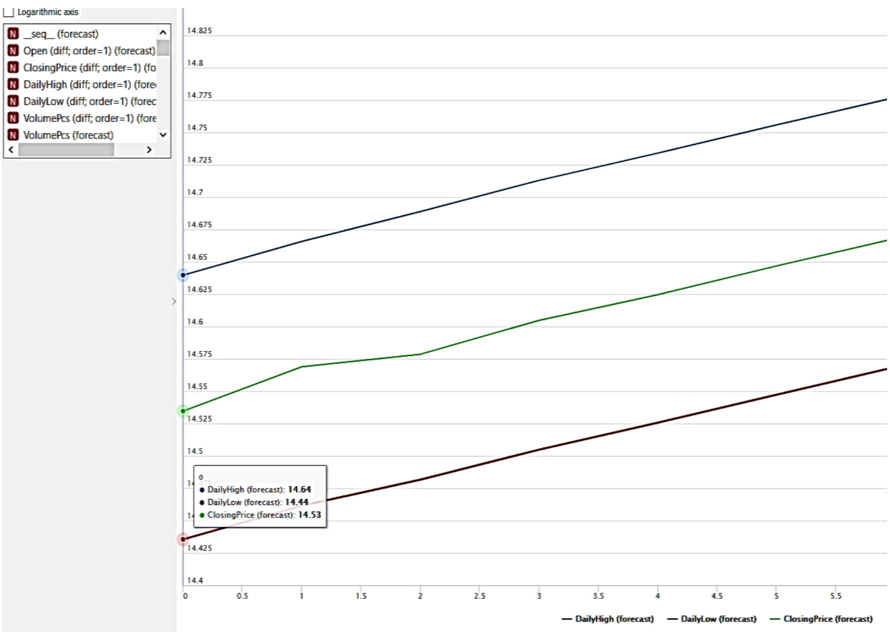
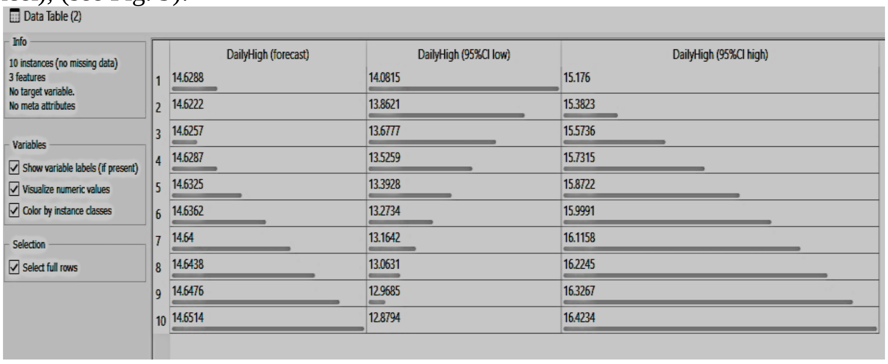


Fig. 8. Graph of the forecast of the main parameters of the stock price using VAR models.

Step 7. Generate the received data in tabular form and save it in an external application (Excel), (see Fig. 9):


Data Table (2)

Info
10 instances (no missing data)
3 features
No target variable.
No meta attributes

Variables
Show variable labels (if present)
Visualize numeric values
Color by instance classes

Selection
Select full rows

	DailyHigh (forecast)	DailyHigh (95%CI low)	DailyHigh (95%CI high)
1	14.6288	14.0815	15.176
2	14.6222	13.8621	15.3823
3	14.6257	13.6777	15.5736
4	14.6287	13.5259	15.7315
5	14.6325	13.3928	15.8722
6	14.6362	13.2734	15.9991
7	14.64	13.1642	16.1158
8	14.6438	13.0631	16.2245
9	14.6476	12.9685	16.3267
10	14.6514	12.8794	16.4234

Fig. 9. Creating the received data in tabular form for saving it in an external application.

We summarize all the results obtained in a table of the following form (see Table 1):

Table 1. Forecast of the main parameters of the stock price using 2 models.

	Open	ClosingPrice	DailyHigh	DailyLow
	12,53	12,71	12,71	12,46
	12,67	12,46	12,74	12,46
	12,53	12,73	12,81	12,53
	12,68	12,50	12,95	12,42
	12,50	12,73	12,74	12,29
	…	…	…	…
	14,67	14,75	14,79	14,57
	14,50	14,62	14,64	14,45
	Open (forecast)	ClosingPrice (forecast)	DailyHigh (fore-cast)	DailyLow (fore-cast)
	14,56977453	14,53798035	14,64327439	14,44413024
	Open (forecast)	ClosingPrice (forecast)	DailyHigh (fore-cast)	DailyLow (fore-cast)
	14,50927999	14,62456582	14,6287543	14,43018422
	14,56	14,4	14,58	14,285
	0,06049454	**-0,08658547**	**0,01452009**	**0,01394602**
	-0,05072001	0,22456582	0,0487543	0,14518422

As can be seen from the results obtained, the VAR model generally gives a more accurate result (3 out of 4) compared to ARIMA.

The methods considered in this paper are not the only means of analyzing the stock market dynamics, but they show a quite high efficiency in predicting and studying the main dependencies and trends in the securities market. Despite the rough assumptions that are rarely fully implemented when working with real data, the models studied are not theoretical constructions, but allow us to study real economic processes with a certain degree of accuracy.

To improve the quality of the technical analysis, the results should be supplemented with a fundamental analysis that includes more detailed information about the issuing company itself, as well as macroeconomic indicators. Factor models that consider the dependence of a time series not only on its history but also on other variables are also widely used. This makes it possible to avoid the influence of a sharp change in exogenous factors, which cannot be included in the considered prehistory of the series.

4 Conclusion

The Russian stock market is relatively young. It started functioning in the 1990s, but due to economic and social tensions in Russia, most of the trade started only in the early 2000s. The remaining 20 years included two major economic crises, which also had negative financial markets. The Russian stock market is still characterized by such problems as high volatility, low investment attractiveness and activity, and high commodity dependence. In general, the Russian stock market is still characterized as developing. In this regard, the issue of correctly predicting the premium on Russian stocks is very important, as this can stimulate the growth of the expected return of investors and increase investment activity in the market as a whole.

Having studied the economic literature on stock market forecasting, we can conclude that there are many approaches and studies on this issue. There are two main and opposite points of view. One of them says that there are certain indicators, which predict the future return of the stock market under certain conditions. The opposite view holds that stock market prices have already been adjusted for all currently available information, so the future stock price is unpredictable.

So far, the most common method that has been used to test the predictability of stock returns is linear regression, estimated by the following methods: VAR and ARIMA. Therefore, this approach was used in our study. As part of sample analysis, we analyzed data on the quotes of the underlying enterprise for the period from 1.04.2019 to 1.04.2021.

The models under study (ARIMA and VAR) use historical data of the indicator, therefore, a large amount of initial information is required for analysis. If there are significant changes in the market (for example, market volatility or correlation between assets), the forecasts obtained from the model become incorrect, since these changes will be taken into account only after a certain period. Thus, the considered models provide qualitative predictions when the market conditions are stable.

Moreover, when the forecast horizon increases, the forecast error increases significantly, so the use of the considered tools is advisable only for short-term forecasts. Nevertheless, the deviations of real values from forecast data during periods of relatively stable economic conditions are quite small, therefore, models can be applied in practice to calculate the approximate value of the indicator in the short term.

Thus, the lack of data, as well as the high volatility and uncertainty of the market associated with political and economic shocks, may be partly responsible for the lack of predictive power that we found in the out-of-sample period. Thus, in the future, we plan to improve this research by applying other approaches to forecasting the stock market, as well as expanding the range of forecast indicators.

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