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BACKCASTING BITCOIN VOLATILITY: ARCH AND GARCH APPROACHES

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ABSTRACT

Purpose- The primary purpose of this study is to model Bitcoin price volatility and forecast its future price returns using advanced econometric models such as ARCH and GARCH. The study aims to enhance risk management strategies and support informed investment decisions by addressing the time-varying nature of Bitcoin's volatility. The research explores the persistence of volatility shocks and the clustering of price movements to provide insights into market dynamics.
Methodology- This research examines daily Bitcoin closing prices over the period from January 2020 to October 2024. The data was preprocessed to ensure reliability, including applying logarithmic transformations to standardize the data and eliminate trends. Stationarity tests, such as the Augmented Dickey-Fuller (ADF), Phillips-Perron (PP), and KPSS tests, were conducted to confirm the series' stationarity. The ARCH-LM test was utilized to detect volatility clustering which is essential for validating the use of ARCH and GARCH models. Following this, ARIMA models were employed to define mean equations and GARCH models were used to estimate conditional variance and capture volatility dynamics. The dataset was split into training and validation subsets with data from July to October 2024 reserved for validation.
Findings- The findings demonstrate that Bitcoin's price movements exhibit significant volatility clustering and persistence of shocks which are key characteristics effectively captured by ARCH and GARCH models. These models provide valuable insights into the volatility patterns of Bitcoin, supporting their application in cryptocurrency analysis. Despite their robustness, the models face limitations in precise return forecasting during highly volatile periods, suggesting the need for further refinement or integration with advanced approaches.
Conclusion- The research concludes that ARCH and GARCH models are effective tools for understanding and forecasting Bitcoin's volatility. The study underscores the importance of acknowledging volatility persistence and clustering effects when analyzing cryptocurrency price behavior. However, it also highlights areas for improvement in econometric modelling by including the exploration of hybrid models and the integration of macroeconomic factors to enhance forecasting accuracy.

Keywords: Bitcoin, ARCH models, GARCH Models, forecasting, ARIMA models
JEL Codes: C58, G10, G12

1. INTRODUCTION

Bitcoin has emerged as a transformative force in the financial sector with its decentralized structure and significant price volatility. Unlike traditional assets, Bitcoin operates outside the control of central banks and this makes it an attractive alternative investment option. However, this independence also introduces high levels of uncertainty and complexity and requires sophisticated analytical approaches.

This study delves into the volatility patterns of Bitcoin by leveraging econometric tools to model its behavior. The primary focus lies on ARCH and GARCH models which are widely recognized for their capability to capture volatility clustering and persistence in financial time series. The research aims to provide actionable insights for investors, policymakers and researchers navigating the dynamic cryptocurrency landscape by applying these models to recent data.

2. LITERATURE REVIEW

The academic discourse on Bitcoin volatility has grown substantially as it reflects the increasing prominence of cryptocurrencies in global markets. This study builds on these findings by applying ARCH and GARCH models to recent Bitcoin data and offers an updated analysis of its volatility characteristics and forecasting potential. **Naimy and Hayek (2018)** explored Bitcoin's price behavior using GARCH models and demonstrated the effectiveness of EGARCH in accounting for asymmetric volatility. Similarly, **Shen et al. (2019)** evaluated the predictive performance of machine learning techniques compared to GARCH models and concluded that neural networks outperform traditional econometric methods during periods of heightened volatility. Further, **Yıldırım and Bekun (2023)** conducted a comparative study of ARCH, GARCH, and EGARCH models and identified GARCH (1,1) as the most reliable model for predicting Bitcoin's weekly return volatility. **Loureiro (2023)** underscored the role of EGARCH models in capturing asymmetric price movements and offered deeper insights into Bitcoin's unique volatility dynamics. Meanwhile**, Quan et al. (2023)** incorporated macroeconomic variables into GARCH frameworks and revealed how external factors such as inflation and market indices influence Bitcoin's price fluctuations.

3. DATA AND METHODOLOGY

The analysis employs a dataset comprising daily Bitcoin closing prices from January 2020 to October 2024. The data underwent preprocessing to ensure accuracy by including logarithmic transformations to remove trends and standardize the series. Stationarity tests were applied to validate the suitability of the data for time-series modeling with the Augmented Dickey-Fuller (ADF), Phillips-Perron (PP), and KPSS tests confirming the return series' stationarity. Volatility clustering was detected using the ARCH-LM test which is a critical step in establishing the appropriateness of ARCH and GARCH models for analyzing Bitcoin's volatility dynamics.

The ARIMA models were used to define the mean equation of the series and formed a foundational basis for subsequent volatility modeling. GARCH models were then applied to estimate conditional variance and assess time-varying volatility and ensure the analysis accounted for both short-term shocks and long-term persistence. The dataset was divided into training and validation subsets with data from July to October 2024 excluded from the initial analysis to evaluate forecasting performance to enhance the model's robustness.

$$Y_t = c + u_t \tag{1}$$

In the ARCH model's equation (1), $\mathbf{Y_t}$ represents the return series, $\mathbf{c}$ is a constant, and $\mathbf{c + u_t}$ denotes the error term which is assumed to follow a normal distribution with zero mean and variance .

$$\sigma_t^2 = \omega + \alpha\varepsilon_{t-1}^2 + \beta\sigma_{t-1}^2 \tag{2}$$

In the GARCH model's equation (2), $\boldsymbol{\sigma_t^2}$ is the conditional volatility, and $\boldsymbol{\varepsilon_{t-1}^2}$ is squared unexpected returns for the previous period. $\boldsymbol{\omega}$ would be positive always; and $\boldsymbol{\alpha}$ and $\boldsymbol{\beta}$ would be non-negative. $\boldsymbol{\varepsilon_{t-1}^2}$ are derived from a conditional mean equation that could be simple random walk model ($\mathbf{r_t = c + e_t}$), or AR (1) model ($\mathbf{r_t = c + \gamma r_{t-1} + e_t}$), or another ARMA model where rt is the returns from a financial series.

4. FINDINGS

The results reveal significant insights into Bitcoin's volatility dynamics, supported by both statistical analysis and forecasting performance evaluations. Before presenting the tables, it is essential to highlight the key findings and the methodological importance of each component.

The first table demonstrates the predictive performance of ARIMA models across different weeks in October 2024. This analysis provides a clear understanding of the models' strengths and weaknesses in handling volatility by examining actual versus forecasted maximum values and their correlations.

Table 1: Weekly Forecasting for Bitcoin (October 2024)

Week	Model	Maximum (Actual)	Maximum (Forecast)	Correlation
Week 1	ARIMA (1,0,0)	0.0019	0.0010	59.13%
Week 2	ARIMA (4,0,2)	0.005	0.001	43.39%
Week 3	ARIMA (6,0,6)	0.0045	0.0045	85.36%
Week 4	ARIMA (0,0,4)	0.0020	0.0004	71.11%

For Week 1, the ARIMA (1,0,0) model shows a modest match between forecasted and actual maximum values with a correlation coefficient of 59.13% and indicates moderate predictive strength. Week 2's results by using the ARIMA (4,0,2) model highlight a weaker correlation of 43.39% and reflect challenges in forecasting under heightened volatility. Week 3 delivers the strongest correlation (85.36%) with the ARIMA (6,0,6) model and shows its ability to capture patterns during stable periods. Finally, Week 4 with a 71.11% correlation from the ARIMA (0,0,4) model demonstrates decent accuracy, although maximum values remain challenging to predict precisely.

The Table 2 provides descriptive statistics for weekly forecasts and offers an in-depth perspective on the deviations between actual and forecasted values. The performance of the forecasting models is further clarified by analyzing the range of values including maximum, minimum, and standard deviation.

Table 2: Descriptive Statistics for Weekly Forecasts

Statistic	Week 1 (Actual/Forecast)	Week 2 (Actual/Forecast)	Week 3 (Actual/Forecast)	Week 4 (Actual/Forecast)
Maximum	0.0019 / 0.0010	0.005 / 0.001	0.0045 / 0.0045	0.0020 / 0.0004
Minimum	-0.0036 / -0.0028	-0.002 / -0.001	-0.0021 / -0.0003	-0.0021 / -0.0021
Std. Dev.	0.0018 / 0.0014	0.003 / 0.001	0.0019 / 0.0016	0.0015 / 0.0010

The descriptive statistics highlight the disparity between actual and forecasted values across the weeks. In Week 1, the forecast underestimates the range of variation as evidenced by lower standard deviations. Week 2 shows similar discrepancies where the forecast fails to capture extreme values adequately. However, Week 3 aligns more closely particularly in terms of maximum values and standard deviations and indicates the model's improved performance during stable market conditions. Week 4 shows mixed results with minimum values aligning well but a notable underestimation of the maximum value and emphasizes the challenges in capturing peak movements in volatile periods.

5. CONCLUSION

This study aims to model Bitcoin price volatility and forecast future price returns using ARCH and GARCH models. Bitcoin price returns from January 2020 to October 2024 were first analyzed with the ARIMA model for the mean equation followed by the GARCH(1,1) model to study volatility. Unit root tests confirmed the stationarity of the return series and made it suitable for further analysis. The GARCH(1,1) results showed that volatility shocks are persistent and meant that significant shocks in one period influence future periods. While the GARCH(1,1) model proved effective for modeling Bitcoin returns, it had limitations, especially for forecasting return values in the last quarter of 2024. Future research could explore non-linear or hybrid models to better capture Bitcoin's price dynamics and improve prediction accuracy. The study underscores the importance of understanding Bitcoin's volatility and calls for further research to enhance forecasting precision in a volatile market.

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