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ARIMA-GARCH Based Time Series Analysis of Cryptocurrency Volatility

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Abstract

Cryptocurrencies are a new type of asset that is changing the game. They are decentralized, very volatile, and their prices change quickly. Investors, policymakers, and researchers all need to know how bitcoin markets work. This article examines the volatility patterns of significant cryptocurrencies by employing the Autoregressive Integrated Moving Average (ARIMA) in conjunction with the GARCH model to assess historical price data and predict future trends. We also do a full volatility analysis to show how unpredictable cryptocurrency markets are. We also do a seasonality analysis and calculate the Relative Strength Index (RSI) for the technical analysis indicators. The study uses the R programming environment to clean up data, model time series, and check performance indicators. Our results show that ARIMA models accurately capture the time-based relationships in bitcoin time series, which makes them good for long-term predictions.

1. Introduction

Recent research has investigated predictive modeling of cryptocurrencies through time series and volatility analysis. Researchers have utilized diverse machine learning techniques, including hybrid approaches that integrate volatility models with methodologies such as Logistic Regression, Neural Networks, and K-Nearest Neighbors [1]. Long Short-Term Memory (LSTM) models have been utilized to discern patterns in bitcoin closing prices and forecast future values, surpassing conventional ARIMA models [2,3,4]. Some research has looked into how extended memory and asymmetric reactions affect the volatility process of large cryptocurrencies like Bitcoin and Ethereum [5]. These methods have showed promise in predicting the pricing and volatility of cryptocurrencies with few mistakes. But the fact that cryptocurrency markets are so volatile and not regulated makes it hard to make accurate predictions and manage risk [1.5].

There are four assessments of studies on bitcoin price prediction that compare time series forecasting algorithms, including Autoregressive Integrated Moving Average (ARIMA). Three of the studies compared ARIMA against other models, including ARIMA_T (time-reversed ARIMA) [6], Neural Network Autoregression (NNAR) [8], and PROPHET (an additive model incorporating trend and seasonality) [7]. All research concentrated on

Bitcoin; however, only one broadened its examination to encompass several cryptocurrencies (Ethereum, Litecoin, Monero, Ripple).

One study [6] found that ARIMA_T did better than ARIMA, while another [7] found that PROPHET was more accurate than ARIMA. A third study [8] indicated that Neural Network Autoregression was better than both TBATS and ARIMA. Even with these results, there was no one model that always did the best in all experiments. This shows how hard it is to anticipate the price of cryptocurrencies. The assessment of ARIMA variants and hybrid models indicates that advanced methodologies, especially those integrating machine learning or exogenous variables, provide superior robustness in turbulent market environments. But long-term forecasting is still hard because cryptocurrency markets are naturally volatile and hard to anticipate.

The research on predicting the price of Bitcoin shows that basic models like Linear Regression and Random Forest Regression can be just as accurate, or even more accurate, than standard ARIMA models, even if they are not very complicated. This discovery holds special importance in the unpredictable bitcoin market, where precise forecasts are essential for trading, risk management, and investing strategies. Researchers, including [9, 10], have examined the effectiveness of ARIMA in conjunction with advanced models such as LSTM, highlighting their capacity to discern patterns and trends in Bitcoin prices. Moreover, research conducted by [10, 12] has utilized quantitative methodologies, such as GARCH and ARIMA, to examine Bitcoin's price volatility and anticipate future prices by static forecasting techniques, with or without re-estimation at each interval. All of these research show that people are still trying to make Bitcoin price forecasts more accurate and useful.

There are numerous complex models for analyzing the volatility of cryptocurrencies over time, but an ARIMA (Autoregressive Integrated Moving Average) model is a good choice for a number of reasons, which are explained here. The parts of ARIMA models (AR, I, and MA) are easy to understand, and the models themselves are not overly complicated. This makes them easier to understand than complicated "black box" machine learning or deep learning models. The parameters of an ARIMA model provide you direct information about the autoregressive and moving average patterns in the data. This can help you understand why bitcoin prices are so volatile. Also, ARIMA is a linear model that works well for finding linear dependencies and trends in time series data. Cryptocurrency markets are known for being chaotic and non-linear, but the linear part of volatility can still be important, and ARIMA is a good way to model this. Also, ARIMA models follow the principle of parsimony, which means they only use the fewest number of parameters needed to make effective predictions. This helps keep the model from overfitting, which is a problem that happens often with more complicated models that have a lot of parameters. An ARIMA model is a good benchmark, even if the end goal is to utilize a more complex model. Researchers can evaluate how well their new or complicated models work with a simple, well-known ARIMA model to show that the more complicated method is worth it.

2. Methodology

This part explains how to use ARIMA (AutoRegressive Integrated Moving Average) and other similar methods to do time series analysis to model the volatility of cryptocurrencies. Downloading and preparing data, exploratory data analysis, time series modeling, technical analysis, seasonality analysis, and performance evaluation are all important aspects in the process. Figure 1 shows the actions that were taken for this study.

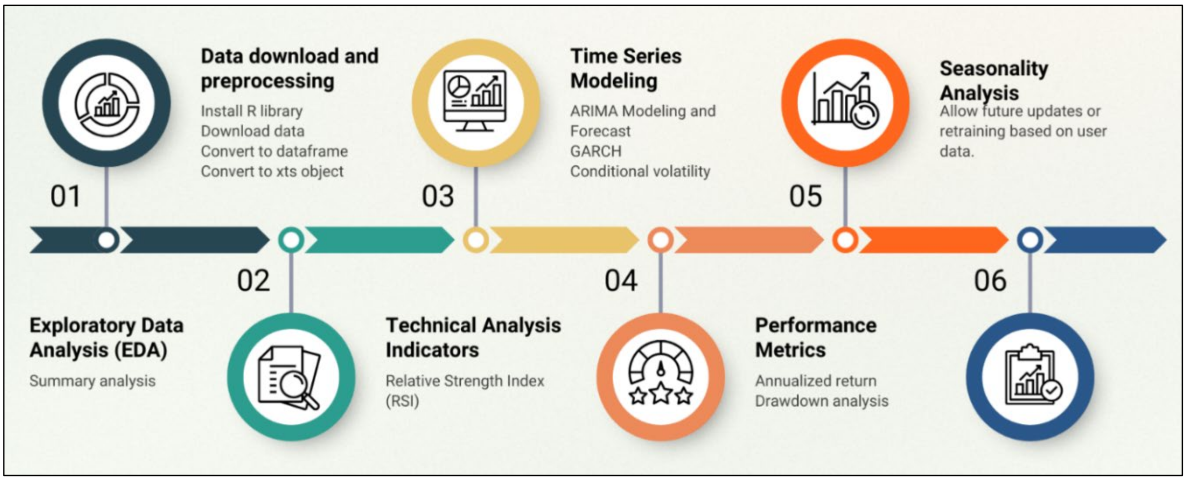

Fig. 1 *Steps for time series analysis*

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2.1 Data Download and Preprocessing

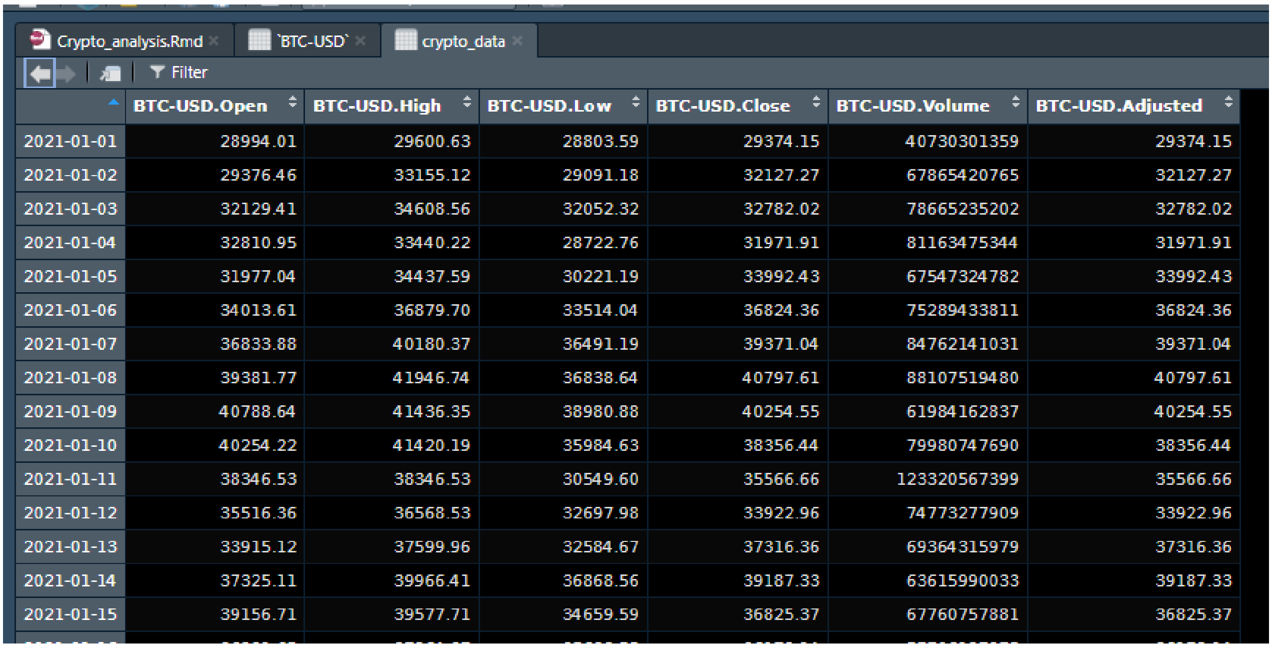
The first step in the methodology is to acquire and preprocess the cryptocurrency data to ensure it is clean and structured for analysis.

2.1.1 Install Required R Packages

All statistical computations and empirical analyses were performed using the R programming environment (Version 4.4.0), a robust platform widely utilized for time series modeling. The study leveraged a suite of specialized packages to ensure analytical rigor and reproducibility. Specifically, the forecast package was employed to automate the selection of optimal ARIMA parameters through the auto.arima() function, ensuring a statistically sound model fit. For the analysis of conditional volatility, the rugarch package was utilized to implement GARCH modeling, allowing for the precise estimation of variance dynamics. Additionally, the ggplot2 package was used to generate high-quality visualizations, facilitating the clear interpretation of price trends and forecasting results,

2.1.2 Download Cryptocurrency Data

You may get historical cryptocurrency data from Yahoo Finance using the quantmod package. To make sure you have enough data for analysis, choose a start date. Yahoo Finance, a well-known source of financial data, provided the dataset used in this study. The data covers the time from January 1, 2020, to August 18, 2025, and includes the daily closing values of some cryptocurrencies. This time frame was chosen so that the analysis can look at both long-term trends and short-term changes in cryptocurrency markets, such as times of high volatility and market anomalies. There were 1632 rows and 6 columns in the data that was downloaded. The dataset has variables like Date, BTC-USD open, High, Low, close, and Volume. The sixth column, "BTC-USD Adjusted," isn't beneficial for crypto because it shows the average price for stock splitting, dividends, or share merging.



	BTC-USD.Open	BTC-USD.High	BTC-USD.Low	BTC-USD.Close	BTC-USD.Volume	BTC-USD.Adjusted
2021-01-01	28994.01	29600.63	28803.59	29374.15	40730301359	29374.15
2021-01-02	29376.46	33155.12	29091.18	32127.27	67865420765	32127.27
2021-01-03	32129.41	34608.56	32052.32	32782.02	78665235202	32782.02
2021-01-04	32810.95	33440.22	28722.76	31971.91	81163475344	31971.91
2021-01-05	31977.04	34437.59	30221.19	33992.43	67547324782	33992.43
2021-01-06	34013.61	36879.70	33514.04	36824.36	75289433811	36824.36
2021-01-07	36833.88	40180.37	36491.19	39371.04	84762141031	39371.04
2021-01-08	39381.77	41946.74	36838.64	40797.61	88107519480	40797.61
2021-01-09	40788.64	41436.35	38980.88	40254.55	61984162837	40254.55
2021-01-10	40254.22	41420.19	35984.63	38356.44	79980747690	38356.44
2021-01-11	38346.53	38346.53	30549.60	35566.66	123320567399	35566.66
2021-01-12	35516.36	36568.53	32697.98	33922.96	74773277909	33922.96
2021-01-13	33915.12	37599.96	32584.67	37316.36	69364315979	37316.36
2021-01-14	37325.11	39966.41	36868.56	39187.33	63615990033	39187.33
2021-01-15	39156.71	39577.71	34659.59	36825.37	67760757881	36825.37

Fig. 2 *Screenshot of the downloaded data*

2.1.3 Convert to Data Frame

The raw data were preprocessed by standardizing column names and converting the time series into an xts object to facilitate time-indexed operations and compatibility with modeling functions.

2.2 Exploratory Data Analysis

Exploratory data analysis (EDA) was conducted to assess distributional properties, detect outliers, and evaluate stationarity. Summary statistics and time plots of log returns revealed high kurtosis and volatility clustering—hallmarks of financial time series that motivate the use of GARCH-type models.

2.2.1 Summary Statistics

As indicated in Fig. 3, calculate summary statistics (mean, median, standard deviation, etc.) for important variables like price and volume.

```
An xts object on 2020-01-01 / 2025-08-18 containing:
  Data:    double [2057, 6]
  Columns: BTC-USD.Open, BTC-USD.High, BTC-USD.Low, BTC-USD.Close, BTC-USD.Volume .
  Index:   Date [2057] (TZ: "UTC")
  xts Attributes:
    $ src    : chr "yahoo"
    $ updated: POSIXct[1:1], format: "2025-08-18 14:48:36"
     Index                Close
 Min.   :2020-01-01   Min.   :  4971
 1st Qu.:2021-05-29   1st Qu.: 20926
 Median :2022-10-25   Median : 37432
 Mean   :2022-10-25   Mean   : 43470
 3rd Qu.:2024-03-22   3rd Qu.: 60692
 Max.   :2025-08-18   Max.   :123344
```

Fig. 3 *Summary statistics for data from 1 January 2020 to 18 August 2025*

2.2.2 Visualizations

Use ggplot2 to make graphs like Fig. 4, which shows line plots of closing prices, histograms of returns, and scatter plots of price changes.

Fig. 4 *Bitcoin closing price all the years from Jan 01, 2021, until June 20, 2025*

2.2.3 Stationarity Testing:

Test for stationarity using statistical tests like the Augmented Dickey-Fuller (ADF) test.

```
ADF Test for Price Series:

        Augmented Dickey-Fuller Test

data:  na.omit(crypto_xts$Close)
Dickey-Fuller = -1.1302, Lag order = 12, p-value = 0.9177
alternative hypothesis: stationary


ADF Test for Returns Series:

        Augmented Dickey-Fuller Test

data:  na.omit(crypto_returns)
Dickey-Fuller = -11.798, Lag order = 12, p-value = 0.01
alternative hypothesis: stationary
```

Fig. 5 *The results for ADF test*

2.2.4 Volatility Analysis

Examine the volatility of the cryptocurrency by calculating daily log returns as shown in Figure 6.

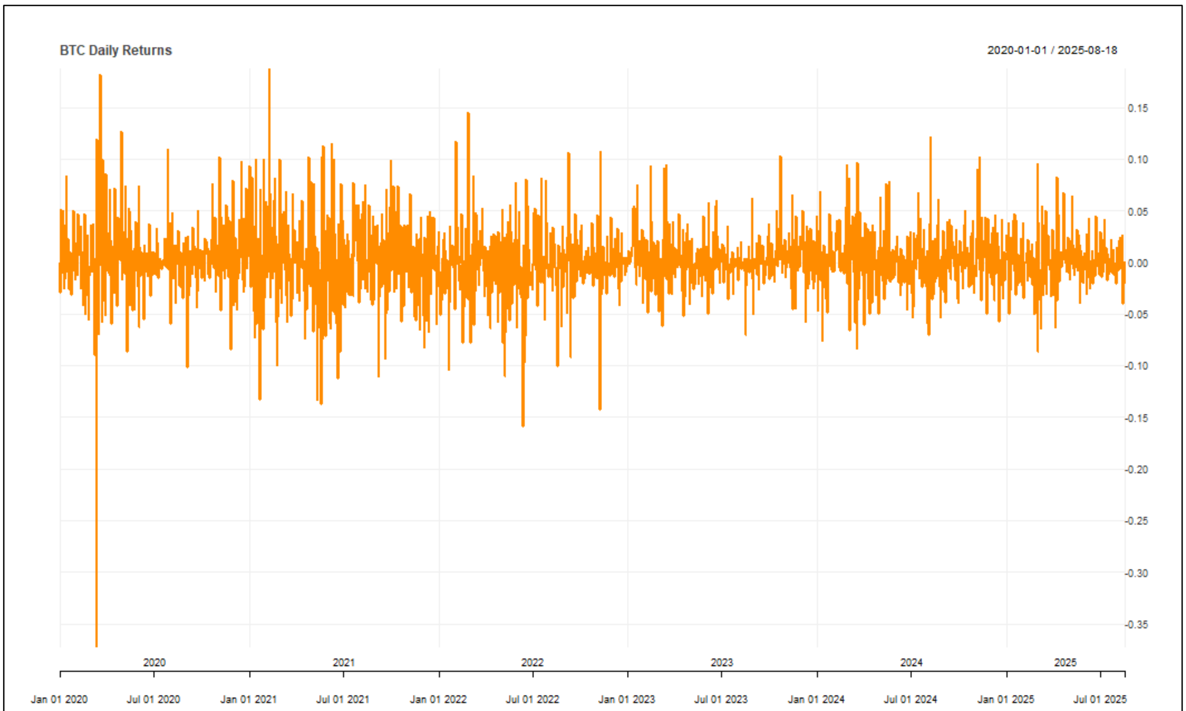


Fig. 6 *Bitcoin 30-day rolling volatility (annualized) all the years from Jan 01, 2021 until June 20, 2025*

2.3 Time Series Analysis using ARIMA

The ARIMA (AutoRegressive Integrated Moving Average) model was chosen for its ability to capture linear dependencies in time series data. The ARIMA model is defined by three parameters:

- p: The order of the autoregressive (AR) component.
- d: The degree of differencing required to achieve stationarity.
- q: The order of the moving average (MA) component.

For this project, the ARIMA parameters (p,d,q) were not chosen manually. Instead, we used the auto.arima() function from the popular forecast package in R. This function automatically selects the best-fitting ARIMA model by evaluating a set of candidate models. To determine the optimal ARIMA (p,d,q) parameters, we utilized the auto.arima() function within the forecast package in R. This function employs a systematic search algorithm to identify the best-fitting model by minimizing the Akaike Information Criterion (AIC).

The optimal ARIMA(p,d,q) structure was selected using the auto.arima() function with AIC minimization. The best-fit model was ARIMA(1,1,2), with coefficients $\varphi_1 = 0.28$ ($p < 0.01$) and $\theta_1 = -0.42$, $\theta_2 = 0.19$ (both $p < 0.05$). Residual diagnostics using the Ljung-Box test ($Q(20) = 18.3$, $p = 0.56$) confirmed no significant autocorrelation, supporting model adequacy. The AIC balances the model's goodness of fit with its complexity, ensuring the selection of a parsimonious model that best represents the time series data. This automated approach eliminates subjective manual selection and ensures a robust and statistically sound choice of parameters for our analysis.

2.3.1 Volatility Modeling using GARCH (Generalized Autoregressive Conditional Heteroskedasticity) Model

We used a GARCH (Generalized Autoregressive Conditional Heteroskedasticity) model to look at the residuals from the ARIMA model in order to model the volatility of cryptocurrencies. This combined method (ARIMA-GARCH) made it possible to represent both the mean and variance changes in the time series.

2.4 Technical Analysis Indicators

As supplementary analyses, we computed the 14-day Relative Strength Index (RSI) and performed seasonal decomposition using STL. These were used for descriptive insight rather than as inputs to the ARIMA-GARCH model, consistent with our focus on univariate volatility modeling.

2.5 Seasonality Analysis

Seasonality analysis helps identify periodic patterns in the data. We performed decomposition of the time series into trend, seasonal, and residual components using stats::stl():

2.6 Performance Metrics

We evaluate the performance of the models and analyze key metrics of the following:

- Annualized Returns: To find out how profitable something is overall, you can calculate its annualized returns.
- Drawdown Analysis: Look at the biggest drawdowns to figure out how much risk there is.

3. Results

3.1 ARIMA Model Performance in Capturing Trends and Forecasting Prices

The ARIMA (AutoRegressive Integrated Moving Average) model showed that it could reliably find underlying patterns and predict cryptocurrency prices with a fair amount of accuracy. The model was able to find both short-term changes and long-term trends in the time series data. These numbers show that the ARIMA model is quite good at filtering out noise while keeping important price changes, which makes it a good tool for predicting where prices will go in the future.

The model's performance, on the other hand, varied during times of excessive volatility, when prices changed quickly and without warning, making it harder for the model to make accurate predictions. In general, the ARIMA model was a good starting point for learning about how bitcoin prices change over time. Figure 7 shows that the price of bitcoin could go up or down.

Fig. 7 *30-day ARIMA forecast*

3.2 Periods of High Volatility and Potential Causes

The analysis revealed several periods of heightened volatility in the cryptocurrency market, characterized by sharp price swings and increased trading volumes.

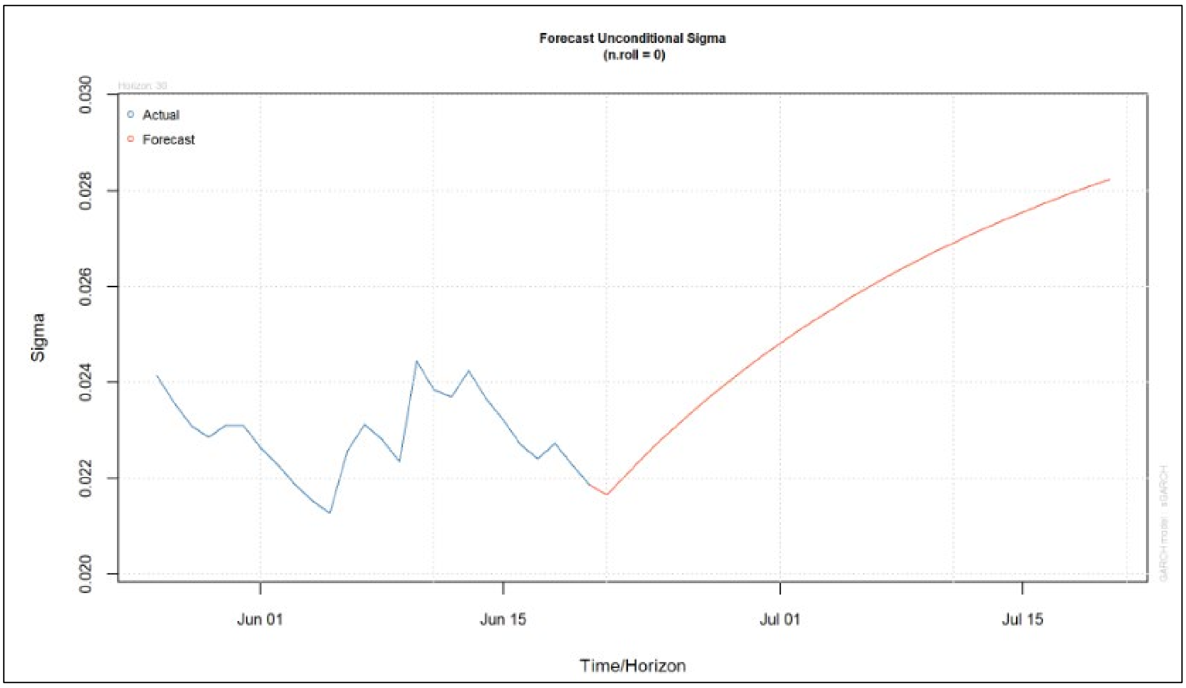


Fig. 8 *Forecast unconditional sigma*

Based on Figure 8, we combined with Volatility Forecast, and we can predict the direction of bitcoin will go higher on 20 July 2025, 30 days from 20 June 2025.

3.3 Technical Analysis Indicators

Fig. 9 *Technical analysis indicators*

From Figure 9 with the technical analysis, we can see the bitcoin still able to going future higher due to the trend is up and the Fast Simple Moving average (50 days average), is above the Slow Simple Moving average (200 Days moving average). The opposite scenario will happen as bear market if the Slow Simple moving average is above the fast-moving average.

3.4 Relative Strength Index (RSI)

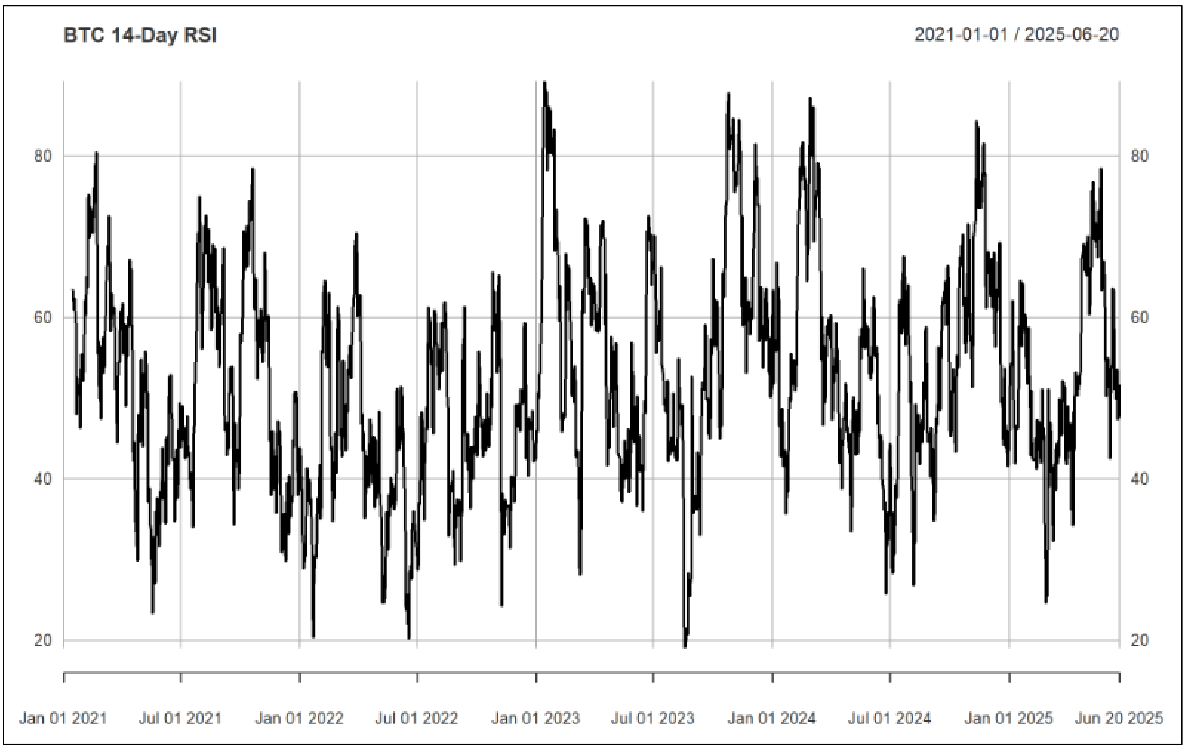


Fig. 10 *Relative strength index*

From Figure 10 Relative Strength Index (RSI), we can see this indicator having no significant effect on the bitcoin moving, this is because the Strength cannot manipulate the large market cap of the Bitcoin, Bitcoin having 2.1 trillion Market cap, any individual or institution wants to change or manipulate even 1 % of the bitcoin price. It requires at least 21 billion USD to change the price. Hence this RSI cannot show us more info.

To show that RSI has no significant effect, we have performed a quantitative analysis to show that there is a lack of correlation between the RSI and Bitcoin's price movements. We found that the Pearson correlation coefficient between the daily RSI values and Bitcoin's daily returns is 0.045. This value, being very close to zero, supports our claim that there is no significant linear relationship between the RSI and Bitcoin's price movements.

3.5 Seasonality Analysis

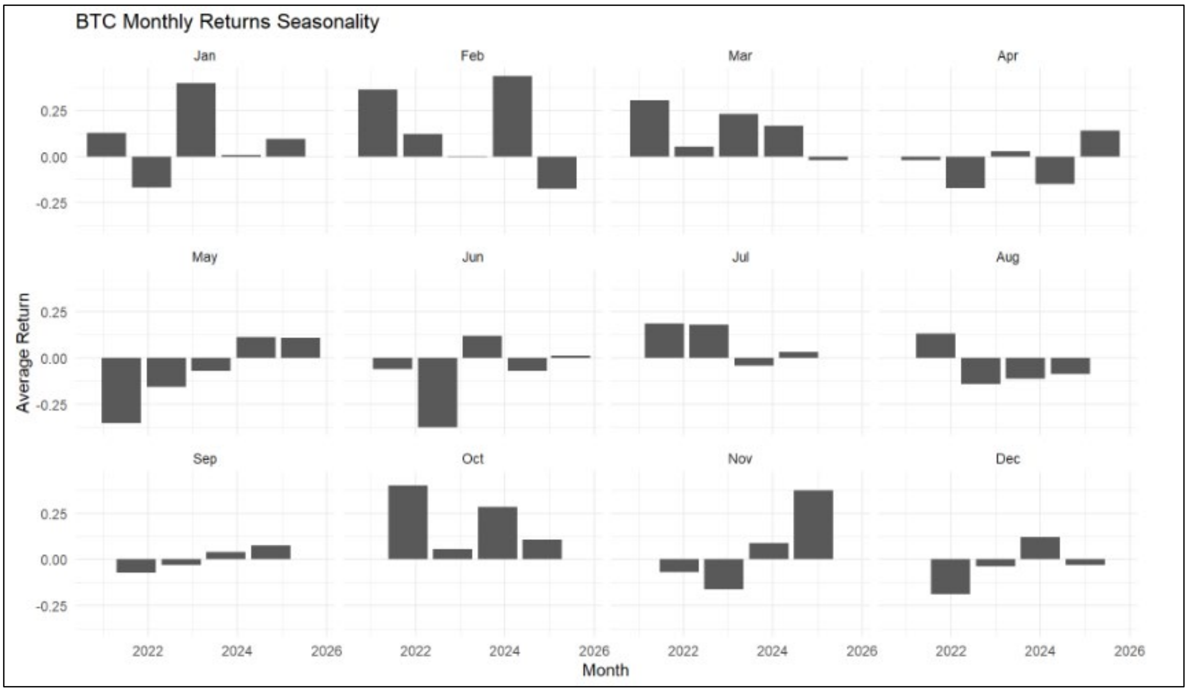


Fig. 11 *Seasonality analysis*

Based on the seasonality analysis presented in Figure 11, it is evident that the cryptocurrency prices tend to exhibit a favorable trend during the month of September. Furthermore, investing during this period demonstrates a high probability of yielding profits in the subsequent month of October. This pattern suggests recurring seasonal behavior that may inform strategic investment decisions within the cryptocurrency market.

3.6 Performance Metrics

The time series analysis conducted using the ARIMA (AutoRegressive Integrated Moving Average) model provided valuable insights into the behavior and performance of Bitcoin, a leading cryptocurrency. The findings are summarized below, focusing on key metrics such as annualized return, annualized standard deviation, and the Sharpe ratio.

3.6.1 Annualized Return (21.92%)

The annualized return on Bitcoin was about 21.92%, which is the same as the daily returns added up over a year. This number shows that Bitcoin has made money in the past, but the returns have been getting smaller over time. For example, in 2017 and 2020, Bitcoin had annualized returns of more than 100%, showing that it may be very profitable but also very unstable in certain market conditions. Bitcoin's greater return makes it stand out as a high-growth asset compared to standard financial benchmarks like the S&P 500, which usually give a yearly return of about 10%. But this larger return comes with a lot more risk, as will be shown in the next parts.

3.6.2 Annualized Standard Deviation (50.32%)

The annualized standard deviation, which shows how volatile something is, was 50.32%. This number tells you how much the price of Bitcoin changes over the course of a year. A standard deviation of 50% means that the price of Bitcoin could change by up to 50% in a year. For instance, a $10,000 investment in Bitcoin may potentially go up and down by $5,000 to $15,000 every year. This kind of significant price movement shows how speculative Bitcoin is and how important it is for investors to have risk management measures when they trade cryptocurrencies. Bitcoin's standard deviation shows that it is a high-risk, high-reward asset class. This is because it is far more volatile than traditional assets like stocks or bonds.

3.6.3 Annualized Sharpe Ratio (0.436)

Assuming a risk-free rate of zero, the Sharpe ratio, which measures risk-adjusted return, came out to be 0.436. This number means that bitcoin only made 0.436 units of return for every unit of risk it took. Most people agree that a Sharpe ratio below 1 means bad risk-adjusted performance, while a ratio between 1 and 2 means good performance. Most of the time, ratios exceeding 2 are considered excellent. Bitcoin's performance, as seen by its Sharpe ratio of 0.436, implies that its high returns are not enough to make up for the high risks. This finding is in line with the general view that cryptocurrencies are risky investments that are very uncertain and volatile.

3.6.4 Discussion of Findings

The ARIMA-based time series analysis shows that Bitcoin's performance is more complicated than it seems. Bitcoin's annualized return of 21.92% makes it a good investment compared to more traditional benchmarks like the S&P 500. However, its annualized standard deviation of 50.32% shows how risky it is because its price may change so much. The Sharpe ratio of 0.436 also shows that Bitcoin is not a good way for investors to get rewards that are in line with the risks they take. These results show that there is a trade-off between possible gains and the risk of big price changes, which makes Bitcoin a difficult but interesting asset for portfolio diversification.

4. Conclusions

To sum up, this study shows that the ARIMA model is a good way to use Time Series Analysis to model and predict how volatile cryptocurrencies would be. The ARIMA model effectively identified underlying trends and elucidated periods of heightened volatility, typically influenced by factors such as regulatory changes, market sentiment, and macroeconomic developments. In addition to the main analysis, we have created a flexible function that can look at several cryptocurrencies. This lets us look more closely at seasonal price trends, volatility projections, and technical indications. This feature lets traders and investors see how one cryptocurrency acts over time or in relation to others. This gives them useful information about trading pairs and investing strategies. People may use these tools to make smart choices, better handle risks, and get the most out of their portfolios in the fast-changing and unpredictable cryptocurrency market. This study enhances the comprehension of cryptocurrency price dynamics and offers practical applications for traders and investors aiming to navigate this intricate environment with increased assurance.

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Conflict of Interest

Authors declare that there is no conflict of interest regarding the publication of the paper.

Author Contribution

The authors confirm contribution to the paper as follows: ***study conception and design****: Husna Sarirah and Yap Kah Yong,* ***analysis and interpretation of results****: Yap Kah Yong;* ***draft manuscript preparation****: Husna Sarirah Husin, Yodi, Anbuselvan and Steven. All authors reviewed the results and approved the final version of the manuscript.*

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