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Modelling the Volatility in Bitcoin

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Abstract: The increase in US interest rates, inflation in the UK and various countries, and geopolitical tensions such as war have contributed to a significant downturn in the US markets, subsequently affecting crypto investments. A research firm reported a 60% decrease in daily trading volumes within just four to five days during 2022. India's largest crypto exchanges, WazirX and ZebPay, published a trader sentiment survey indicating that 27% of respondents sold 50% of their assets, while 83% of traders reduced their trading frequency. The world's largest cryptocurrency, Bitcoin, experienced a dip of over 45% in less than three months and was trading around $20,000 (INR 16 lakh) as of July 5, 2022. During 2020-21, Bitcoin never fell below Rs 35 lakhs. Most popular cryptocurrencies witnessed a drop in value ranging from 60% to 80%. The study examines the volatility in Bitcoin, analyzing the daily closing prices over a period of 10 years from January 2014 to April 2024. GARCH models were employed to model volatility.

Keywords: Volatility, GARCH, Bitcoin, Cruptocurrency, Extreme market conditions, Information arrival

INTRODUCTION

The global economic landscape is intricate, influenced by various interconnected elements that wield considerable influence over financial markets. Recent developments such as the uptick in US interest rates, mounting inflation in the UK and elsewhere, and geopolitical tensions, including conflict, have precipitated a notable downturn in global markets. This downturn has reverberated into the realm of cryptocurrency investments, impacting many investors adversely. With the escalation of interest rates, borrowing costs have surged, rendering funds acquisition more expensive for businesses and individuals alike. Consequently, this uptick in costs may curtail expenditure and investment, potentially resulting in diminished profits for companies and a subsequent decline in stock prices. In response, investors may adopt a more risk-averse stance, prompting a divestment of assets, including cryptocurrencies. Likewise, the escalation of inflation, particularly in the UK and other nations, introduces an element of uncertainty and volatility into financial markets. Elevated inflation rates often translate to higher prices for goods and services, diminishing consumer purchasing power and impeding economic expansion. This economic backdrop may also contribute to a reduction in stock prices, including those of cryptocurrencies. The cryptocurrency market is characterized by its segmentation according to market capitalization, hosting a plethora of digital currencies. Serving as an alternative to traditional currency, cryptocurrencies facilitate cost-effective transactions within a burgeoning payment ecosystem. The cumulative market capitalization of cryptocurrencies globally stands at USD 2.62 trillion, with leading entities including Bitcoin, Ethereum, Tether, BNB, and Solana. Bitcoin, in particular, boasts a storied evolution since its inception in 2008 as a decentralized currency under the enigmatic pseudonym Satoshi Nakamoto. Notable for its initial commercial transaction involving the exchange of 10,000 Bitcoins for two pizzas in 2010, Bitcoin has traversed a tumultuous path marked by extensive trading, including within illicit markets. Despite regulatory challenges from numerous jurisdictions, Bitcoin has demonstrated resilience, buoyed by institutional acceptance and state recognition. Noteworthy events such as halving events have punctuated Bitcoin's price trajectory, engendering significant fluctuations. Throughout its journey, Bitcoin has been a catalyst for transformative change, reshaping the cryptocurrency landscape and exerting a profound influence on global financial markets.

A research firm's findings highlight a substantial 60% decrease in daily trading volumes of cryptocurrencies within just four to five days in July 2022. In terms of Indian Rupees, the value of one Bitcoin never fell below Rs 35 lakhs during the fiscal year 2020-21, reaching as high as Rs 56 lakhs within the same period. Bitcoin's trading volume hovered around 7 billion, contributing to its market capitalization of USD 1 trillion. The trading activity within the cryptocurrency markets underscores its highly speculative nature. A recent sentiment survey conducted by prominent Indian crypto exchanges, WazirX and ZebPay, sheds light on the prevailing outlook among Indian crypto traders. Approximately 27% of respondents disclosed that they have sold off 50% of their crypto assets, signaling a significant trend of liquidation possibly triggered by recent market volatility and uncertainty. Moreover, the survey revealed that about 83% of traders have scaled back their trading frequency, indicative of a cautious sentiment prevailing among Indian crypto traders. This caution may be attributed to the regulatory ambiguity surrounding cryptocurrencies in India, with the government yet to provide clear directives for crypto trading and investment. These survey findings mirror the broader sentiment within the Indian crypto community. The current study seeks to explore the volatility of Bitcoin throughout the years, particularly its heightened volatility from 2021 to 2022, followed by a resurgence in 2023.

REVIEW OF LITERATURE

Cryptocurrencies, which utilize encryption for transaction verification, have gained widespread recognition in recent years. Zhang et al. (2023) investigated the impact of Covid-19 regulations in China on cryptocurrency market volatility, noting a decrease in stock market returns during pandemic spikes, accompanied by reduced investor response to regulations. Increased volatility in the cryptocurrency market was observed as investors perceived regulatory measures negatively. Gupta et al. (2022) analyzed the volatility and interdependency of major currencies like Bitcoin, Ether, Litecoin, and XRP from 2017 to 2022, highlighting their high volatility and risky nature for investments. They found a univariate relationship where Ether and XRP influenced Bitcoin returns, and XRP influenced Ether returns, with volatility increasing during negative news for Bitcoin and Ether. Soylu et al. (2020), Abakah et al. (2020), and Sensoy et al. (2021) identified high volatility clustering and long-term memory persistence. Baur et al. (2012) suggested investment in gold as a superior hedge against portfolio risk compared to cryptocurrencies, which exhibit behavior akin to stock markets during negative news (Gupta et al., 2022). Malladi et al. (2021) examined the relationship between returns and volatility of Bitcoin (BTC) and Ripple (XRP), finding higher Bitcoin volatility and negligible causal effects of global stock markets and gold on BTC returns, while XRP was more sensitive to gold prices and stock market volatility. Kyriazis et al. (2019) analyzed volatility across 12 cryptocurrencies, revealing complementary relationships with primary coins and herding behavior. Geuder et al. (2019) explored Bitcoin price dynamics from 2016 to 2018, detecting multiple bubble periods using the PSY methodology and log-periodic power law, indicating recurrent bubble behavior. Feng et al. (2018) assessed crypto currencies' safety as diversification assets for stocks, highlighting their uncorrelated left tails with selected indices. Zhang et al. (2018) investigated the correlation between the cryptocurrency market and the Dow Jones Industrial Average, introducing a Cryptocurrency Composite Index (CCI) showing cross-correlation with the Dow Jones Industrial Average. Jakub (2015) scrutinized whether Bitcoin adheres to the efficient market hypothesis, concluding that Bitcoin prices follow this hypothesis, reacting promptly to new public information.

RESEARCH DESIGN AND METHODOLOGY

The current study delves into the volatility of Bitcoin (BTC), which stands as the pioneering and enduringly dominant currency across various markets and among investors. The investigation spans the daily closing prices from January 1, 2014, to April 30, 2024. This study period has been segmented into smaller intervals, reflecting the heightened volatility of Bitcoin during the years 2021 and 2022. The aim of this paper is to comprehend the volatility dynamics of Bitcoin amidst extreme market conditions. Initially, the study scrutinizes the statistical properties and stationarity of the variable data through measures such as mean, standard deviation, skewness, kurtosis, and the Augmented Dickey-Fuller (ADF) test. Subsequently, a robust regression analysis is conducted, followed by residual diagnostics tests such as serial correlation and heteroskedasticity testing. Thirdly, to further probe volatility, models including GARCH (1, 1), TGARCH (1, 1), and EGARCH (1, 1) are employed.

Objectives of the Study:

- To investigate the persistence of volatility.
- To model the impact of new information arrival on Bitcoin returns.
- To analyze the relationship between trading volume and returns.

DATA ANALYSIS AND RESULTS

The obtained data has been visually represented through a graph illustrating the price trends (Figure 01 – left) and the trading volume trends (Figure 01 – right). Bitcoin prices exhibit both bullish and bearish trends from 2020 to 2024. Additionally, high volatility in trading volumes is observed during this period. Daily returns and log returns have been determined using the following formula:

$$\text{BTC Returns} = [(P_t - P_{t-1}) / P_{t-1}] * 100$$
$$\text{BTC log Returns} = \ln [P_t / P_{t-1}]$$

Where ln represents natural log, P_t represents today's price and P_{t-1} represents yesterday's price.

Figure 01: Bitcoin Price and Trading Volume

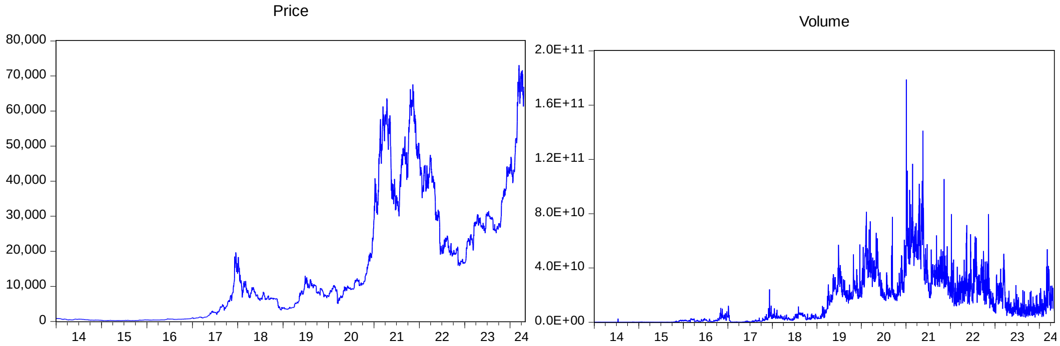

Table 01: Descriptive Statistics

Stats	BTC	BTC Returns
Mean	14,979.81	0.19
Median	7,824.38	0.13
Maximum	73,068.26	33.26
Minimum	172.15	-35.19
Std. Dev.	17,614.85	3.71
Skewness	1.27	0.00
Kurtosis	3.62	10.91
Jarque-Bera	1075.45	9817.53
Probability	0.00*	0.00*

*significant at 515 level

Descriptive statistics presented in Table 1 indicate that the average price of a Bitcoin is 14979, while the average of daily returns is 0. A noticeable increase in Bitcoin prices can be observed, as reflected by the minimum and maximum values. These values also reveal that Bitcoin has provided returns of -35% and 33% during extreme market conditions. The standard deviation values indicate that Bitcoin returns and prices have been highly volatile. Additionally, the high kurtosis values suggest that returns and prices are asymmetrically distributed. The p-values of the Jarque-Bera test indicate that the data is not normally distributed

Table 02: Augmented Dickey Fuller Test

Factor	1% level	5% level	10% level	t-Statistic	Prob.*
Trend and Intercept	-3.960	-3.411	-3.127	-62.908	0.000*
Intercept	-3.432	-2.862	-2.567	-62.914	0.000*

*significant at 515 level

The Augmented Dickey Fuller Test was conducted to assess the stationarity of the variables at both the 99% and 95% significance levels, and the results are presented in Table 2. The confirmation of a unit root in the variable is evident as the p-value is less than 0.05. Regression analysis was then employed to ascertain whether the lagged returns of Bitcoin have predictive power over present or future returns. The stability of the regression model was evaluated using the serial correlation LM test and ARCH heteroskedasticity test. The results in Table 3 indicate that the error terms are devoid of serial correlation but exhibit heteroskedasticity.

Table 03: Residual Test

Test	F-statistic	Obs*R-squared
Heteroskedasticity Test: ARCH	71.803	70.496
	0.000*	0.000*
Breusch-Godfrey Serial Correlation LM Test:	0.841	1.682
	0.432	0.431

*significant at 515 level

Upon confirming the ARCH effect in the variable, the GARCH (1, 1) model was utilized to comprehend the presence of volatility persistence. The model results presented in Table 4 indicate that past errors and variance contribute to present volatility, as the sum of alpha (0.1249) and beta (0.8390) for the full sample period (2014 – 2024) is less than 1 and statistically significant. Notably, during the period 2021, the high beta value (0.9453) suggests significant volatility persistence, whereas the low beta value (0.4013) during 2022 indicates diminished volatility persistence. These findings underscore the varying nature of volatility across time as revealed by the GARCH (1, 1) model. Moreover, the influence of past variance on present variance is pronounced during bullish trends and attenuated during bearish trends.

Table 04: GARCH (1, 1)

GARCH	2014 - 2024		2021		2022	
	Coefficient	Prob.	Coefficient	Prob.	Coefficient	Prob.
C	0.6263	0.0000*	0.0000	0.1729	0.0004	0.0001*
Alpha	0.1249	0.0000*	0.0268	0.0829	0.2273	0.0000*
Beta	0.8390	0.0000*	0.9453	0.0000*	0.4013	0.0008*

TARCH (1,1) model has been estimated to understand the impact of new information on volatility of a variable. The results presented in table 5 indicates that the magnitude of volatility due to negative news shocks is higher than that of a positive news. The positive gamma coefficient (0.048) for the full sample confirms the same. When the asset demonstrate a bullish trend the impact of negative news shocks on volatility (gamma = 0.140) is insignificant which also means there is no evidences of negative news arrivals. When the asset demonstrate a bearish trend the impact of negative news shocks on volatility (gamma = 0.578) is significant and high. This also the economic factors that affected the global economy has had a strong negative impact on the prices of the variable**.**

Table 05: TARCH (1, 1)

TARCH	2014 - 2024		2021		2022	
	Coefficient	Prob.	Coefficient	Prob.	Coefficient	Prob.
C	0.664	0.000	0.001	0.100	0.001	0.000
Alpha	0.104	0.000	-0.055	0.240	-0.006	0.873
Gamma	0.048	0.000	0.140	0.147	0.578	0.000
Beta	0.834	0.000	0.512	0.086	0.277	0.002

*significant at 515 level

Based on the tests conducted, it is evident that negative news arrivals create more turbulence in investors' minds or instill fear. This fear among investors leads to more selling of assets, resulting in price drops.

CONCLUSION

The cryptocurrency market is highly volatile. While past literature suggests that investing in cryptocurrencies is risky and that the market is not influenced by macroeconomic aggregates, the present study indicates that each asset has unique properties, and past findings cannot be generalized. Based on the results obtained, investing in Bitcoin is risky due to its susceptibility to high volatility. However, the nature of volatility varies over time and market conditions. Further studies can be conducted to understand the association between macroeconomic factors and crypto assets during extreme market behaviors. Such studies would provide insights into how various factors are interconnected at different points in time.

SCOPE FOR FUTURE RESEARCH

Exclusive studies aimed at understanding the impact of events such as increases in US interest rates, inflation across several countries, wars, etc., on individual crypto assets would enable fund managers, traders, and investors to make more informed decisions when evaluating their investment choices in cryptocurrencies.

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