

US Monetary Policy Uncertainty and Changes in Cryptocurrency Market: Evidence from ARIMA Model

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Abstract. In 2022, the US Federal Reserve implemented multiple monetary policy to control inflation, significantly impacting the financial markets. This study focuses on examining the impact of the Federal Reserve's announcements of rising interest rates on the price of Bitcoin. By utilizing the ARMA model and analyzing historical price data, the research aims to uncover the price dynamics of Bitcoin in response to changes in the Federal Reserve's interest rate decisions. The findings indicate that ultra-short term of the Bitcoin prices is not influenced by interest rate hikes. However, there is a notable correlation, where higher interest rates are associated with lower Bitcoin prices in the short term. The study's findings provide crucial insights into how the cryptocurrency market responds to the actions taken by the Federal Reserve, thus offering valuable information for investors and analysts in this domain. Policymakers should exercise caution in observing cryptocurrency movements and consider the impact of monetary policy on digital assets as they continue to play an increasingly significant role in the overall economy.

Keywords: Cryptocurrency, Bitcoin, US, Federal Reserve, interest rates, inflation, ARMA model.

1. Introduction

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2.1.1 Sub heading

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3. Introduction

On March 16, 2022, Federal Reserve authorized a 0.25 percent point rate rise, marking the end of the era of maintaining zero increase in interest rates since the beginning of Covid pandemic [1]. This momentous decision was driven by the need to address the pressing issue of spiraling inflation. Soon, as reported by CNBC, stock market initially responded with a negative reaction to the announcement

but then bounced back within the day. Meanwhile, there was a monetary increase in bond yields, with the benchmark 10-year Treasury note rising to 2.22% in the immediate aftermath of the announcement [1].

The decisions of the Federal Reserve to adjust interest rates have significant implications, setting off a chain of reactions across various asset classes. During the Covid pandemic, Federal Reserve responded the crisis with an easing monetary policy, reducing the interest rate to a range of 0%-0.25% [2]. Traditional financial instruments, including stocks, bonds, and cash investments [3], are among the assets that directly respond to changes in interest rates. Characterized by lower interest rates, the stock market achieved notable gains. In 2020, the stock market surged by 18.40%, and in 2021, it experienced a substantial increase of 28.71% [4].

In 2022, as anticipated, the stock market witnessed a significant downturn due to rising interest rates. On January 3, 2022, the S&P 500 index stood at \$4796.56, but by the last trading day of the year, it had plummeted to \$3839.50. This sharp drop in value amounted to a staggering 19% decrease in the index value during the year.

Amidst this economic uncertainty, cryptocurrencies, with Bitcoin at the forefront, have been attracting substantial attention.

Statista data reveals that Bitcoin's closing price on March 31, 2022, stood at \$45,538.68, representing a remarkable increase of 16.3% within the month, as compared to the previous closing price of \$39,137.80 on February 25, 2022 [5]. However, it is essential to acknowledge that this apparent rise in Bitcoin's value was eventually followed by a decline to around \$20,000 in June 2022.

Existing studies indicated that Bitcoin is predominantly used as a speculative investment rather than as a means of exchange, mainly due to its high volatility [6]. Bouri et al.'s research further revealed that the cryptocurrency market is influenced by herding behavior, which changes over time and is largely driven by economic policy uncertainty [7]. Additionally, Kristoufek's study demonstrated that crypto investors often seek information through online sources such as search engines, online chat platforms, and social media [8].

According to Silbert, the individual behind the Bitcoin Investment Trust, the current phase of cryptocurrency could be the global consumer adoption phase, representing the final stage of the five well-defined stages in the general progression of cryptocurrencies [9]. As Bitcoin gains greater adoption, comprehending the factors that impact its price dynamics becomes crucial for investors and policymakers since the adoption of cryptocurrencies is likely to be linked to the level of regulation in specific jurisdictions in the future. [10].

A study conducted by Havidz S A H et al. found that foreign liquidity ratio, exchange, and gold positively influence Bitcoin price. In contrast, the interest rate has a detrimental effect on Bitcoin price. The stock market index was observed to have a negative effect on Bitcoin price that was not statistically significant [11].

Colon T et al.'s study showed a short-lived positive correlation between forward inflation expectations and both Bitcoin and Ethereum, occurring at the onset of the COVID-19 crisis, but little evidence of cryptocurrencies acting as a hedge during periods of rising forward inflation expectations outside of this period [12].

This paper aims to delve into the further study of relationship between Federal Reserve interest rate hikes and the price of Bitcoin through the utilization of an ARIMA model. The study will analyze Bitcoin price data to investigate how the announcement of the Fed's interest rate hike impacted the price movements in ultra-short term and short term.

The remaining sections of this paper are as follows: Section 2 provides detailed information about the data source, data stability, and the specification of the ARMA model used in this study. Section 3 presents a comprehensive analysis of the results obtained from applying the ARMA model to the logarithm price of Bitcoin. Finally, Section 4 offers a concise recapitulation of the final conclusions derived from the findings.

4. Research Design

4.1. Data source

The data utilized in this research encompasses the daily, weekly, and monthly closing prices of BTC price in USD, spanning from February 2, 2012, to July 5, 2023. This data was sourced from Investing.com, a financial markets platform, in conjunction with Yahoo Finance. To facilitate a comprehensive analysis, the study focuses on two distinct periods: the time frame preceding the Federal Reserve's announcement and the duration following the announcement. March 16, 2022, is selected as the pivotal date to demarcate these two periods. The hypothesis posits that the data before this date remains unaffected by the Fed's announcement and is considered clean. Then, this assumption is utilized to construct the price movement after this date, using the data before the announcement as a basis. Finally, the constructed data is used to compare against the actual movement of Bitcoin.

The data underwent several preprocessing steps to facilitate further analysis. Firstly, it was sorted in ascending order based on the date, allowing us to establish the chronological sequence. Subsequently, a new variable called "time" was created to represent the time index, transformed the data into a time-series format, enabling us to examine temporal patterns and trends. Additionally, to better capture the price dynamics, the Bitcoin prices were transformed into their logarithmic values. This logarithmic transformation helps stabilize variance and allows for a more accurate representation of percentage changes in price.

With the data now in a suitable format, Stata was employed for further exploration and analysis. This includes the construction of models to investigate the factors influencing Bitcoin prices and to gain valuable insights into its price dynamics over time.

4.2. Weak Stationarity Test

After data collection and model construction, it is crucial to test the stationary of the data before proceeding with further analysis. Using the ADF test in Stata, the p-values were calculated for the 1st-order of the logarithmic daily, weekly, and monthly closing prices of BTC. However, the PACF and ACF of the 1st-order differenced series (returns) do not exhibit clear patterns for determining the order. Hence, the 2nd-order differencing was employed to address this issue. The p-values for these differences are found to be equal to 0, indicating they are statistically significant. Conversely, the p-values for the logarithmic raw daily, weekly, and monthly closing prices of BTC are not equal to zero. This finding presents strong evidence refuting the existence of a unit root in the first and second order differences of the logarithmic BTC closing price. Consequently, the model developed using this data is valid, and the data can be considered stationary.

Table 1. Weak stationarity test

		t	p
	Daily		
Raw		-1.923	0.6426
1st order difference		-42.098	0.0
2nd order difference		-74.695	0.0
	Weekly		
Raw		-2.710	0.2318
1st order difference		-14.052	0.0
2nd order difference		-25.825	0.0
	Monthly		
Raw		-2.924	0.1546
1st order difference		-6.939	0.0
2nd order difference		-11.949	0.0

4.3. ARMA model

The ARMA model is a widely used time series forecasting method, combining the Autoregressive (AR) $\phi_0 + \sum_{i=1}^p \phi_i Bitcoin_{t-i}$ and Moving Average (MA) components $\alpha_i - \sum_{i=1}^q \phi_i \alpha_{t-i}$. In equation (1), the AR component (AR(p)) is denoted by the term involving past Bitcoin prices from February 2012 to July 2023. It captures the relationship between current and past values of the Bitcoin price to estimate future values. On the other hand, the MA component (MA(q)) forecasts future values based on an error term, representing the difference between actual and predicted values.

$$Bitcoin_t = \phi_0 + \sum_{i=1}^p \phi_i Bitcoin_{t-i} + \alpha_i - \sum_{i=1}^q \phi_i \alpha_{t-i} \quad (1)$$

The ARMA model is a powerful tool for time series analysis and prediction, enabling us to leverage historical data to make informed projections of future Bitcoin prices. By considering both the AR and MA components, a comprehensive model can be built that accounts for both the short-term dependencies between consecutive observations and the influence of past observations on future behavior.

5. Empirical results and analysis

5.1. Order of ARMA model

PACF of a stationary time series is a function of ACF. It serves as a valuable tool in determining the appropriate order for the AR models when analyzing time series data. A straightforward and effective approach to introduce the PACF model is by sequentially considering a series of AR models as follows:

$$Bitcoin_t = \phi_{0,1} + \phi_{1,1} Bitcoin_{t-1} + e_{1t} \quad (2)$$

$$Bitcoin_t = \phi_{0,2} + \phi_{1,2} Bitcoin_{t-1} + \phi_{2,2} Bitcoin_{t-2} + e_{2t} \quad (3)$$

$$Bitcoin_t = \phi_{0,3} + \phi_{1,3} Bitcoin_{t-1} + \phi_{2,3} Bitcoin_{t-2} + \phi_{3,3} Bitcoin_{t-3} + e_{3t} \quad (4)$$

ϕ_1, \dots, ϕ_p are the parameters of the model and e_t is the white noise. The function above is PACF which is a statistical tool used in time series analysis to examine the direct correlation between an observation and its lags, while controlling for the influence of intermediate lags. It quantifies the unique correlation between a data point and its specific lag, excluding the effects of all other intermediate lags.

In the context of forecasting Bitcoin price in logarithmic terms, the lag orders for the AR and MA components of the ARMA model can be determined using PACF and ACF plots. Using Maximum Likelihood Estimation (MLE), predicting high order functions becomes challenging. To avoid overfitting and account for the limitations of the ARMA model in long-term predictions, the choices are limited to lag values up to 10 for accurate forecasting.

Analyzing PACF and ACF plots of Bitcoin's daily price movements (as shown in Fig. 1), the values beyond the critical limits extend up to 10. This indicates that both the AR(p) and MA(q) components of the ARMA model have an order of 10, implying those past observations up to 10 days significantly influence future price movements in daily data.

For Bitcoin's weekly price movements, an order of 8 is selected based on the analysis of PACF and ACF plots. Similarly, for monthly price movements, the chosen order is 7.

By adopting this approach of limiting lag orders and selecting appropriate values from PACF and ACF plots, effective ARMA models can be constructed, customized to the specific time scales of Bitcoin price movements.

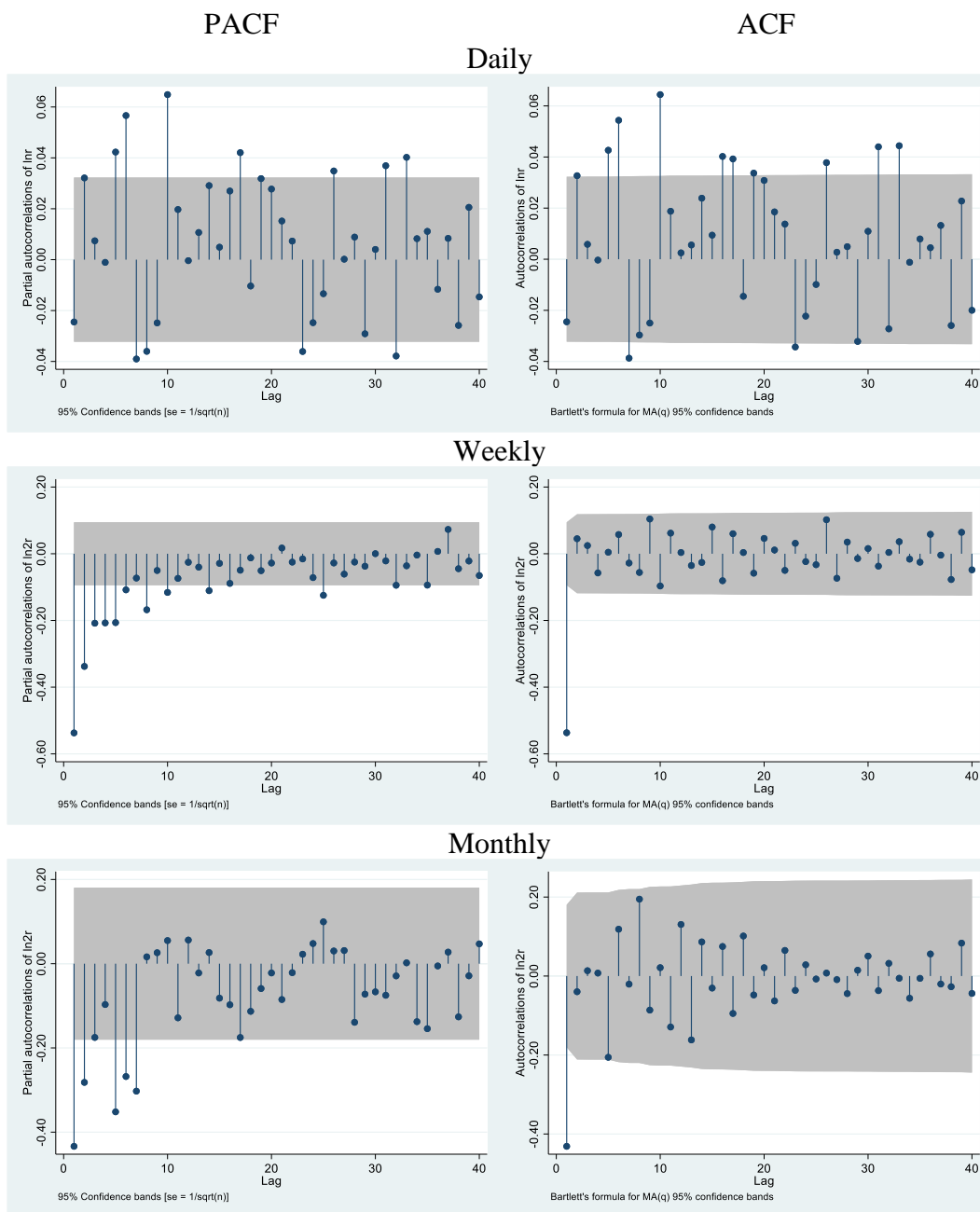


Figure 1. ARMA (p, q) identification (Photo credit: Original)

5.2. Estimation Results

Table 2 displays the outcomes of the residual tests for the different ARIMA models used to analyze the logarithmic daily, weekly, and monthly prices of Bitcoin. The Portmanteau (Q) statistic is utilized to evaluate the overall goodness-of-fit of each model to the data, while the associated probability value (Prob > chi2) is used to assess the adequacy of the model's fit to the data.

For the daily ARIMA (10, 1, 10) model, the Q statistic, and its associated probability value (p-value) suggest a reasonably good fit to the data, as the p-value (0.4585) is higher than the typical significance level of 0.05. This indicates that the model adequately captures the underlying patterns in the daily data.

Similarly, the weekly ARIMA (8, 2, 1) model exhibits an acceptable fit, with a Q statistic of 20.7915 and a probability value of 0.9948. The high p-value of 0.9948 suggests that the observed Q statistic could have occurred by chance alone, and the model captures the underlying patterns in the weekly data effectively.

The Monthly-ARIMA (7, 2, 1) model demonstrates a strong fit, with a Q statistic of 16.2688 and a probability value of 0.9997. The high probability value of 0.9997 indicates that the model's residuals do not exhibit significant autocorrelation beyond what would be expected under a good model fit. This confirms that the Monthly-ARIMA (7, 2, 1) model appropriately captures the monthly data's underlying patterns and fluctuations.

Overall, the results of the residual tests suggest that all three models provide a good fit to the data. The daily model shows a slightly higher Q statistic, indicating some remaining autocorrelation or pattern in the residuals that the model has not fully captured. However, this effect is less significant, given the lower probability value. The weekly and monthly models exhibit strong fits with no significant autocorrelation in the residuals.

The residual tests support the notion that all three ARIMA models effectively capture the price dynamics of Bitcoin for the respective time frames. These results provide valuable insights into the modeling of Bitcoin's price movements and its relationship with key economic events and indicators.

Table 2. Residual test

Model	Portmanteau (Q) statistic	Prob > chi2
Daily-ARIMA (10, 1, 10)	40.2658	0.4585
Weekly-ARIMA (8, 2, 1)	20.7915	0.9948
Monthly-ARIMA (7, 2, 1)	16.2688	0.9997

Based on the data and analysis presented in Figure 2, it can be observed that the announcement of the Federal Reserve's interest rate hike in March 2022 had no significant impact on Bitcoin's price movements within the ultra-short term. Despite the announcement, the actual value of Bitcoin's price continued its upward trend throughout the entire month of March. This suggests that in the immediate aftermath of the announcement, investors' reaction to the interest rate hike may not have been strong enough to alter the prevailing trend in the Bitcoin market.



Figure 2. Actual value and fitted value, daily (Photo credit: Original)

However, a different scenario unfolds when analyzing Figure 3 and Figure 4, representing the weekly and monthly actual values of Bitcoin's price compared to the fitted values based on the prediction assuming no announcement. In both cases, a clear negative impact of the announcement on the short term price of Bitcoin can be observed. The actual values for both the weekly and monthly price fall below the corresponding fitted values, indicating a deviation from the expected price trajectory in the absence of the announcement.

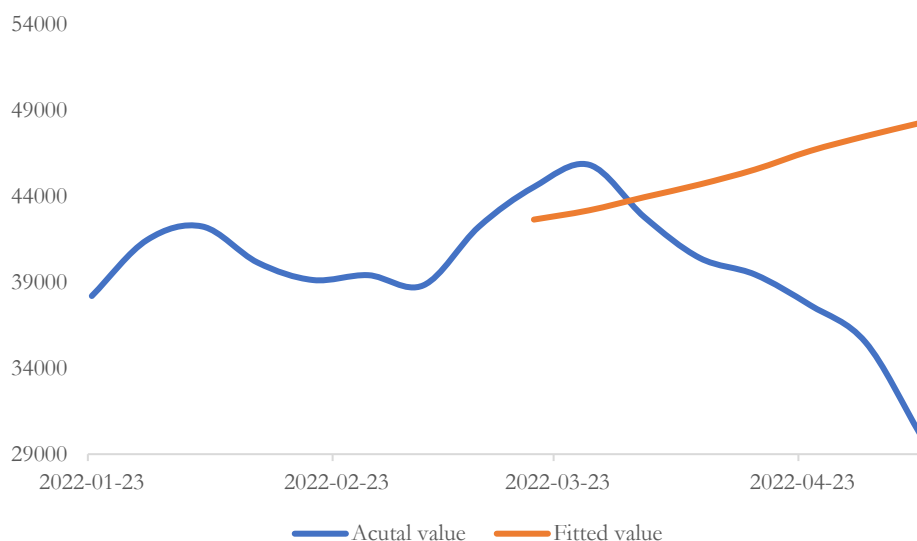


Figure 3. Actual value and fitted value, weekly (Photo credit: Original)

One possible explanation for this negative impact could be the time lag of monetary policy [12]. The effects of interest rate changes may take some time to fully manifest in the economy and financial markets, and Bitcoin may not have immediately reflected the implications of the interest rate hike. Additionally, investors' reaction to such announcements may also exhibit a lag, as they may take time to reassess their investment strategies and evaluate the potential impact of the rate hike on various assets, including Bitcoin [13].

Furthermore, the lag in investors' reaction could be influenced by the unique characteristics of the cryptocurrency market. As a relatively young and rapidly evolving market, the cryptocurrency space often experiences heightened volatility and speculative trading. Consequently, investor sentiment and market behavior in response to external events, such as the interest rate hike, may exhibit some delay and unpredictability.



Figure 4. Actual value and fitted value, monthly (Photo credit: Original)

The findings of this study contrast with Atmander E's research, which utilized the EGARCH model and concluded that the FOMC interest rate change has no significant impact on Bitcoin's volatility [14]. Furthermore, the results also differ from using future discounted value as a predictor for Bitcoin's price, which also concluded that Bitcoin remains unresponsive to both monetary and macroeconomic news [15].

It is important to note that various other factors could have contributed to the observed negative impact on Bitcoin's price following the announcement. Global economic conditions, regulatory developments, and market sentiment may have interacted with the interest rate hike news to influence the short-term price movement. Additionally, Azari A's research highlights that using Bitcoin's historical closing price for predictions can lead to large MSE values due to the cryptocurrency's price volatility and employing a smaller time window for predictions can help reduce the MSE value [16].

6. Conclusion

The objective of this paper is to investigate how the Fed raise interest rate impact on the price of Bitcoin. The ARMA model is introduced for this purpose.

The analysis suggests that the interest rate hike announcement had no immediate impact on Bitcoin's price movements in the ultra-short term. However, in the short term, both the weekly and monthly price values showed a decline below the fitted values, indicating a negative impact. The delayed reaction of Bitcoin's price to the interest rate hike may be attributed to the time lag of monetary policy effects and the unique characteristics of the cryptocurrency market.

Although cryptocurrencies operate within a unique decentralized framework, they remain part of the interconnected global financial system. Thus, interest rates and monetary policy decisions can have short term significant effects on Bitcoin and are important considerations for crypto investors and policymakers on the discourse of overall economy.

The drawback of this article is that the ARIMA model is difficult to make long-term predictions and simulation. Further research on the long-term effect of interest rate and ongoing monitoring of market dynamics are suggested to gain a comprehensive understanding of the complex relationship between interest rate decisions and Bitcoin's price movements.

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