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Forecasting bitcoin prices using the ARIMA–GARCH model: A volatility-based time series approach

Hizbul Watan[a,*], Rini Oktavia[b], Fitria Lestari[c]

[a] Department of Mathematics, Faculty of Mathematics and Natural Sciences, Universitas Syiah Kuala, Banda Aceh, Aceh 23111, Indonesia
[b] Department of Mathematics, Faculty of Mathematics and Natural Sciences, Universitas Syiah Kuala, Banda Aceh, Aceh 23111, Indonesia
[c] Departement of Mathematics Education, Universitas Muhammadiyah Lampung, Bandar Lampung, Lampung 35132, Indonesia

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ABSTRACT

Bitcoin is one of the most actively traded digital assets and is characterized by high price volatility, making accurate forecasting essential for investment decision-making. This study aims to determine the best ARIMA–GARCH model for forecasting Bitcoin prices and to analyze future price movements based on historical weekly data. The dataset consists of 157 weekly Bitcoin closing prices collected from August 12, 2018, to August 8, 2021, obtained from Investing.com. The forecasting process was conducted for the subsequent five-week period from August 15, 2021, to September 12, 2021. The analysis began with stationarity testing using the Augmented Dickey–Fuller (ADF) test and Box–Cox transformation. Since the original series was non-stationary in the mean, first-order differencing was applied. Several ARIMA models were identified using the ACF and PACF plots, followed by diagnostic checking and ARCH-LM testing to detect heteroskedasticity effects. The presence of volatility clustering justified the implementation of the GARCH model. Model selection was based on parameter significance and the minimum Akaike Information Criterion (AIC) value. The results indicate that the ARIMA(0,1,2)-GARCH(1,3) model is the best model for forecasting Bitcoin prices. Forecasting results show a gradual decline in Bitcoin prices over the next five periods. The model achieved a Mean Absolute Percentage Error (MAPE) value of 3%, indicating excellent forecasting performance. These findings demonstrate that the ARIMA–GARCH approach is effective for modeling and forecasting highly volatile cryptocurrency price movements.

1. Introduction

The rapid development of digital technology has significantly transformed various sectors of modern society, including communication, commerce, transportation, and especially the financial sector. One of the most influential innovations in financial technology (fintech) is the emergence of cryptocurrency, a decentralized digital asset that utilizes cryptographic systems to secure transactions and control the creation of new units. Unlike conventional currencies issued and regulated by central banks, cryptocurrencies operate through blockchain technology and peer-to-peer networks without centralized authority. This decentralized characteristic has attracted global attention because it offers transparency, transaction efficiency, and broader accessibility in digital financial activities [1, 2].

Among the many cryptocurrencies currently available, Bitcoin remains the most dominant and widely recognized digital asset. Introduced by Satoshi Nakamoto in 2009, Bitcoin was designed as an alternative electronic payment system independent of government or banking institutions. Over time, Bitcoin evolved not only as a digital payment instrument but also as a highly attractive speculative investment asset. Its popularity has increased dramatically due to its high return potential, growing institutional adoption, and extensive media exposure. Consequently, Bitcoin has become one of the most actively traded assets in global financial markets [3–5].

Despite its popularity, Bitcoin is characterized by extremely high price volatility compared to traditional financial instruments such as stocks, commodities, and foreign exchange currencies. Bitcoin prices can fluctuate drastically within short periods due to various internal and external factors, including market demand and supply, investor sentiment, global economic conditions, government regulations, technological developments, and social media influence. Such volatility creates both opportunities and risks for investors. While substantial profits may be obtained from rapid price increases, investors may also experience significant losses due to unpredictable market movements [6, 7].

* Corresponding author.
E-mail address: hizbulwataan@gmail.com (H. Watan).

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The uncertainty of Bitcoin price movements makes forecasting an essential aspect of cryptocurrency investment and risk management. Accurate forecasting can assist investors, traders, and financial analysts in understanding market trends, minimizing investment risks, and making more informed financial decisions. Forecasting methods are generally developed based on historical data patterns to estimate future price movements. In financial time series analysis, forecasting approaches are commonly categorized into statistical methods, machine learning techniques, and hybrid models [8–10].

One of the most widely used statistical approaches in time series forecasting is the Autoregressive Integrated Moving Average (ARIMA) model developed by Box and Jenkins. The ARIMA model is capable of modeling linear relationships in stationary time series data and has been extensively applied in economic and financial forecasting studies. ARIMA combines autoregressive (AR) and moving average (MA) processes with differencing procedures to handle non-stationary data. The model is recognized for its simplicity, interpretability, and strong short-term forecasting performance [3, 11].

However, financial time series data, particularly cryptocurrency prices, often exhibit heteroskedasticity and volatility clustering, where periods of high volatility tend to be followed by high volatility and periods of low volatility tend to be followed by low volatility. This phenomenon violates the assumption of constant variance required by conventional ARIMA models. As a result, ARIMA alone may not adequately capture the dynamic variance structure commonly found in Bitcoin price movements [12, 13].

To overcome this limitation, Engle (1982) introduced the Autoregressive Conditional Heteroskedasticity (ARCH) model to model time-varying volatility in financial data. Later, Bollerslev (1986) generalized the ARCH model into the Generalized Autoregressive Conditional Heteroskedasticity (GARCH) model by incorporating both past residuals and past variances into the conditional variance equation. The GARCH model has become one of the most important tools in financial econometrics because of its ability to effectively model volatility behavior in financial markets [10].

The integration of ARIMA and GARCH models provides a powerful framework for forecasting financial time series data with volatility characteristics. In this hybrid approach, ARIMA is used to model the conditional mean process, while GARCH is applied to capture the conditional variance process. The combination enables researchers to produce more accurate forecasts and better represent the stochastic properties of highly volatile assets such as Bitcoin [6].

Several previous studies have investigated cryptocurrency forecasting using time series models. In previous research, [5] applied the ARIMA model to forecast Bitcoin prices and found that the model performed adequately for short-term prediction. Nevertheless, the study primarily focused on mean forecasting and did not explicitly address volatility effects. Other studies demonstrated that volatility models such as ARCH/GARCH provide superior performance in capturing heteroskedastic behavior in financial data. Research conducted, for example, utilized GARCH modeling for stock market analysis and highlighted the importance of volatility modeling in financial forecasting accuracy [7].

Although numerous studies have explored Bitcoin forecasting, research combining ARIMA and GARCH models using weekly Bitcoin price data remains relatively limited, especially in the context of short-term cryptocurrency forecasting. Furthermore, the increasing volatility of Bitcoin prices following the global economic uncertainty and the rapid growth of cryptocurrency adoption have created the need for more reliable forecasting approaches capable of modeling both mean and variance dynamics simultaneously.

Therefore, this study aims to develop the best ARIMA–GARCH model for forecasting Bitcoin prices based on weekly closing price data. The study evaluates the stationarity characteristics of the data, identifies the optimal ARIMA model, tests for ARCH effects, and constructs the most appropriate GARCH specification to model volatility behavior. Model performance is assessed using Akaike Information Criterion (AIC) and Mean Absolute Percentage Error (MAPE) values to determine forecasting accuracy.

The novelty of this research lies in the integration of ARIMA and GARCH models for short-term Bitcoin price forecasting using weekly cryptocurrency data while simultaneously analyzing volatility clustering behavior. Unlike conventional forecasting studies that only focus on trend estimation, this study emphasizes both mean and variance modeling to improve prediction reliability in highly volatile digital asset markets.

The findings of this research are expected to contribute both theoretically and practically. Theoretically, this study enriches the application of financial econometric models in cryptocurrency analysis. Practically, the forecasting results may provide useful information for investors, traders, and policymakers in understanding Bitcoin market behavior and managing investment risks more effectively.

2. Materials and Methods

2.1. *Study area and data collection*

This study employed a quantitative approach using time series analysis to forecast Bitcoin prices through the integration of the Autoregressive Integrated Moving Average (ARIMA) and Generalized Autoregressive Conditional Heteroskedasticity (GARCH) models. The ARIMA model was utilized to analyze and forecast the conditional mean behavior of Bitcoin prices, while the GARCH model was applied to capture the volatility characteristics and heteroskedasticity commonly observed in cryptocurrency market data.

The overall research framework consisted of several stages, including data collection, stationarity testing, ARIMA model identification, residual diagnostic checking, ARCH effect testing, GARCH model estimation, forecasting, and forecasting accuracy evaluation. The objective was to determine the most appropriate ARIMA–GARCH model capable of producing accurate Bitcoin price forecasts under highly volatile market conditions [6, 14, 15].

The data used in this study consisted of weekly Bitcoin closing prices obtained from the financial market platform Investing.com. The observation period covered 157 weekly observations from August 12, 2018, to August 8, 2021. The forecasting horizon was conducted for the subsequent five weeks, spanning from August 15, 2021, to September 12, 2021.

Weekly closing price data were selected to reduce excessive short-term fluctuations and to better capture medium-term market trends and volatility behavior. Bitcoin prices were expressed in United States Dollar (USD) units [4, 16].

2.2. *Variables and research object*

The primary variable analyzed in this study was the weekly closing price of Bitcoin, denoted by Y_t, where t represents the observation period. Bitcoin price data are classified as financial time series data because observations are recorded sequentially over time. Financial time series data often exhibit several important characteristics, including trend movement, non-stationarity, volatility clustering, and heteroskedasticity. Therefore, advanced econometric modeling approaches such as ARIMA and GARCH are required to adequately model both the mean and variance structures of the data [17, 18].

2.3. ARIMA model

The Autoregressive Integrated Moving Average (ARIMA) model developed by Box and Jenkins is one of the most widely used approaches for time series forecasting. The ARIMA model combines autoregressive (AR), differencing (I), and moving average (MA) components into a single framework [3, 6, 16]. The general ARIMA(p,d,q) model can be expressed as equation (1).

$$\phi_p(B)(1-B)^d Y_t = \theta_q(B)\varepsilon_t \qquad (1)$$

where: Yt : observed time series data at time t, B : backward shift operator, p : autoregressive order, d : differencing order, q : moving average order, $\phi p\ (B)$: autoregressive polynomial, $\theta q\ (B)$: moving average polynomial, εt : white noise residual. The ARIMA modeling procedure followed the Box–Jenkins methodology consisting of:

- Stationarity testing,
- Model identification using ACF and PACF plots,
- Parameter estimation,
- Diagnostic checking,
- Forecasting.

Stationarity is an important assumption in ARIMA modeling because the statistical properties of the data, such as mean and variance, must remain constant over time. Stationarity in variance was examined using the Box–Cox transformation see equation (2).

$$Y_t^{\lambda} = \begin{cases} \frac{Y_t^{\lambda}-1}{\lambda}, & \lambda \neq 0 \\ \ln(Y_t), & \lambda = 0 \end{cases} \qquad (2)$$

where λ denotes the transformation parameter. Stationarity in mean was evaluated using the Augmented Dickey–Fuller (ADF) test with the following hypotheses:

$$H_0 = Data\ are\ non-stationary$$
$$H_1 = Data\ are\ stationary$$

If the series was found to be non-stationary, differencing procedures were applied until stationarity was achieved. Residual diagnostic checking was conducted to ensure that the selected ARIMA model satisfied white noise assumptions. The Ljung–Box test was applied to determine whether residual autocorrelation remained in the fitted model [19–21]. The hypotheses for the Ljung–Box test are:

$$H_0 = Residuals\ are\ independently\ distributed$$
$$H_1 = Residuals\ are\ autocorrelated$$

A model was considered adequate if the residuals behaved as white noise. Financial time series data frequently exhibit volatility clustering and heteroskedasticity. Therefore, the residuals from the ARIMA model were tested for ARCH effects using the ARCH-LM test. The hypotheses are:

$$H_0 = No\ ARCH\ effect\ exists$$
$$H_1 = ARCH\ effect\ exists$$

If the null hypothesis was rejected, the GARCH model was implemented to model conditional variance behavior.

2.4. GARCH model

The Generalized Autoregressive Conditional Heteroskedasticity (GARCH) model developed by Bollerslev extends the ARCH model by incorporating past conditional variances into the variance equation [3, 6, 16]. The general GARCH (p,q) model is defined as equation (3).

$$\sigma_t^2 = \omega + \sum_{i=1}^{q} \alpha_i\, \varepsilon_{t-i}^2 + \sum_{j=1}^{p} \beta_j\, \sigma_{t-j}^2 \qquad (3)$$

where: σ_t^2 : conditional variance, ω : constant term, α_i : ARCH parameters, β_j : GARCH parameters, ε_{t-i}^2 : past squared residuals, σ_{t-j}^2 : past conditional variances.

Several GARCH specifications were estimated, and the best model was selected based on parameter significance and minimum AIC value. After determining the best ARIMA–GARCH model, Bitcoin prices were forecasted for the next five observation periods. The forecasting process generated estimated future Bitcoin prices along with volatility behavior over the forecasting horizon. The forecasting results were then compared with actual observed prices to evaluate model performance [6, 14, 15].

2.5. Forecast accuracy measurement

Forecast accuracy measurement is an essential stage in time series forecasting because it evaluates how well the proposed model predicts future observations compared to actual data. In forecasting studies, the accuracy level of a model determines whether the model can be reliably used for practical decision-making and future prediction analysis. A forecasting model with high accuracy indicates that the estimated values are close to the actual observed values, while a model with poor accuracy suggests that the forecasting results may not adequately represent real market behavior [19–21].

In financial time series analysis, particularly cryptocurrency forecasting, accuracy measurement becomes increasingly important due to the highly volatile and unpredictable nature of the market. Bitcoin prices frequently experience rapid fluctuations caused by investor sentiment, macroeconomic conditions, global financial uncertainty, government regulations, and speculative trading activities. Therefore, evaluating forecasting performance is necessary to ensure that the selected ARIMA–GARCH model is capable of capturing both trend movements and volatility behavior effectively.

In this study, forecasting accuracy was evaluated using the Mean Absolute Percentage Error (MAPE). MAPE is one of the most commonly used statistical indicators in forecasting studies because it measures forecasting error in percentage form, making the interpretation easier and more intuitive. MAPE calculates the average absolute difference between actual values and forecasted values relative to the actual observations. Mathematically, MAPE is defined as follows equation (4).

$$MAPE = \frac{1}{n}\sum_{t-1}^{n}\left|\frac{Y_t-\hat{Y}_t}{Y_t}\right| \times 100\% \qquad (4)$$

where:
Y_t = represents the actual Bitcoin price at time t,
$\hat{Y}_t$ = denotes the forecasted Bitcoin price at time t,
n = the total number of forecasting observations.

The absolute percentage error is computed for each observation period to avoid negative and positive forecasting errors canceling each other out. The average of all percentage errors then provides an overall measure of forecasting performance. The selection of MAPE in this study is motivated by several advantages. First, MAPE expresses forecasting error in percentage units, allowing easier comparison between models regardless of the scale of the data. Second, MAPE is widely applied in financial forecasting studies because it provides a straightforward interpretation of forecasting quality. Third, MAPE is highly suitable for evaluating short-term forecasting performance in volatile financial markets such as cryptocurrency trading.

Table 1
The interpretation of MAPE values

MAPE Value	Forecast Interpretation
(<10%)	Very accurate forecasting
(10%-20%)	Good forecasting
(20%-50%)	Reasonable forecasting
(>50%)	Poor forecasting

A smaller MAPE value indicates higher forecasting accuracy because the forecasted values are closer to the actual data. Conversely, a larger MAPE value indicates greater forecasting deviation and lower predictive performance.

In this research, the forecasting performance of the ARIMA–GARCH model was evaluated by comparing forecasted Bitcoin prices with actual observed prices over the forecasting horizon. The resulting MAPE value was used as the primary criterion for assessing the effectiveness of the proposed forecasting model. A low MAPE value would indicate that the ARIMA–GARCH approach is capable of modeling Bitcoin price movements accurately despite the presence of volatility clustering and heteroskedasticity in cryptocurrency market data [14, 22, 23].

Furthermore, the use of MAPE in this study also supports the selection of the optimal forecasting model among several candidate ARIMA–GARCH specifications. The best model was identified not only based on statistical significance and Akaike Information Criterion (AIC) values, but also on its forecasting performance as reflected by the smallest MAPE value. Therefore, the accuracy evaluation stage plays an important role in validating the reliability and practical applicability of the forecasting model developed in this study.

3. Results and discussion

3.1. Descriptive analysis of bitcoin price data

The queueing system observed in this study was the teller service system at the bank branch under investigation. Based on field observations, customers arrived randomly during operational hours and formed a single waiting line before being served by available tellers. The service discipline implemented by the bank followed the First Come First Served (FCFS) principle, where customers were served according to their arrival order. The service facility consisted of multiple parallel tellers operating simultaneously, thereby forming a multi-channel queueing structure.

The observed system was modeled using the (M/M/s):(FCFS/∞/∞) queueing model. This model assumes that customer arrivals follow a Poisson distribution, service times follow an exponential distribution, the queue capacity is unlimited, and the customer population is infinite [24]. Such assumptions are commonly used in banking queue analysis because customer arrivals are generally random and independent. The conceptual framework of the research process is illustrated in Fig. 1.

3.2. Arrival and service rate analysis

The descriptive analysis was conducted to characterize the weekly Bitcoin closing price data used in this study. The dataset consisted of 157 weekly observations from 12 August 2018 to 8 August 2021. The statistical summary is presented in Table 2.

Table 2
Descriptive statistics of weekly Bitcoin closing prices

Variable	Observations	Minimum	Mean	Median	Maximum	Standard Deviation
Bitcoin price (USD)	157	3,228.70	16,088.80	9,379.50	61,195.30	15,611.05

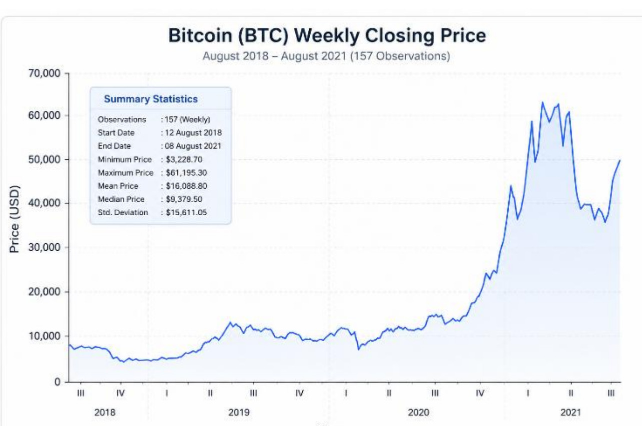

Fig. 1. Weekly Bitcoin price series from August 2018 to August 2021

The results show that Bitcoin prices fluctuated substantially during the observation period. The minimum price was USD 3,228.70, while the maximum price reached USD 61,195.30. The mean price was USD 16,088.80, whereas the median was USD 9,379.50, indicating a right-skewed distribution caused by the sharp increase in Bitcoin prices during 2020–2021. The relatively high standard deviation of USD 15,611.05 confirms the presence of strong price variability, which is consistent with the high-volatility nature of cryptocurrency markets.

The weekly price movement is shown in Fig. 1. The time-series plot indicates that Bitcoin prices were relatively stable from 2018 to early 2020 but increased sharply toward the end of 2020 and throughout 2021. This pattern suggests the presence of non-stationarity and volatility clustering, making ARIMA–GARCH modeling appropriate for the data [20, 21, 25].

3.3. Stationarity testing

Stationarity testing was performed before estimating the ARIMA model. In time-series modeling, stationarity is required to ensure that the statistical properties of the series, particularly its mean and variance, remain stable over time [16, 26, 27]. The Augmented Dickey–Fuller (ADF) test was first applied to examine stationarity in the mean. The result is shown in Table 3.

Table 3
ADF test result for the original Bitcoin price series

Test Statistic	5% Critical Value	p-value	Decision
-0.3431	-2.8803	0.9144	Non-stationary

The ADF test result shows that the p-value was 0.9144, which is greater than the 5% significance level. Therefore, the null hypothesis of a unit root could not be rejected. This indicates that the original Bitcoin price series was non-stationary in the mean. To achieve stationarity, first-order differencing was applied. The ADF test was then repeated, and the result is presented in Table 4.

Table 4
ADF test result after first-order differencing

Test Statistic	5% Critical Value	p-value	Decision
-6.2142	-2.8803	0.0000	Stationary

After first-order differencing, the ADF test produced a p-value of 0.0000, which is lower than 0.05. Therefore, the null hypothesis was rejected, indicating that the differenced series was stationary in the mean. This result confirms that the integration order of the ARIMA model is *d=1*. Stationarity in variance was examined using the Box–Cox transformation approach. The maximum likelihood values for several λ values are summarized in Table 5.

Table 5
Box–Cox maximum likelihood values for selected λ

λ	-1	-0.75	-0.50	-0.25	0.001	0.25	0.50	0.75	1
L_{max}	-2513.42	-2194.78	-1893.19	-1624.09	-1415.80	-1300.63	-1255.68	-1239.92	-1235.45

The maximum likelihood value was obtained when λ=1, indicating that no additional variance transformation was required. Thus, the differenced Bitcoin price series was considered stationary in both mean and variance.

3.4. ARIMA model identification and selection

After achieving stationarity, the ARIMA model was identified using the ACF and PACF plots of the differenced Bitcoin price series. The ACF plot showed a cut-off pattern after lag 2, while the PACF plot indicated possible autoregressive structures up to lag 3. Therefore, several candidate ARIMA models were evaluated, including ARIMA(0,1,2), ARIMA(2,1,0), ARIMA(2,1,2), ARIMA(3,1,0), and ARIMA(3,1,2). The ACF and PACF patterns are presented in Fig. 2.

Parameter estimation was conducted using the Conditional Least Squares method. The results of parameter significance testing and AIC values are summarized in Table 6. Among the candidate models, ARIMA (0,1,2) was selected as the most appropriate mean model because all of its parameters were statistically significant and it produced the lowest AIC value. The selected ARIMA model can be written as:

$$Z_t = 257.89 + Z_{t-1} - 0.2508e_{t-1} + 0.2569e_{t-2} + e_t$$

This model represents the conditional mean structure of Bitcoin price changes before volatility modeling.

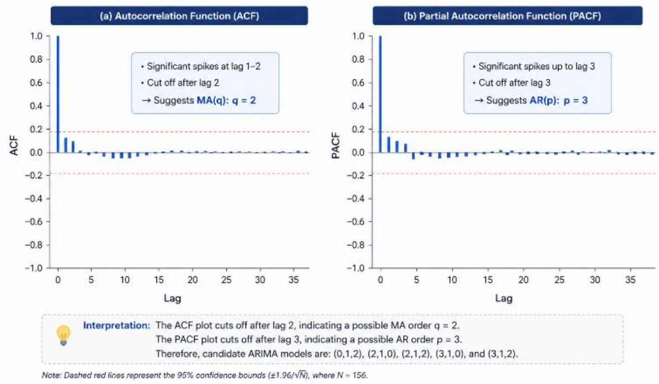

Fig. 2. Autocorrelation Function (ACF) and Partial Autocorrelation Function (PACF) plots of the first-order differenced Bitcoin price series from August 2018 to August 2021.

Table 6
Parameter significance and AIC values of candidate ARIMA models

Model	Parameter	Estimate	Std. Error	t-statistic	p-value	Decision	AIC
ARIMA(0,1,2)	MA(1)	0.2508	0.0793	3.1629	0.0019	Significant	18.6056
	MA(2)	-0.2569	0.0577	-3.2391	0.0015	Significant	
ARIMA(2,1,0)	AR(1)	0.1454	0.0787	1.8482	0.0665	Not significant	18.6443
	AR(2)	-0.2631	0.0789	-3.3331	0.0011	Significant	
ARIMA(2,1,2)	AR(1)	-0.4331	0.4748	-0.9121	0.3632	Not significant	18.6306
	AR(2)	-0.2251	0.2940	-0.7658	0.4450	Not significant	
	MA(1)	0.6455	0.4845	1.3322	0.1848	Not significant	
	MA(2)	0.0345	0.4075	0.0846	0.9327	Not significant	
ARIMA(3,1,0)	AR(1)	0.2035	0.0807	2.5224	0.0127	Significant	18.6196
	AR(2)	-0.2893	0.0784	-3.6903	0.0003	Significant	
	AR(3)	0.2121	0.0829	2.5598	0.0115	Significant	
ARIMA(3,1,2)	AR(1)	0.7263	0.2339	3.1059	0.0023	Significant	18.6269
	AR(2)	-0.3579	0.2413	-1.4832	0.1402	Not significant	
	AR(3)	0.3500	0.0849	4.1220	0.0001	Significant	
	MA(1)	-0.5564	0.2495	-2.2303	0.0272	Significant	
	MA(2)	-0.0089	0.2440	-0.0365	0.9709	Not significant	

3.5. *Diagnostic checking of the ARIMA model*

Diagnostic checking was performed to evaluate whether the selected ARIMA model produced residuals satisfying the white noise assumption [28, 29]. The Ljung–Box test results for all ARIMA candidates are shown in Table 7.

Table 7
Ljung–Box test results for ARIMA residuals

Model	Ljung–Box Statistic	Chi-Square Critical Value	p-value	Decision
ARIMA(0,1,2)	42.629	48.602	0.147	White noise
ARIMA(2,1,0)	48.297	48.602	0.053	White noise
ARIMA(2,1,2)	41.732	46.194	0.116	White noise
ARIMA(3,1,0)	40.112	47.399	0.184	White noise
ARIMA(3,1,2)	41.168	44.985	0.105	White noise

The results indicate that all candidate ARIMA models satisfied the white noise assumption. However, the Jarque–Bera normality test showed that the residuals were not normally distributed, as presented in Table 8.

Table 8
Jarque–Bera normality test results for ARIMA residuals

Model	Jarque–Bera Statistic	Chi-Square Critical Value	p-value	Decision
ARIMA(0,1,2)	184.9780	5.991	0.000	Non-normal residuals
ARIMA(2,1,0)	192.1198	5.991	0.000	Non-normal residuals
ARIMA(2,1,2)	174.6585	5.991	0.000	Non-normal residuals
ARIMA(3,1,0)	174.5895	5.991	0.000	Non-normal residuals
ARIMA(3,1,2)	172.0575	5.991	0.000	Non-normal residuals

The non-normal residuals indicate that the error distribution contains heavy tails, which is common in cryptocurrency markets. This condition may also suggest the presence of volatility clustering and heteroskedasticity. Therefore, the ARCH-LM test was applied to examine whether the residuals contained ARCH effects [30].

3.6. *ARCH-LM test for the selected ARIMA model*

The ARCH-LM test was applied to the residuals of ARIMA (0,1,2) to detect conditional heteroskedasticity. The test result is shown in Fig. 3 and Table 9.

Table 9
ARCH-LM test result for ARIMA (0,1,2)

Test	Statistic	p-value	Decision
F-statistic	92.5568	0.0000	ARCH effect exists
Obs*R-squared	58.4236	0.0000	ARCH effect exists

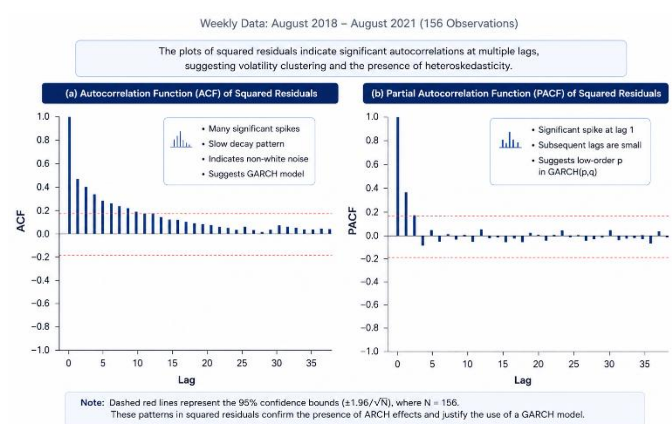

Fig. 3. Autocorrelation Function (ACF) and Partial Autocorrelation Function (PACF) plots of the squared residuals from the ARIMA (0,1,2) model for weekly Bitcoin prices during August 2018–August 2021. The ACF plot exhibits a gradual decay with several significant autocorrelation spikes, while the PACF plot shows a dominant spike at lag 1 followed by smaller fluctuations. These patterns indicate the presence of volatility clustering and conditional heteroskedasticity in the residual series, confirming the existence of ARCH effects and supporting the application of the GARCH modeling approach for volatility estimation.

The p-value of 0.0000 indicates that the null hypothesis of no ARCH effect was rejected. This confirms that the residuals of the ARIMA (0,1,2) model contained heteroskedasticity. Therefore, the GARCH model was required to capture the conditional variance behavior of Bitcoin price movements.

3.7. *GARCH model identification and estimation*

The GARCH model was identified using the ACF and PACF plots of the squared residuals from the selected ARIMA model. The plot showed significant dependence in the squared residuals, indicating volatility clustering in Bitcoin prices. This finding supports the use of GARCH modeling [31].

Several GARCH specifications were evaluated, including GARCH(0,1), GARCH(1,1), GARCH(1,2), GARCH(1,3), and GARCH(1,4). The GARCH(1,3) model was selected as the best variance model because it produced the lowest AIC value and all parameters were statistically significant. The selected conditional variance equation is:

$$\sigma_t^2 = 61363.35 + 0.714370e_{t-1}^2 + 0.440947\sigma_{t-1}^2 - 0.28651\sigma_{t-2}^2 + 0.352506\sigma_{t-3}^2$$

This result indicates that Bitcoin volatility is influenced not only by previous shocks but also by conditional variances from several previous periods. Such behavior is consistent with volatility persistence commonly observed in cryptocurrency markets.

After estimating the GARCH model, diagnostic checking was conducted to ensure that the selected model adequately captured the heteroskedasticity structure. The Ljung–Box test showed that all GARCH residuals satisfied the white noise assumption, as presented in Table 10.

Table 10
Ljung–Box test results for GARCH residuals

Model	Ljung–Box Statistic	Chi-Square Critical Value	p-value	Decision
GARCH(0,1)	31.628	49.802	0.584	White noise
GARCH(1,1)	27.876	48.602	0.761	White noise
GARCH(1,2)	27.889	47.399	0.761	White noise
GARCH(1,3)	28.297	46.194	0.743	White noise
GARCH(1,4)	25.048	44.985	0.868	White noise

The ARCH-LM test was then repeated for the selected GARCH(1,3) model to confirm whether heteroskedasticity remained in the residuals. The results are summarized in Table 11.

Table 11
ARCH-LM test results after GARCH(1,3) estimation

Order	LM Statistic	Chi-Square Critical Value	Decision
1	0.8890	3.8415	No ARCH effect
2	1.0551	5.9915	No ARCH effect
3	1.1346	7.8147	No ARCH effect
4	1.0993	9.4877	No ARCH effect
5	1.7890	11.0705	No ARCH effect
6	1.9203	12.5916	No ARCH effect
7	2.0796	14.0671	No ARCH effect
8	2.3239	15.5073	No ARCH effect
9	2.4379	16.9190	No ARCH effect
10	2.6379	18.3070	No ARCH effect
11	2.9901	19.6750	No ARCH effect
12	3.0646	21.0260	No ARCH effect

The LM statistics were consistently lower than the corresponding Chi-Square critical values, indicating that no remaining ARCH effects existed in the residuals. Therefore, the ARIMA(0,1,2)–GARCH(1,3) model was considered adequate for forecasting Bitcoin prices. The selected ARIMA(0,1,2)–GARCH(1,3) model was used to forecast Bitcoin prices for five weekly periods from 15 August 2021 to 12 September 2021. The forecasting results are presented in Table 12.

The forecast results show that Bitcoin prices were predicted to remain within a relatively narrow range of approximately USD 47,500–47,600. The highest forecasted price occurred on 22 August 2021, while the lowest forecasted price occurred on 12 September 2021. Overall, the forecast indicates a gradual downward movement after a slight increase in the second forecast period.

The comparison plot shows that the forecasted values were close to the actual Bitcoin prices. This indicates that the ARIMA–GARCH model was able to capture the short-term movement of Bitcoin prices reasonably well, despite the strong volatility in cryptocurrency markets.

Forecast accuracy was evaluated using the Mean Absolute Percentage Error (MAPE). The MAPE calculation compared the forecasted Bitcoin prices with the actual observed prices over the five-week forecasting horizon. The obtained MAPE value was 3%. Based on the commonly used MAPE interpretation criteria, a value below 10% indicates very accurate forecasting performance. Therefore, the ARIMA(0,1,2)–GARCH(1,3) model demonstrated excellent predictive accuracy for short-term Bitcoin price forecasting.

This finding confirms that integrating ARIMA and GARCH improves forecasting performance by modeling both the conditional mean and conditional variance of Bitcoin prices. While ARIMA captures the average price movement, GARCH effectively accounts for volatility clustering and heteroskedasticity. Consequently, the combined ARIMA–GARCH approach is appropriate for forecasting highly volatile assets such as Bitcoin.

Table 12
Forecasted Bitcoin prices using ARIMA(0,1,2)–GARCH(1,3)

Forecast Period	Forecasted Price (USD)
15 August 2021	47,549.35
22 August 2021	47,585.56
29 August 2021	47,557.08
05 September 2021	47,528.59
12 September 2021	47,500.11

Overall, the results demonstrate that the proposed ARIMA–GARCH model provides a statistically reliable and practically useful framework for short-term cryptocurrency price forecasting. However, given the dynamic and speculative nature of cryptocurrency markets, future studies should consider incorporating additional explanatory variables such as trading volume, market sentiment, macroeconomic indicators, and regulatory news to improve forecasting robustness [32].

4. Conclusion

This study proposed an ARIMA–GARCH approach to model and forecast weekly Bitcoin prices using data from August 2018 to August 2021. The analysis began with descriptive statistical evaluation, which revealed substantial volatility in Bitcoin prices, as indicated by the high standard deviation and the occurrence of extreme price fluctuations during the observation period. The stationarity test using the Augmented Dickey–Fuller (ADF) method showed that the original series was non-stationary in the mean, requiring first-order differencing to achieve stationarity. Meanwhile, the Box–Cox transformation analysis indicated that the data were already stationary in variance.

Based on the ACF and PACF identification results, several candidate ARIMA models were developed and evaluated. Among these models, ARIMA(0,1,2) was selected as the most appropriate mean model because it produced the smallest Akaike Information Criterion (AIC) value and satisfied the parameter significance requirements. However, residual diagnostic analysis demonstrated the presence of heteroskedasticity effects, which indicated that the variance of the residuals was not constant over time. This finding justified the application of ARCH/GARCH modeling to capture volatility behavior in the Bitcoin price series.

Further analysis identified several candidate GARCH models, and the GARCH(1,3) model was selected as the optimal volatility model due to its lowest AIC value and statistically significant parameters. The ARCH-LM test confirmed that the final ARIMA(0,1,2)–GARCH(1,3) model successfully eliminated the heteroskedasticity effect, indicating that the model adequately captured the volatility clustering characteristics commonly observed in cryptocurrency markets.

The forecasting results showed that Bitcoin prices during the forecast horizon tended to fluctuate within a relatively stable interval, with a gradual downward tendency toward the end of the prediction period. In addition, the forecasting performance evaluation using Mean Absolute Percentage Error (MAPE) produced an error value of approximately 3%, indicating that the proposed ARIMA–GARCH model achieved very high forecasting accuracy. The comparison between actual and forecasted values further demonstrated that the model was capable of closely following real market movements.

Overall, the findings suggest that the ARIMA–GARCH framework is effective for modeling and forecasting highly volatile financial time series such as Bitcoin prices. The study contributes to the literature by demonstrating that integrating ARIMA for mean estimation and GARCH for volatility estimation provides reliable short-term forecasting performance for cryptocurrency markets. Future studies may extend this work by incorporating exogenous macroeconomic variables, investor sentiment indicators, or hybrid machine learning techniques to improve forecasting performance under rapidly changing market conditions.

CRediT authorship contribution statement

Hizbul Watan: Writing – review & editing, Writing – original draft, Supervision, Software, Resources, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Rini Oktavia:** Writing – review & editing, Investigation. **Fitria Lestari:** Formal analysis, Writing – review & editing, Investigation.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

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