Analysis of Bitcoin Price Forecasting and Related Influencing Factors

Jiaxin Wang[a]
School of Mathematical Sciences, University of Southampton, 58 Salisbury Road, Southampton, SO17 1BJ, U.K.

Keywords: Price Prediction, ARIMA Model, Macroeconomic Indicators, Market Sentiment, Volatility.

Abstract: This paper focuses on the factors affecting the price of Bitcoin and its predicted future price trends. As the most iconic cryptocurrency, Bitcoin has received widespread attention from investors, policymakers, and researchers due to its high volatility and potential ability to transform the financial system. Understanding the determinants of Bitcoin's price is important for assessing its role in financial markets, improving risk management capabilities, and developing effective investment strategies. This study examines a variety of internal and external factors that may affect the price of bitcoin, including market supply and demand, investor sentiment, macroeconomic indicators, regulatory policy changes, and technological advances. In terms of price forecasting, this paper employs statistical and machine learning methods, focusing on the use of ARIMA model, to model and analyse the long-term trend of Bitcoin. The study incorporates historical data to test the effectiveness of the model. This study helps to deepen the understanding of Bitcoin's market behaviour, provides reference for investors to optimise their asset allocation in the context of the evolving digital economy, and provides theoretical support for financial stability analysis and regulatory policy formulation.

1 INTRODUCTION

Bitcoin was launched in 2008 by a developer under the pseudonym Satoshi Nakamoto, followed by the Bitcoin Genesis block in 2009, and is now the leading cryptocurrency and has revolutionized the financial sector (Yu et al, 2025). As a decentralized digital currency, Bitcoin operates over a network without the need for a central authority or intermediary, based on blockchain technology that ensures the transparency, security, and immutability of transactions. Since its launch, Bitcoin has grown significantly in terms of market capitalization and market acceptance, attracting widespread attention from individual investors, financial institutions, and regulators. The total supply is limited to 21 million units, a scarcity that has led it to be considered "digital gold". However, the volatility of the price of Bitcoin remains an important area of research, raising widespread concern about the drivers behind its price fluctuations. Understanding these influences is critical not only for investors looking to maximize returns on their investments but also for policymakers and financial analysts to understand the role and impact of Bitcoin in the wider financial system. This paper will explore the key factors that influence bitcoin price dynamics, consolidate existing research findings, and highlight the importance of understanding bitcoin price volatility in the context of financial market and economic stability.

Over the past decade, researchers have conducted extensive studies on the factors influencing the price of Bitcoin. Early research primarily focused on the technical and structural characteristics of Bitcoin, such as its limited supply, decentralized nature, and mining difficulty. These intrinsic features laid the foundation for Bitcoin's unique behaviour in the financial market (Chang and Liu, 2008).

Subsequent studies explored Bitcoin's dual nature as both a speculative asset and a financial hedging instrument. Dirk et al. highlighted that Bitcoin's price is highly sensitive to market sentiment and macroeconomic uncertainty, reflecting its speculative characteristics as well as its potential role in risk diversification (Dirk et al., 2018). However, market fundamentals such as supply, and demand can only partially explain the high volatility in Bitcoin's price. Acikgoz argued that speculative trading and market speculation play a more significant role in driving price fluctuations (Acikgoz, 2025). Macroeconomic

[a] https://orcid.org/0009-0009-6425-3318

Wang, J.
Analysis of Bitcoin Price Forecasting and Related Influencing Factors.
DOI: 10.5220/0013834500004708

In *Proceedings of the 2nd International Conference on Innovations in Applied Mathematics, Physics, and Astronomy (IAMPA 2025)*, pages 620-625
ISBN: 978-989-758-774-0

indicators have also emerged as key determinants of Bitcoin's price. Factors such as interest rates and inflation influence investor behaviour and, consequently, Bitcoin valuation. For instance, Shahzad et al. found that Bitcoin tends to exhibit a negative correlation with traditional financial assets during periods of market stress, suggesting its potential as a haven under specific conditions (Shahzad et al., 2020). Beyond economic fundamentals, behavioural and psychological factors are increasingly recognised as important influences. Klein stated that Bitcoin's value is heavily shaped by market narratives, media coverage, and investor sentiment, often resulting in "boom-bust" cycles. This behaviour is closely linked to investor psychology and herd behaviour (Klein, 2017). Supporting this view, Beckmann et al. demonstrated that social media activity and online search trends are strongly correlated with Bitcoin price movements, underlining the critical role of public perception and sentiment in shaping market dynamics (Beckmann et al., 2024).

Finally, regulatory developments and government policies represent another major area of influence. Regulatory announcements-including restrictions on cryptocurrency trading, tax policies, and central bank interventions-have been shown to trigger sharp fluctuations in Bitcoin prices. Lashkaripour found that the Bitcoin market reacts strongly to regulatory policy changes, with the direction and magnitude of these reactions depending on the nature of the measures implemented (Lashkaripour, 2024). A prominent example is the Chinese government's ban on Initial Coin Offerings (ICOs) and cryptocurrency trading in 2017, which resulted in a significant decline in Bitcoin prices, highlighting the market's sensitivity to regulatory uncertainty (Okorie and Lin, 2020).

2 METHODOLOGY

2.1 Data Source

The data used in this study is from Kaggle, and the dataset is owned by Zielak. It has a high usability rating of 10.0 and has been downloaded over 172000 times, indicating its popularity and reliability among data analysts and researchers. The dataset contains detailed information on a total of 3,649 participants, is provided in CSV format, and notably does not have any missing values, which ensures the integrity and completeness of the analysis. Additionally, the dataset has been widely used in various machine learning and statistical modeling tasks, making it a suitable and credible source for this study.

2.2 Sample Selection

In order to understand the long-term trend of the Bitcoin price, this paper will use a time series model to analyse the price trend using time series data. The steps include data collection, preprocessing, feature engineering, model training and evaluation. The following figure shows the initial time series plot of the data .

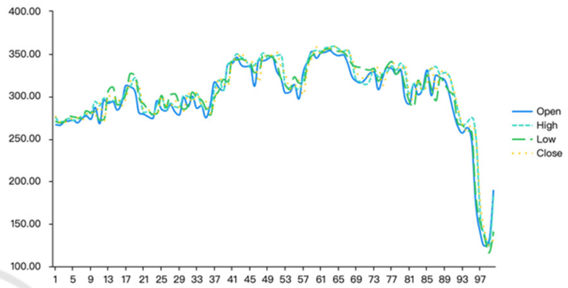

Figure 1: 2017-2023 Bitcoin Price Action (Picture credit: Original)

This time series plot Figure 1 illustrates the trend of Bitcoin prices from 2017 to 2023. Several prominent surges and drops can be observed, corresponding to key market events such as bull runs in late 2017 and early 2021, as well as sharp declines during regulatory crackdowns and macroeconomic tightening. The pronounced volatility highlights the need for robust time series models to account for non-stationary behaviours.

2.3 Experimental Design

The core model used in this study is the AutoRegressive Integrated Moving Average (ARIMA) model, which is well-suited for univariate time series forecasting (Zhang et al., 2003). The general form of an ARIMA(p,d,q) model is:

$$Y_t = c + \varphi_1 Y\{t-1\} + \cdots + \varphi_p Y\{t-p\} + \theta_1 \varepsilon\{t-1\} + \cdots + \theta_q \varepsilon\{t-q\} + \varepsilon t \quad (1)$$

Where p is the autoregressive order, d is the degree of differencing, and q is the moving average order. The model selection was based on Autocorrelation Function (ACF) and Partial Autocorrelation Function (PACF) plots. The final selected model was ARIMA (3,1,1), which demonstrated robust forecasting performance in both the training and test sets.

3 RESULTS AND DISCUSSION

3.1 Definition of the Variables

This table 1 provides a clear definition of the key variables used in the analysis. 'Open', 'High', 'Low', and 'Close' represent the opening, highest, lowest, and closing prices of Bitcoin, respectively. These variables are critical for constructing meaningful features in time series modelling. Among them, the closing price is selected as the main dependent variable for prediction, as it best reflects the daily summary value and is widely used in financial forecasting.

Table 1: Name and Definition of the Variables

Name of Variables	Definition of the Variables
Open	Bitcoin Opening Price (US $)
High	Bitcoin Opening Price (US $)
Low	Bitcoin Opening Price (US $)
Close	Bitcoin Opening Price (US $)

3.2 ADF Test Analyse

This table 2 presents the results of the Augmented Dickey-Fuller (ADF) test applied to the closing price series. The test statistic is -9.744 with a p-value of 0.000, which is lower than all critical values at the 1%, 5%, and 10% levels. This strongly rejects the null hypothesis of a unit root, confirming that the first-order differenced series is stationary and suitable for ARIMA modelling.

Table 2: Close-ADF Check list

Difference Order	t	p	Critical Value		
			1%	5%	10%
1	-9.744	0.000	-3.499	-2.892	-2.583

The figure 2 shows the transformed series after applying first-order differencing. The resulting data appear to fluctuate around a constant mean with relatively stable variance, indicating that the non-stationarity in the original series has been removed.

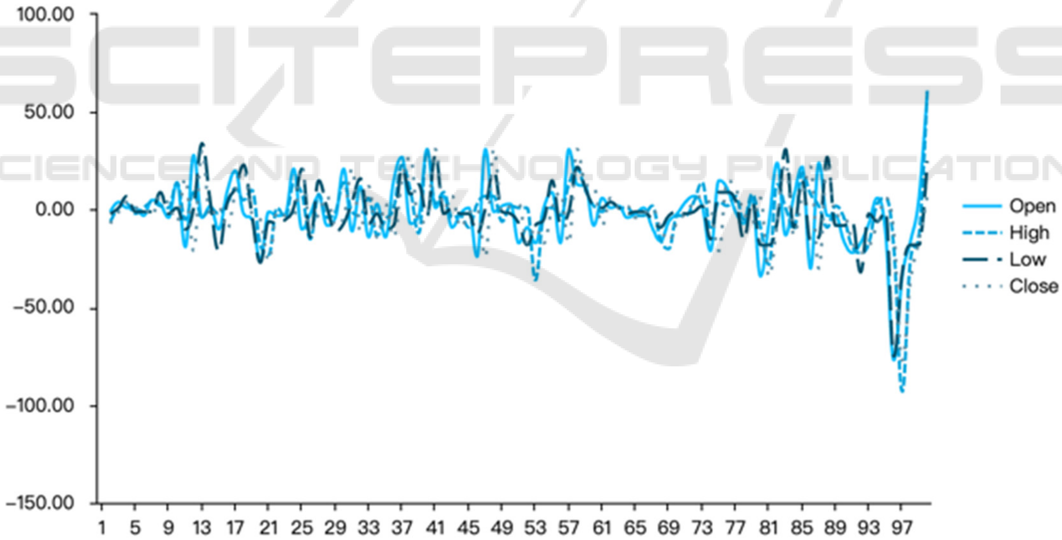

Figure 2: First order difference sequence diagram (Picture credit: Original).

3.3 ACF and PACF Test

The Figure 3 ACF plot displays significant correlations at lags 1 to 3, gradually tapering off. This pattern suggests the presence of a moving average (MA) component in the time series data, which plays a vital role in modelling the random shock effects of prior periods on current Bitcoin prices. Specifically, the sustained correlation at early lags indicates that recent past errors still carry predictive power for future observations. In the context of Bitcoin price movements, this result reflects the asset's susceptibility to short-term noise and external events, such as sudden news, regulatory developments, or investor reactions to macroeconomic announcements.

These transient shocks-whether driven by a market crash, positive sentiment on social media, or abrupt liquidity movements-create residual effects that persist for a few days before fading.

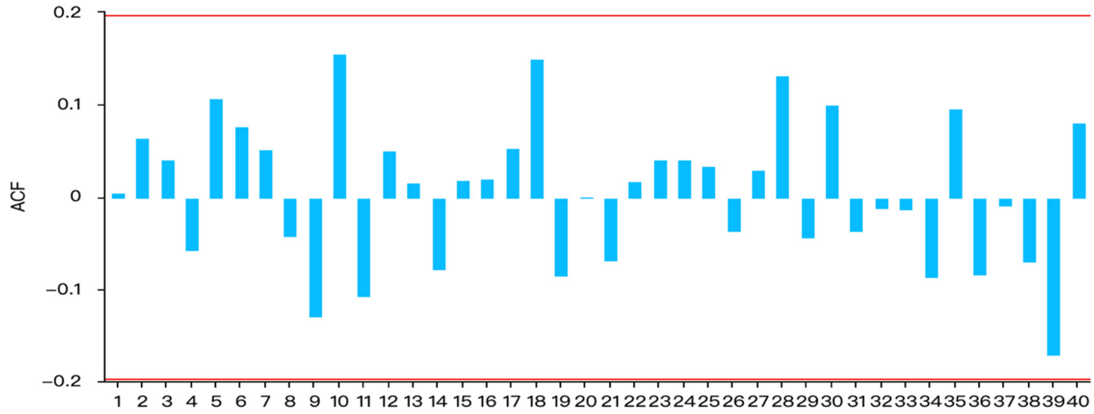

Figure 3: ACF plot (Picture credit: Original)

By identifying these lagged relationships, the MA component in the ARIMA model helps smooth out short-term volatility, enabling the model to better estimate the underlying price trend. Given Bitcoin's well-documented sensitivity to speculation and high-frequency trading, incorporating the MA(q) structure allows for a more refined capture of these temporary distortions. Therefore, the findings from the ACF plot are not just statistically informative-they directly support a more accurate forecasting approach for a financial asset like Bitcoin, which is frequently affected by episodic market behaviours. These insights justify the inclusion of a single moving average term ($q = 1$) in the ARIMA (3,1,1) model, balancing responsiveness to shocks while avoiding overfitting in a high-volatility environment.

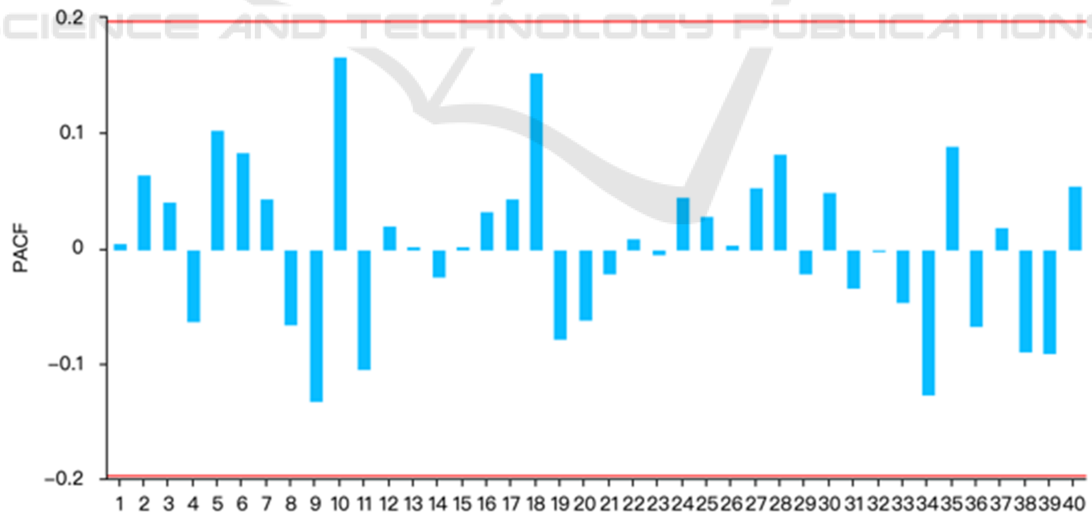

Figure 4: PACF plot (Picture credit: Original)

The PACF plot shows significant spikes at lags 1 to 3 before cutting off, indicating the presence of a strong autoregressive (AR) structure in the time series (Figure 4). Each spike implies a direct relationship between Bitcoin's current closing price and its values in the preceding days, independent of intermediate lags. This autocorrelation pattern reveals that Bitcoin prices exhibit temporal dependencies-meaning recent price levels have a strong and direct influence on subsequent prices. In financial terms, this behaviour is consistent with momentum trading, market memory, and investor psychology-where previous gains or losses tend to influence current market behaviour due to trend-following strategies or fear-of-missing-out (FOMO) phenomena.

By incorporating up to three AR terms ($p = 3$), the model captures this serial dependence, allowing it to learn from recent trends and apply them to future predictions. This is particularly important in cryptocurrency markets, where price inertia often emerges from collective behaviour and delayed reactions to news. For example, a bullish trend initiated by positive regulatory news or institutional adoption may persist over several days as more participants join the market. Likewise, a sudden drop may extend over multiple sessions due to panic selling. The PACF structure helps capture this lagged momentum. As a result, the choice of $p = 3$ in the ARIMA (3,1,1) model is not arbitrary-it reflects the behavioural underpinnings of the Bitcoin market and enhances the model's ability to replicate its empirical price dynamics. When used in tandem with differencing ($d = 1$) and MA components, the AR terms help stabilize forecasts while accounting for intrinsic patterns in the data.

3.4 ARIMA Model

The ARIMA model results show that among the autoregressive (AR) and moving average (MA) terms, some parameters are statistically significant. Specifically, the second autoregressive term (α_2) has a coefficient of 0.937 with a p-value of 0.000, indicating a strong positive and statistically significant effect at the 1% level. This suggests that past values, particularly those lagged by two periods, have a substantial influence on the current price trend. In contrast, the first autoregressive term (α_1) and the third autoregressive term (α_3) are not statistically significant (p-values of 0.816 and 0.632 respectively), implying their limited explanatory power in the model (Table 3).

For the moving average component, β_1 is estimated at 0.945 with a p-value of 0.000, demonstrating a significant positive impact. The high significance of β_1 suggests that past forecast errors are highly influential in shaping the current observations, reflecting the market's sensitivity to unexpected shocks or noise. The model achieves an Akaike Information Criterion (AIC) of 851.152 and a Bayesian Information Criterion (BIC) of 866.783, indicating a reasonably good model fit relative to alternative specifications.

The strong significance of the second-order autoregressive term (α_2) highlights the inertia and memory effect in Bitcoin prices, where movements from two periods ago exert a lasting impact on the present. This characteristic aligns with the speculative nature of cryptocurrency markets, where price trends are often amplified over short time horizons due to herd behaviour and momentum trading.

Similarly, the significant moving average term (β_1) reflects the persistence of shocks in the market. A large β_1 coefficient implies that deviations from expected prices are not rapidly corrected but instead influence future prices, underscoring the market's inefficiency and the role of sentiment-driven volatility. This is consistent with the behaviour observed in Bitcoin markets, where news events, regulatory changes, and speculative trading can create price distortions that last over multiple periods.

Table 3: ARIMA (3,1,1) model results

Term		Coefficient	Standard error	z	p	95% CI
Constant term	c	14.143	23.351	0.606	0.545	-31.624 ~ 59.910
	α1	0.063	0.271	0.232	0.816	-0.468 ~ 0.594
AR	α2	0.937	0.222	4.225	0.000	0.502 ~ 1.372
	α3	-0.054	0.112	-0.479	0.632	-0.273 ~ 0.166
MA	β1	0.945	0.263	3.587	0.000	0.429 ~ 1.461

Remarks：AIC= 851.152

BIC= 866.783

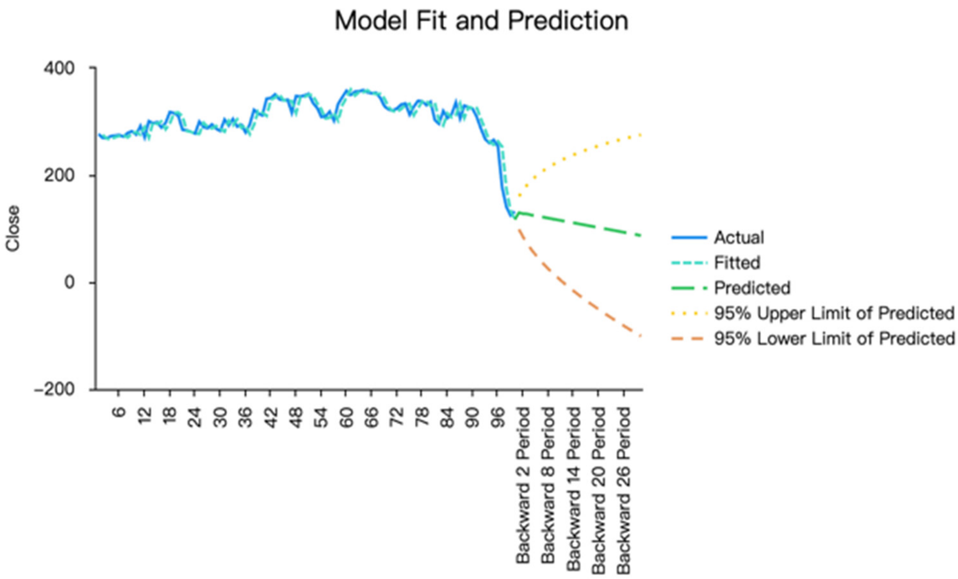

Figure 5: Model Fit and Prediction (Picture credit: Original).

This graph compares the fitted ARIMA model values with actual observed Bitcoin prices (Figure 5). The model tracks the historical trends well, especially during the mid-term periods, although some deviation occurs during extremely volatile price movements. Nonetheless, the model provides a reliable foundation for short-term forecasting.

4 CONCLUSION

Since the birth of Bitcoin in 2009, its price has experienced drastic fluctuations, which makes Bitcoin price forecasting and influencing factors a popular topic in financial market research. Since the Bitcoin market is affected by various factors such as supply and demand, macroeconomic policies, investor sentiment, etc., how to use a suitable time series model to make effective forecasts is a question worth exploring. ARIMA, as a classic time series analysis method, can fit the price trend better after data smoothing. Therefore, in this paper, the ARIMA (3,1,1) model is used for Bitcoin price prediction and its performance is evaluated. And the prediction was made based on the historical data from 2017-2023. The experimental results show that the model can effectively capture the long-term trend of bitcoin price and has high prediction accuracy in the short term. Through model evaluation, this paper finds that ARIMA (3,1,1) outperforms the linear regression model in terms of mean square error (MSE) and root mean square error (RMSE).

REFERENCES

Acikgoz, T. 2025. Gold and Bitcoin as hedgers and safe havens: *Perspective from nonlinear dynamics, Resources Policy*, 102, 105489.

Beckmann, J., Geldner, T. Wustenfeld, J. 2024. The relevance of media sentiment for small- and large-scale bitcoin investors, *Journal of International Financial Markets, Institutions and Money*, 92, 1042-4431.

Chang, P.C., Liu, C H. 2008. A tsk type fuzzy rule based system for stock price prediction. *Expert Systems with Applications,* 34(1), 135-144.

Dirk, G., Thomas, D., Konstantin, K. 2018. Bitcoin, gold and the US dollar-A replication and extension, *Finance Research Letters, Elsevier,* 25, 103-110.

Klein, T. 2017. Dynamic correlation of precious metals and flight-to-quality in developed markets, *Finance Research Letters*, 23, 283-290.

Lashkaripour, M. 2024. Some stylized facts about bitcoin halving. *Finance Research Letters*, 69, 106198.

Okorie, D., Lin, B. 2020. Did China’s ICO ban alter the Bitcoin market? *International Review of Economics & Finance*, 69, 977-993.

Shahzad, S., Bouri, E., Roubaud, D., Kristoufek, L. 2020. Safe haven, hedge and diversification for G7 stock markets: *Gold versus bitcoin, Economic Modelling*, 87, 212-224.

Yu, Y., Tong, Y., Qiu, X.Y. 2025. Analysis of Factors Influencing Bitcoin Price Volatility. *Finance and Management,* 5, 54-58.

Zhang, L., et al. 2003. Energy clearing price prediction and confidence interval estimation with cascaded neural networks. *IEEE Transactions on Power Systems.*