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Medium-Term Forecasting Of Investment Portfolio Profitability

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Abstract: This study explores medium-term forecasting of investment portfolio profitability by analyzing the stock prices of six Uzbek joint-stock companies using time series models. The research compares classical statistical models such as ARIMA with nonlinear models like GARCH and LSTM to determine their accuracy in volatile market conditions. Over 848 ARIMA model combinations were tested, and the most optimal models were selected based on statistical indicators such as AIC, BIC, and significance of parameters. Findings revealed that combining ARIMA with GARCH models improves forecast precision due to the volatility observed in stock returns. The study also highlights that while residuals exhibit autocorrelation and non-normality, the models remain statistically robust for forecasting daily prices from August 2024 to December 2027. The research supports the need for hybrid approaches to better capture the dynamics of financial markets.

Keywords: ARIMA, GARCH, Stock Price Forecasting, Time Series Models, Investment Portfolio, Financial Market Volatility, Uzbekistan Stock Market, Forecast Accuracy, Nonlinear Models, Econometric Analysis, ARCH Effect, Neural Networks (LSTM, ANN).

Introduction: Stock price forecasting has a huge impact on the country's economy. After all, the financial market plays an important role in the country's economy. Being able to forecast market movements increases interest in it, thereby contributing to the development of the financial market. Data on the financial market mainly consists of time series data. Therefore, financial market forecasting is carried out based on historical data. Based on the principle that "history repeats itself" in the financial market, investors and financial analysts forecast stock returns based on the current market situation. Choosing the optimal model is important when forecasting the return on an investment portfolio, stocks, and the financial market in general. Because, accordingly, the investor determines the entry and exit points of the market, which, based on sound information, helps to make the right decision to invest capital in the financial market and get high profits. Different economists have used different models to implement this forecast. However, prioritizing any one model still remains a complex process. Because the financial market is a non-linear, highly volatile market, the uncertainty of the data in it and the shortcomings of forecasting models complicate the forecasting process. In addition, the presence of various factors such as the irrational or rational behavior of investors, their emotional and psychological state make the movement in the financial market more dynamic. The fact that stock prices also have sharp and unstable fluctuations under the influence of internal and external factors such as various news and published reports can lead to errors in forecasting. According to Shah, the growth of social and Internet-based media has had a significant impact on the interaction between public opinion and stock market dynamics.

The following figure shows the main models used in financial market forecasting: (See Figure 4.9)

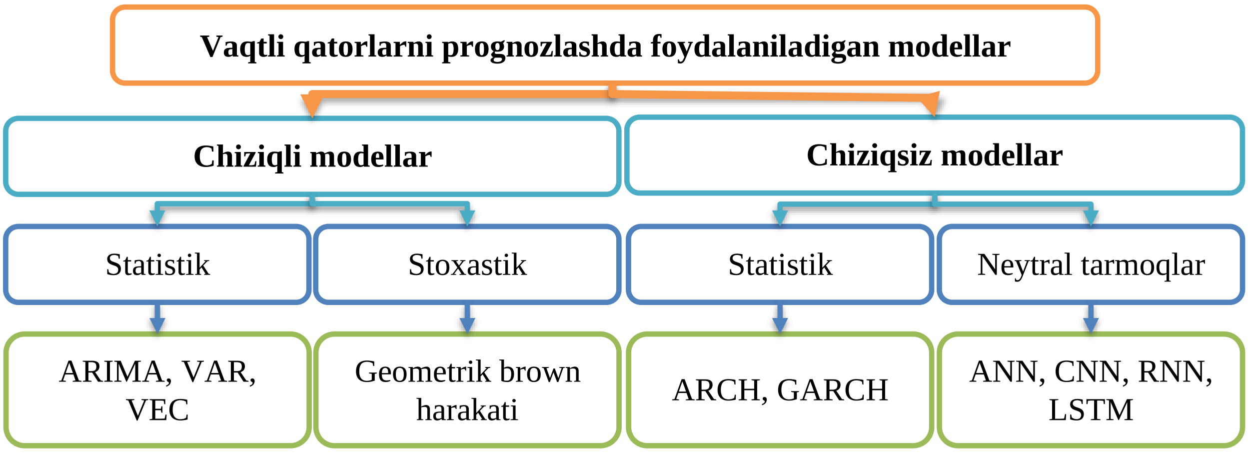

Figure 4.9. Models used in time series forecasting 430

Autoregressive (linear statistical) models study the coefficients that model the relationship between several time steps for a target percentage characteristic. One of the popular autoregressive methods is the autoregressive integrated moving average (ARIMA) model. It was proposed by Kumar and Jain in 2010. ARIMA predicts the future as a linear combination of historical values and errors, eliminating the trending nature of the variables by implementing differentiation. It is especially effective for short-term forecasting. The advantages of these models are their short-term forecasting efficiency, ease of description, and ability to detect seasonality. However, the inability to model nonlinear relationships between variables in multivariate forecasts is considered their main disadvantage.

Most researchers use ARIMA and LSTM models to forecast financial markets. However, these models are also not without their drawbacks. For example, Islam and Nguyen point out that the most popular ARIMA model has some limitations in dealing with nonlinear, non-stationary and seasonal data in time series . In addition, it is difficult to perform long-term forecasting using this model. According to Banerjee and Nayak, the LSTM model does not have parameters predetermined like ARIMA, and hyperparameters must be properly tuned to use the model. A group of scientists led by Agrawal proved that the LSTM model is superior to MA, LR and ARIMA models , while a group of scientists led by Srivastava found the LSTM model to be the most suitable model for working with time series data among other neutral network models. A number of other scientists have compared neutral network models with classical statistical models and noted that neutral network models are more powerful in many respects. For example, scientists such as Namini and Rhanoui have shown in their studies that LSTM is superior to ARIMA, and Gurushin has proven that even models that combine statistical and neutral network models (GARCH-ANN, EGRACH-ANN) are less effective than a simple ANN model. The fact that stock prices are associated with volatility makes it possible to forecast them using the GARCH model. Since GARCH is the most effective method for forecasting volatility. According to a study conducted by a group of scientists led by Zareemba, volatility is considered very important for the functioning of financial markets, as it is an indicator of stress associated with financial investments, uncertainty, and financial risk.

According to Cont, the most valuable characteristic of financial risk is the presence of variability in it. Because this variability has a structure such as volatility and clustering tendency. To better assess this effect, the corresponding family of autoregressive conditional heteroskedasticity models is used. The following table presents the characteristics of heteroskedastic models. (See Table 4.8)

Table 4.8

Heteroscedasticity models

Model	Year	Scientist	Formula	Limitation
ARCH[1]	1982	Angle	$\sigma_t^2 = \alpha_0 + \alpha_1 u_{t-1}^2$	$\alpha_0 > 0$, $\alpha_1 \geq 0$

[1] Engle, RF Autoregressive conditional heteroskedasticity with estimates of the variance of the United Kingdom inflation // Econometrica – 1982 – Vol. 50, Issue 4. – P. 987-1007. - New York, Cambridge University Press, 1982.

ARCH[2]	1986	Bollerslev	$\sigma_t^2 = \alpha_0 + \alpha_1 u_{t-1}^2 + \beta_1 \sigma_{t-1}^2$	$\alpha_0 > 0$, $\alpha_1 \geq 0$, $\beta_1 \geq 0$
Integrated GARCH (IGARCH)[3]	1986	Engle and Bollerslev	$\sigma_t^2 = \alpha_0 + (1 + \beta_1) u_{t-1}^2 + \beta_1 \sigma_{t-1}^2$	$\alpha_0 > 0$, $\beta_1 \geq 0$
Exponential GARCH (EGARCH)[4]	1991	Nelson	$log\sigma_t^2 = \alpha_0 + \gamma(\lvert z_{t-1}\rvert - E[\lvert z_{t-1}\rvert]) + \psi z_{t-1} + \beta_1 log\sigma_{t-1}^2$	-
Glosten-Jagannathan-Runkle GARCH (GJR-GARCH)[5]	1993	Glosten and others	$\sigma_t^2 = \alpha_0 + \alpha_1 u_{t-1}^2 + \gamma_1 P_{t-1}^- u_{t-1}^2 + \beta_1 \sigma_{t-1}^2$	$\alpha_0 > 0$, $\alpha_1 \geq 0$, $\beta_1 \geq 0$, $\alpha_1 + \gamma_1 \geq 0$
Threshold GARCH (TGARCH)[6]	1994	Zakoian	$\sigma_t = \alpha_0 + \alpha_1 \lvert u_{t-1}\rvert + \gamma_1 P_{t-1}^- \lvert u_{t-1}\rvert + \beta_1 \sigma_{t-1}^2$	$\alpha_0 > 0$, $\alpha_1 \geq 0$, $\beta_1 \geq 0$, $\alpha_1 + \gamma_1 \geq 0$

This in research , dynamic o ' variability clear forecast can popular , popular ARIMA model with together in vibration effective working ARCH from models used without under study of enterprises action prices forecast This was done . models together use forecast accuracy to increase help gives . Forecast done increase for , 7 under study stock ownership societies from January 1, 2017 August 1, 2024 until daily action grades received .

Table 4.9

Test results for forecasting

		KWTS	QZSM	KUMZ	UZMC	AGMK	TNGK	KYEZ
Dickey-Fuller test (p-value)								
	0 difference	0.0839	0.5252	0.0056	0.0864	0.0012	0.0000	0.0000
	Difference I	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
	Difference II	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
Phillips-Perron test (p-value)								
	0 difference	0.4239	0.6995	0.3960	0.0224	0.0347	0.0000	0.0006
	Difference I	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
	Difference II	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
Lags outside the confidence interval								
AR	0 difference	9	4	9	17	5	3	6

[2] Bollerslev , T. (1986). Generalized autoregressive conditional heteroskedasticity . Journal of Econometrics, 31(3), 307–327.
[3] Engle, RF, & Bollerslev , T. (1986). Modeling the persistence of conditional variances. Econometric Reviews, 5(1), 1–50
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[6] Zakoian , JM 1994. Threshold heteroskedastic models. Journal of Economic Dynamics and Control 18: 931-955.

	Difference I	**8**	**7**	**8**	20	**8**	**2**	**12**
	Difference II	20	23	21	**23**	22	28	27
I	Lag	1	1	1	2	1	1	1
MA	Difference I	**7**	**4**	**7**	14	**8**	**2**	**15**
	Difference II	6	2	6	**10**	7	7	15
ARCH effect test								
0	chi2	1785.89	1837.81	1798.81	1754.98	1686.9	1689.9	1298.9
	p-value	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
I	chi2	21,272	88,191	37,511	2.856	37,511	0.003	0.367
	p-value	**0.0000**	**0.0000**	**0.0000**	0.0910	**0.0000**	**0.9593**	**0.5446**
II	chi2	360,554	385,533	466,675	426,650	466,675	459,632	476,590
	p-value	0.0000	0.0000	0.0000	**0.0000**	0.0000	0.0000	0.0000

Above table from the information to see possibly Dickey - Fuller test to the results see KVTS , QZSM and UZMC action prices first level stationary , remaining all under study of enterprises action prices stationary Phillips - Perron test to the results see but only TNGK action prices first level stationary to be , to remain enterprises shares are 2nd level stationary Therefore , the value of I in the ARIMA forecast is 1 in KVTS, QZSM and UZMK

, and 0 in the rest .

In order to evaluate the GARCH model in combination with ARIMA in stock price estimation, it is necessary to have volatility in stock prices. For this, an ARCH test was conducted. According to it, at the level of difference 0, the p-value is equal to 0 in all enterprises, which means that the H 0 null hypothesis is rejected and the alternative hypothesis is accepted. This means that stock prices have volatility and they have an ARCH effect. Accordingly, it was considered appropriate to use the ARCH and GARCH models in stock price forecasting. However, although UZMK achieved stationarity at level I, the ARCH effect at this level has not been proven. The remaining enterprises are forecasted at level I. Because the MA lags are outside the confidence interval at level 0, this is a sign of non-stationarity.

In the AR indicator, all enterprises except UZMK accept the results of 0 difference. That is, in KVTS the AR value is from 1 to 9, in QZSM it is from 1 to 4, etc. The results of the MA value can also be described in the same way. Based on the above, a total of 848 ARIMA combinations were formed, of which 56 for KVTS, 28 for QZSM, 56 for KUMZ, 460 for UZMK, 64 for AGMK and 180 for KYEZ. From the formed ARIMA combination models of each joint-stock company, the most optimal model with the minimum number of statistically significant indicators, logarithmic probability, AIC and BIC indicators was selected. The indicators of these models are given in the table below. (See Table 4.10)

Table 4.10

The most optimal models

AJ	ARIMA	Parameter	Log likelihood	AIC	BIC	Hair	L/l	AIC	BIC
KWTS	**(7,1,5)**	**16(15)**	-12195.1	**24422.3**	24510.8	+		+	
QZSM	**(1,1,1)**	**6(5)**	**-10741.2**	**21494.5**	**21527.6**		+		+
KUMZ	**(1,1,1)**	**6(5)**	**-9055.93**	**18123.9**	**18157.1**	+	+		+
UZMC	**(18,1,9)**	**31(30)**	**-15099.2**	**30260.4**	**30431.9**			**+**	**+**
AGMK	**(1,1,1)**	**6(5)**	**-14989.3**	29990.6	**30023.8**	+	+		+

KYEZ	**(6,1,7)**	**17(16)**	-11031.4	**22096.8**	**22190.6**			+	

From this table, it can be seen that out of the 56 models calculated for KVTS, the most optimal was the value of ARIMA (7,1,5). In this model, out of 16 indicators, 15 were found to be statistically significant, and the AIC indicator was lower than in other models. Therefore, this model was selected for forecasting. For the QZSM enterprise, out of the 28 models formed, ARIMA (1,1,1) was selected for its superiority in terms of logarithmic likelihood and BIC indicator.

Table 4.11

Regression results of GARCH and ARIMA models

VARIABLES	KWTS	QZSM	KUM Z	UZMC	AGMK	KYEZ
L.ar	0.621***	-0.00861	0.145***	0.115***	0.296***	-0.569***
	(0.0622)	(0.0740)	(0.0514)	(0.0343)	(0.0554)	(0.0335)
L2.ar	-0.685***			0.414***		0.546***
	(0.0784)			(0.0265)		(0.0432)
L3.ar	-0.927***			-0.223***		1.023***
	(0.0955)			(0.0245)		(0.0329)
L4.ar	0.488***			0.199***		0.767***
	(0.0847)			(0.0238)		(0.0315)
L5.ar	-0.666***			0.00201		-0.323***
	(0.0625)			(0.0166)		(0.0375)
L6.ar	-0.208***			-0.0259		-0.815***
	(0.0483)			(0.0166)		(0.0259)
L7.ar	-0.0845**			0.353***		
	(0.0376)			(0.0184)		
L8.ar				0.245***		
				(0.0195)		
L9.ar				-0.320***		
				(0.0211)		
L10.ar				-0.0795***		
				(0.0229)		
L11.ar				-0.179***		
				(0.0170)		
L12.ar				0.0624***		
				(0.0118)		
L13.ar				-0.117***		
				(0.0122)		
L14.ar				0.00229		
				(0.0126)		
L15.ar				0.153***		
				(0.0137)		
L16.ar				-0.135***		
				(0.0128)		
L17.ar				-0.00103		
				(0.0139)		
L18.ar				-0.0846***		
				(0.0118)		
L.ma	-0.959***	-0.401***	-0.676***		-0.623***	0.225***
	(0.0506)	(0.0657)	(0.0355)		(0.0420)	(0.0522)
L2.ma	0.850***					-0.824***
	(0.0683)					(0.0379)
L3.ma	0.770***					-0.919***

	(0.0860)					(0.0426)
L4.ma	-0.894***					-0.440***
	(0.0631)					(0.0627)
L5.ma	0.878***					0.601***
	(0.0436)					(0.0458)
L6.ma				0.327***		0.765***
				(0.0117)		(0.0279)
L7.ma				-0.360***		-0.293***
				(0.0147)		(0.0438)
L8.ma				-0.386***		
				(0.0109)		
L9.ma				0.582***		
				(0.0177)		
L.arch	0.191***	0.206***	0.125***	3.460***	0.0477***	0.127***
	(0.0311)	(0.00889)	(0.00936)	(0.187)	(0.00232)	(0.0118)
L. though	0.365***	0.832***	0.821***	0.190***	0.951***	0.853***
	(0.0815)	(0.00490)	(0.00871)	(0.0123)	(0.00163)	(0.00930)
Constant ARCH	15,144***	78.23***	77.46***	3,167***	2,975***	576.7***
	(1,936)	(4.152)	(3.785)	(589.3)	(225.6)	(37.42)
Constant	0.523	0.206***	-0.0858	-20.97***	-0.837	0.309
	(4.280)	(0.00889)	(0.315)	(0.801)	(8.153)	(0.759)
Observations	1,867	1867	1867	1867	1867	1867

Standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

The model selected for the KUMZ enterprise outperformed the calculated models in 3 indicators, namely, the number of statistically significant indicators, the probability of the graph, and the minimum value of the BIC indicator. The presence of volatility in the share prices of enterprises indicated the possibility of using ARCH and GARCH models with 1 lag. In addition, in all calculated models, ARCH and GARCH indicators were found to be statistically significant. The table above shows the regression results of the selected models. According to it, most of the indicators are statistically significant, which means that it is possible to forecast using these models. The positive correlation between the ARCH and GARCH indicators indicates that the share prices are positively correlated with their volatility.

Using these models, daily stock price forecasts were made from 1.08.2024 to 29.12.2027. The results are presented in the following figure: (See Figure 4.10)

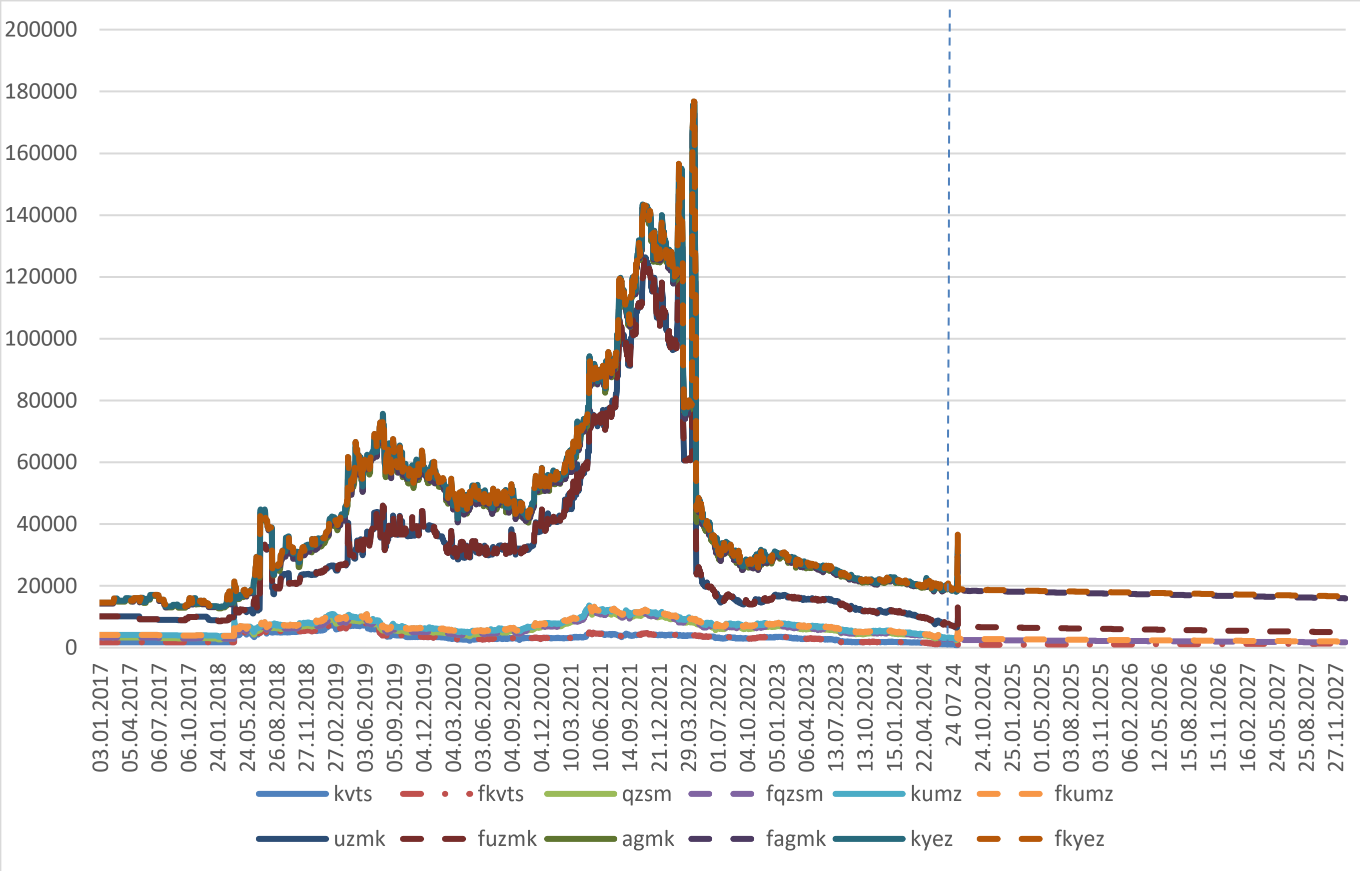

Figure 4.10. Forecast results (daily)

above , it can be seen that the share prices of the studied enterprises were stable. The main reason for this was that the share prices of the enterprises were relatively stable in the period after 2022, compared to the periods before. Also, the fact that the forecast in this figure consists of only a straight line is due to the sharp increases in UZMK shares in previous periods. If each joint-stock company were taken separately with their forecast indicators, or if the data of the UZMK enterprise were removed from this figure, the real pace would be shown. - The annexes present the forecasts of individual prices and volatility of each of the studied enterprises.

To assess the level of error in the forecast, it is necessary to examine the forecast standard error, that is, how much the forecast indicators differ from the actual indicator. The following table presents the analytical statistics of the forecast standard error. (See Table 4.12)

Table 4.12

Standard error analytical statistics

Descriptive Statistics

Variable	Obs.	Mean	Std. Dev.	Min	Max
errorkvts	1867	-1.479	175,141	-1158.586	4984.217
errorqzsm	1867	2.479	108,865	-965.373	732,833
errorkumz	1867	-.576	36,291	-180.927	410,226
erroruzmk	1867	47,519	3566.179	-64869.043	85363.547
erroragmk	1867	9.161	911,087	-7579.332	4424.676
errorkeyz	1846	-1.002	142,334	-1691.111	2781.728

This from the table to see maybe , what is being studied of enterprises action prices every one enterprise for 1867 from information consists of was if only KYEZ enterprise 1846 information Because this enterprise 2024 August from the month starting information presented not yet , maybe his/her shares Tashkent Republic fund from the stock exchange delisting done increased to be possible . In general when received , all in enterprises standard error big not , only UZMC in the enterprise o ' average 47.5 units organization This is relatively high indicator , this of the enterprise action prices high o ' to variability has that with is characterized .

Table 4.13

Test for "white noise"

	KWTS	QZSM	KUMZ	UZMC	AGMK	KYEZ
Portmanteau (Q) statistic	57,845	145,656	118,754	1166.91	66.2425	250,212
Prob>Chi2(40)	0.0336	0.0000	0.0000	0.0000	0.0056	0.0000
Bartlett's (B) statistic	1.55	3.58	3.17	10.54	1.21	3.80
Probe > B	0.0162	0.0000	0.0000	0.0000	0.1080	0.0000

This test to the results Therefore , H 0 - 0 hypothesis refusal mature , alternative hypothesis acceptance These residuals are not stationary, they do not contain white noise, but they indicate the presence of serial autocorrelation. Because the model has an ARCH effect .

The following table checks whether the forecast is normally distributed. (See Table 4.14)

Table 4.14

Normal distribution test

Shapiro-Wilk W test for normal data

Variable	Obs.	W	V	z	Prob>z
erkwts	1,867	0.525	529,480	15,914	0.000
erqzsm	1,867	0.832	187,456	13,279	0.000
my dear	1,867	0.844	174,002	13,090	0.000
eruzmk	1,867	0.353	720,698	16,696	0.000
eragmk	1,867	0.853	164,280	12,944	0.000
old man	1,846	0.566	478,979	15,653	0.000

From the results of this test , it can be seen that the residuals are not normally distributed. Therefore, the null hypothesis H 0 - 0 is rejected and the alternative hypothesis is accepted.

In conclusion, many scientific studies have been conducted to forecast stock prices and profitability, and these forecasts are mainly carried out using time series forecasting models. These models can be conditionally divided into 2 groups: linear and nonlinear models. Linear models include statistical (AR, MA, ARMA, ARIMA) and stochastic (Geometric Brownian motion) models, and nonlinear models include statistical (ARCH, GARCH, etc.) and neutral network (ANN, CNN, RNN, LSTM, etc.) models. Since the shares of joint-stock companies are volatile, ARIMA models based on the GARCH model were used for forecasting. 848 models of ARIMA models were created to forecast the share prices of 6 joint-stock companies. The most optimal models were selected. The presence of the ARCH effect on the share prices of the studied enterprises was assessed, and since the test result was positive, ARIMA and GARCH regression analysis was conducted. Since these generated models were found to be statistically significant, a daily medium-term forecast was implemented from August 2024 to December 2027.

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