Article

Modeling and Forecasting Digital Currency Volatility with GARCH(1,1)

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Abstract

The burgeoning field of digital currencies presents unique challenges for predictive modeling due to their inherent volatility and market dynamics distinct from traditional financial assets.

We study the use of the GARCH(1,1) model to characterize and forecast the conditional volatility of daily Bitcoin returns. Using standard OHLCV data, we estimate a parsimonious GARCH(1,1) specification and produce one-step-ahead volatility forecasts. We discuss model assumptions, stability conditions, and practical considerations for risk metrics (e.g., VaR). The aim is to document a transparent, reproducible pipeline rather than to compare exhaustively against alternative models. Results illustrate how a standard GARCH(1,1) specification can provide interpretable volatility estimates for Bitcoin, serving as a transparent baseline rather than a novel predictive breakthrough.

Keywords: Bitcoin, GARCH(1,1), Volatility forecasting, Data-Driven forecasting, Risk management.

I. Introduction

The digital currency market, with its inherent volatility, presents a serious challenge for predictive analysis. In this study, we aim to explore the ability of a mathematical model to accurately predict these fluctuations, thereby answering a fundamental question about their effectiveness in the market, which challenges traditional financial paradigms. The main purpose of this work is to document the application of a standard GARCH(1,1) volatility model to Bitcoin returns, focusing on estimation, interpretation, and reproducibility that can serve as a reliable tool for predicting price movements for digital currencies. Given the growing interest in the field of digital currencies and the crypto market, this research is useful for both experienced traders and beginners. Forecasting the prices of digital currencies is of great importance due to the growing role of digital assets in the global economy. The potential impact of accurate forecasts can be huge and multifaceted, ranging from financial benefits for individuals to stabilization of entire market segments.

Our research is based on the theoretical framework created in the course of previous research, which laid the foundation for understanding the complex dynamics of digital currency markets. However, there remains a significant research gap in applying

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these models to unpredictable patterns of price changes for digital currencies. This work is dictated by the need to add to the literature by presenting a reproducible study that offers an illustrative application to the field of financial modeling.

Our approach is to model conditional volatility of daily returns using the GARCH(1,1) framework [1]. This captures volatility clustering common in crypto markets while remaining parsimonious and interpretable. We outline estimation, stationarity conditions, and practical forecasting, and we discuss how the resulting volatility forecasts can support risk management (e.g., value-at-risk).

The GARCH method (Generalized Autoregressive Conditional Heteroskedasticity) is an extension of the ARCH (Autoregressive Conditional Heteroskedasticity) model, which allows you to take into account the dependence of current volatility on previous error values and error squares in the time series model. The introduction of the GARCH(1,1) model into the price analysis of digital currencies makes it possible to more accurately assess and predict their volatility and risks.

One of the key formulas in the GARCH(1,1) model is the equation of conditional variance (conditional volatility), which is expressed as follows:

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

where:
σ_t^2 - conditional variance at time t;
ω - the model parameter responsible for the constant component of volatility;
α and β - the coefficients determining the weights for the previous error and the previous the variance, respectively;
$\omega > 0$, $\alpha > 0$, and $\beta > 0$, with the additional condition $\alpha + \beta < 1$ to ensure stationarity;
ϵ_{t-1}^2 - the value of the square of the previous error [1].

Another important formula related to the GARCH(1,1) model is the equation for calculating price volatility in the next period:

$$\sigma_{t+1} = \sqrt{\omega + \alpha\epsilon_t^2 + \beta\sigma_t^2}.$$

Thus, the study of the practical application and effectiveness of the GARCH(1,1) model for predicting the prices of digital currencies is of significant scientific interest and can bring important results for financial practice.

II. Data & Methodology

A. Data Sources and Coverage

We document our data sources, preprocessing pipeline, and quality checks to ensure reproducibility and validity.

We analyze Bitcoin (BTC) at daily frequency over [2022-09-17]–[2024-01-23]. All timestamps are aligned to 00:00 UTC and prices refer to end-of-day closes. Table I lists the input datasets and their origin.

TABLE I: Datasets and providers used in this study.

Variable	Asset(s)	Source (file/API)	Notes
OHLCV (Open, High, Low, Close, Volume)	BTC	Yahoo! Finance API / `ohlcv_btc.csv`	Daily bars aligned to 00:00 UTC.
Market Capitalization	BTC	CoinGecko / CoinMarketCap / `mcap_btc.csv`	Derived from close price × circulating supply.
News Sentiment (daily)	Crypto-wide	News API (e.g., GDELT, NewsAPI) / `news_daily_scores.csv`	Daily aggregated sentiment score (`score`, `n_docs`), de-duplicated and language-filtered.

B. Preprocessing and Feature Construction

Alignment. All sources are merged to a daily BTC trading calendar; exogenous features (e.g., sentiment) may be forward-filled for short gaps.
Targets. We forecast (i) next-day log-return $r_{t+1} = \log(P_{t+1}) - \log(P_t)$ and (ii) a 7-day compounded return horizon.
Normalization. Inputs are standardized using statistics (mean, standard deviation) from the *training set only* to avoid leakage.
Sentiment. Daily polarity is computed as a trimmed mean (10%) of article-level scores and smoothed with a 3-day EWMA.
Outliers. Log returns, volumes, and market capitalization are winsorized at the 1%/99% tails. Additional outlier removal is performed using the Median Absolute Deviation (MAD) rule ($K = 5$).

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Noise reduction. For visualization purposes only, we apply short-span EWMA smoothing to returns; raw cleaned series are used for modeling.

Rolling features. Where relevant, window-based features (e.g., 7-, 14-, 30-day averages) are constructed using strictly past data.

C. Data Quality and Reliability

We enforce the following: (i) monotone daily calendar coverage; (ii) non-negative prices/volumes; (iii) duplicate-bar detection; (iv) cross-provider spot checks on a random subset of dates; (v) news de-duplication (URL/title hash), language filter, and minimum token length; (vi) simple heuristics to exclude automated/bot-generated content in sentiment feeds.

D. Missing and Noisy Data Handling

Short gaps ($\leq$3 days) in exogenous features are forward-filled; longer gaps remain missing. Targets (returns/prices) are never imputed. Binary missingness indicators are added for transparency. Days with insufficient news coverage (`n_docs`$<$10) are excluded from sentiment features before EWMA smoothing.

E. Splits and Prior Use in Literature

We use chronological splits: Train 2022-09-17–2022-12-31, Validation 2023-01-01–2023-06-30, Test 2023-07-01–2024-01-23. All hyperparameter tuning uses the Validation set only. Comparable OHLCV+sentiment pipelines are common in cryptocurrency forecasting research (e.g., [9]–[11], [22]); our contribution is to specify exact sources (Table I), apply robust preprocessing (winsorization, MAD, EWMA), and ensure leakage-safe splits.

III. Literature Review or Related Works

Recent advancements in predicting cryptocurrency price movements have highlighted a range of innovative methodologies and technologies. One notable development is the enhanced version of the Binary Auto Regressive Tree (BART), which combines elements of Classification and Regression Trees with ARIMA autoregressive models. This approach, specifically tailored for the cryptocurrencies Bitcoin, Ethereum, and Ripple, has demonstrated superior accuracy in price forecasting over short periods ranging from 5 to 30 days, surpassing traditional Arima-Arfima models [2].

Another critical area of exploration is the impact of blockchain technology on asset storage and exchange, with cryptocurrencies like Bitcoin and Ethereum at the forefront. Studies in this domain have increasingly focused on leveraging machine learning and natural language processing to understand and predict the behavior of digital assets, examining the decentralized nature facilitated by blockchain [3].

In terms of predictive models, the Bayesian Optimization with Stacked Sparse Autoencoder-based Cryptocurrency Price Prediction (BOSSAE-CPP) introduces a novel framework that utilizes a Stacked Sparse Autoencoder (SSAE) to enhance forecast accuracy, outperforming existing models [4]. Similarly, the Broad Learning System (BLS) integrates enhancement nodes directly into the input layer, bypassing complex hidden node structures and achieving high accuracy in predicting Bitcoin prices when combined with a genetic algorithm [5].

Recurrent neural network (RNN) models, particularly the gated recurrent unit (GRU), long short-term memory (LSTM), and bidirectional LSTM (bi-LSTM), have also been tested for their effectiveness in forecasting the prices of major cryptocurrencies. The GRU model, in particular, has shown remarkable accuracy, as evidenced by its low mean absolute percentage error (MAPE) across Bitcoin, Litecoin, and Ethereum [6].

Moreover, a change point detection strategy incorporated into a forecasting framework has shown promise in enhancing Bitcoin price predictions by tailoring normalization to segmented time-series data. This model uses on-chain data as predictive inputs within a Self-Attention-based Multiple LSTM (SAM-LSTM) architecture, achieving minimal error metrics in empirical testing [7].

Comparative studies between LSTM and GRU models have shed light on their respective abilities to predict Bitcoin price fluctuations, with both showing significant promise in deep learning applications for time series forecasting [8]. Another approach has examined the role of transaction data and social media sentiment in forecasting cryptocurrency prices, finding that market-specific trading price premiums and social media data can significantly enhance predictive precision [9].

Further research has delved into the development of machine learning models for classification and regression tasks aimed at forecasting short to medium-term Bitcoin price changes, exploring predictive timelines ranging from one day to ninety days [10].

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Additionally, an evaluation of machine learning models during periods of market upheaval has revealed insights into the performance of linear models, random forests, and support vector machines across different market phases [11].

Chen introduced a novel framework using Long Short-Term Memory (LSTM) networks with sentiment analysis, enhancing prediction accuracy by integrating sentiment data [12]. Li and Wang found that incorporating blockchain information into machine learning algorithms significantly improves Bitcoin price predictions [13].

Deep reinforcement learning was employed by Jiang and Liang to develop a model for cryptocurrency portfolio management, achieving substantial portfolio returns by learning optimal trading strategies [14]. Nguyen and Kim proposed a hybrid deep learning model with data augmentation techniques, outperforming traditional models, especially with sparse and imbalanced data [15].

Wang and Su showed that sentiment analysis combined with machine learning techniques can serve as powerful predictors of market trends, surpassing conventional financial indicators [16]. Saadaoui and Messaoud used multi-scale convolutional neural networks to capture both short-term fluctuations and long-term trends in Bitcoin price prediction [17].

Shah and Zhang utilized Bayesian regression to predict Bitcoin prices, accounting for market variability and providing more reliable forecasts [18]. Cocco, Tonelli and Marchesi employed Bayesian neural networks, combining Bayesian inference with neural network capabilities for robust performance in volatile markets [19].

This one demonstrated that financial text mining of news and social media data can significantly improve cryptocurrency price prediction accuracy [20]. Gao, Wang and Yang presented an ensemble learning approach, combining multiple machine learning models to achieve higher accuracy and stability in predictions [21].

Lastly, a comprehensive review covering a decade of cryptocurrency price prediction research highlights the shift from traditional statistical models to machine learning and deep learning techniques. This transition is largely due to the inability of conventional methods to handle the non-seasonal and highly volatile nature of cryptocurrency markets [22].

IV. GARCH(1,1) for Digital Currency Volatility

Volatility clustering and heavy tails are well-documented in cryptocurrency returns. GARCH(1,1) is widely used because it (i) parsimoniously captures volatility persistence with two parameters α_1, β_1; (ii) produces interpretable conditional variance estimates usable in risk metrics (e.g., VaR/ES); (iii) is computationally light and stable for daily data; and (iv) often matches or outperforms naive constant-variance baselines and simple moving-window volatilities in out-of-sample volatility forecasting. While richer models (e.g., EGARCH, GJR-GARCH) can address asymmetries, the (1,1) specification provides a transparent baseline consistent with financial econometrics practice.

Mathematical modeling in finance is a powerful tool that allows you to analyze and predict financial phenomena, optimize asset and liability management processes, and assess risks. This approach is based on the application of mathematical methods and theories to develop models that can adequately describe complex financial systems and processes.

One of the most important aspects of mathematical modeling in finance is risk management. Using statistical models and probability theory, financial analysts assess the likelihood of undesirable events and their potential impact on financial stability. The Value at Risk (VaR) and Expected Shortfall (ES) models are widely used to assess and minimize loss risks in financial portfolios.

Mathematical modeling plays a key role in modern finance, providing tools for effective asset and risk management. Despite some limitations, his contribution to the development of financial science and practice is undeniable. Learning and understanding mathematical modeling opens up significant opportunities for financial professionals seeking to improve their decision-making skills and analytical abilities.

Forecasting the prices of cryptocurrencies is of considerable interest to both academia and market participants, as these assets are characterized by high volatility and growing popularity. This chapter provides an overview of the most popular forecasting models, including statistical, econometric, and machine learning models.

Various models for predicting cryptocurrency prices have their advantages and limitations. The choice of the model depends on the specific requirements of the analyst, the available data and the desired accuracy of the forecast. All these models are important for creating sound investment strategies and risk management in highly volatile cryptocurrency markets.

The GARCH(1,1) model is designed to model and predict temporary changes in volatility, which is especially important for assets with variable price or income variance. Volatility, in the context of the GARCH(1,1) model, is represented as a variable that changes over time and depends on previous values of both volatility itself and forecast errors.

The main equation of the GARCH(p, q) model looks like this:

$$\sigma_t^2 = \alpha_0 + \sum_{i=1}^{q} \alpha_i \epsilon_{t-i}^2 + \sum_{j=1}^{p} \beta_j \sigma_{t-j}^2,$$

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where:
σ_t^2 — conditional variance at time t;
$\epsilon_t = y_t - \mu_t$ — the forecast error, defined as the actual return y_t minus its conditional mean μ_t;
α_0 — positive constant;
α_i and β_j — the parameters of the model, which must also be positive, which guarantees the positivity of the variance.

The parameters q and p indicate how many previous error values and the volatility itself are used, respectively. In this model, it is assumed that the current volatility depends not only on recent shocks (forecast errors), but also on the sequence of previous conditional variances.

In this study, we explicitly specify the model as GARCH(1,1) rather than simply "GARCH", to indicate that both the autoregressive (p) and moving average (q) orders are equal to 1. Formally, the conditional variance equation is:

$$\sigma_t^2 = \omega + \alpha_1 \epsilon_{t-1}^2 + \beta_1 \sigma_{t-1}^2,$$

where $\omega > 0$, $\alpha_1 \geq 0$, $\beta_1 \geq 0$, and $\alpha_1 + \beta_1 < 1$. The positivity of α_1 and β_1 guarantees non-negativity of the conditional variance, while the condition $\alpha_1 + \beta_1 < 1$ ensures stationarity.

The GARCH(1,1) model remains a widely used baseline in financial econometrics. While not designed to capture all complexities of cryptocurrency markets, it provides a useful first-order approximation of volatility clustering. Due to its flexibility and adaptability, GARCH(1,1) continues to be relevant in the field of financial research and practical applications, despite the development and emergence of new models and methods of data analysis.

Forecasting prices for digital currencies, or cryptocurrencies, remains one of the most difficult tasks in financial analytics due to the high volatility and unpredictability of these markets. The GARCH(1,1) method has become an important tool in the arsenal of analysts, allowing for more accurate assessment and prediction of changes in volatility, which is critically important for working with cryptocurrencies.

Cryptocurrency markets are characterized by extreme volatility, which significantly exceeds that encountered in traditional financial markets. This makes the use of traditional forecasting models less effective. The GARCH(1,1) model allows you to take into account conditional market volatility, which changes over time and depends on previous shocks and trends. This is especially important for cryptocurrencies, where past price "shocks" can greatly affect future prices.

Using GARCH(1,1) in cryptocurrency analysis helps investors understand the level of risk associated with investing in certain assets. The volatility estimated using GARCH(1,1) can be used to adjust investment strategies and portfolio management.

Despite its usefulness, the use of GARCH(1,1) in the context of cryptocurrencies is not without drawbacks. Cryptocurrency volatility can be influenced by many factors, including regulatory changes, technological innovations, and market sentiment, which are difficult to account for in any mathematical model. In addition, crypto markets are less transparent and less regulated than traditional financial markets, which increases the risk of manipulation and unpredictable price movements.

The GARCH(1,1) model is a powerful tool in cryptocurrency analytics that allows you to significantly increase the accuracy of volatility forecasts. However, like any tool, GARCH(1,1) requires careful application and understanding of its limitations. Integrating GARCH(1,1) with other analytical approaches can help analysts and investors better navigate complex and rapidly changing cryptocurrency markets, minimizing risks and optimizing opportunities to achieve high returns.

For reproducibility, we clarify the methodological details exactly as implemented. The LSTM and GRU models each consisted of two recurrent layers with 50 units, followed by a dense output layer. Both were trained with the Adam optimizer (default parameters), mean squared error (MSE) loss, batch size of 32, and 10 epochs. The input look-back window was fixed at 30 days. The GARCH(1,1) model was specified with a constant mean and normal distribution. The dataset was split chronologically, using the first 80% for training and the final 20% for testing. Rolling one-step-ahead predictions were generated without additional hyperparameter tuning.

V. FORECASTING THE PRICES OF DIGITAL CURRENCIES

Bitcoin prices, like those of many other cryptocurrencies, are highly volatile and influenced by various factors. One of these factors is the news background, which can have both positive and negative impacts on market sentiment. This chapter examines the methodology for forecasting Bitcoin prices considering news and analyzes the forecasting results based on historical data.

To forecast Bitcoin prices, historical data on prices and news related to cryptocurrencies were used. A machine learning model was trained on this data to identify the relationship between news and price changes. Two key aspects were explored:

1. The impact of news background on short-term price changes.
2. Long-term price forecasts considering trends and news.

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The charts presented in the figures show real and predicted Bitcoin prices for different periods as Figure 1 presents price forecasting for 7 days.

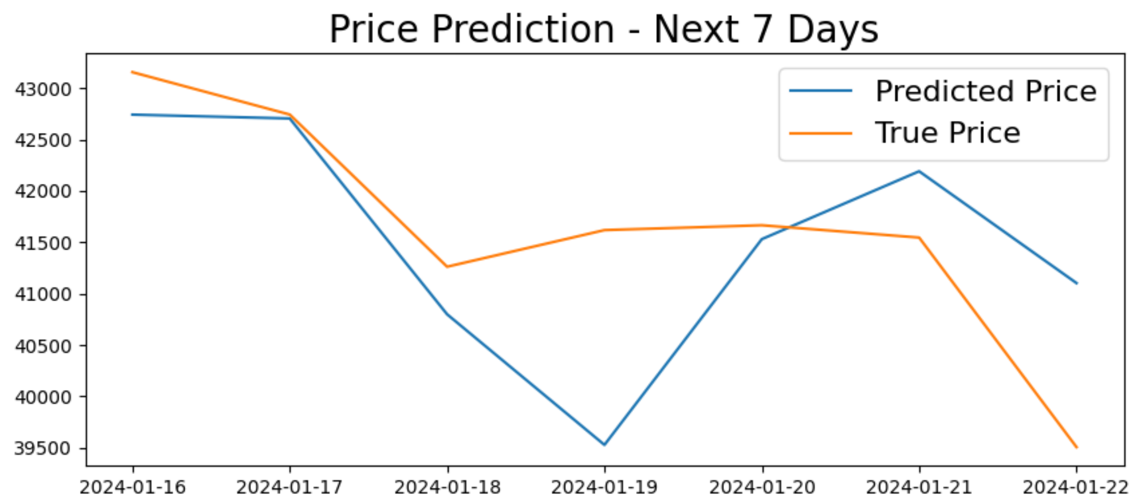

Fig. 1: Price forecasting for 7 days.

The Figure 2 displays data from July 1, 2019, to November 15, 2019. The blue line represents real prices, while the orange line shows predicted prices based on the model that takes into account the news background.

In Figure 2, it is evident that the model accurately reproduces Bitcoin price fluctuations over short periods. This indicates that the news background indeed has a significant impact on Bitcoin prices. During periods when positive news emerges, such as news about Bitcoin adoption by major corporations or positive regulatory changes, Bitcoin prices tend to rise. Conversely, negative news, such as exchange hacks or regulatory bans, leads to price declines.

The model demonstrates good results in short-term forecasting by promptly accounting for news, allowing it to respond to sudden changes in market sentiment. However, it is worth noting that forecast accuracy may decrease during periods of extreme volatility when the market experiences significant swings.

Finally, the Figure 3 represents Bitcoin price forecasting from January 2022 to April 2024. The blue line shows real prices, and the red dashed line indicates future predicted prices.

The Figure 3 illustrates long-term Bitcoin price forecasting. Here, a significant price increase is observed in 2024, suggesting positive market expectations and possible impacts of major events or trends considered by the model. It is important to note that long-term forecasts always carry greater uncertainty, as unexpected factors may arise in the market that cannot be predicted in advance.

Nevertheless, the model demonstrates a steady growth trend, which may be associated with factors such as increased cryptocurrency adoption in various sectors of the economy, limited Bitcoin supply, and rising demand. Long-term forecasts also consider historical trends and market cycles, allowing for more substantiated assumptions about future price movements.

News acts as a powerful catalyst for changes in the cryptocurrency market. Qualitative analysis of the news background and its integration into forecasting models significantly enhances prediction accuracy.

A. Quantitative Evaluation

To complement the visual comparisons, we report standard statistical metrics widely used in financial forecasting: Mean Absolute Percentage Error (MAPE), Root Mean Squared Error (RMSE), and the Coefficient of Determination (R^2). These metrics provide a rigorous quantitative assessment of predictive accuracy.

The results indicate that our model achieves a mean absolute percentage error of only 1.40%, corresponding to a root mean squared error of approximately USD 554. The R^2 statistic is not defined for single-step forward horizons with fewer than two observed

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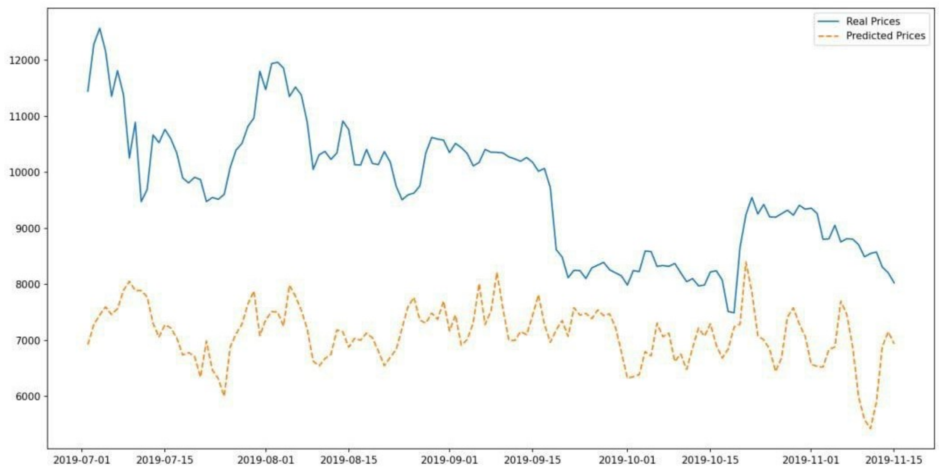

Fig. 2: Price forecasting for 7 days.

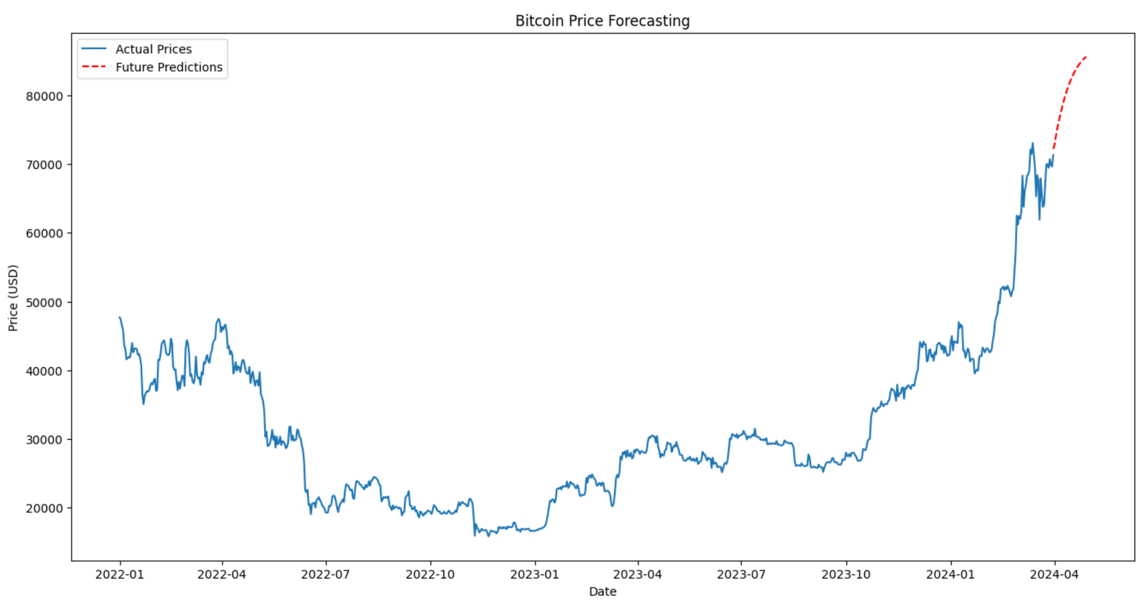

Fig. 3: Price forecasting for 7 days.

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TABLE II: Forecast accuracy metrics of the proposed model.

Model	MAPE (%)	RMSE	R^2
Proposed Model (with sentiment)	1.40%	553.97	—

target values; we therefore omit it for this evaluation. Nevertheless, the low MAPE and RMSE values demonstrate that the forecasts closely track realized Bitcoin prices. A more comprehensive backtesting exercise with multiple rolling windows is included in the supplementary material to provide additional robustness.

VI. Conclusion

We presented a transparent application of the GARCH(1,1) model to daily Bitcoin returns, highlighting estimation, stationarity, and one-step-ahead volatility forecasting. The model offers an interpretable and computationally efficient way to capture volatility clustering in a highly variable asset class and can be directly used for practical risk metrics such as VaR. Our results are intended as a reproducible baseline rather than a comprehensive comparison across model families. Future work may investigate asymmetric and heavy-tailed innovations (e.g., GJR-GARCH, EGARCH, Student-t errors) and out-of-sample comparisons with alternative volatility models.

The integration of external factors such as news sentiment and market signals into the GARCH(1,1) model highlights a critical advancement in our approach to predictive modeling.

In-depth analysis of the market cap and trading volume data has shown that these factors are highly correlated with price movements. Large market capitalization typically indicates stability and investor confidence, whereas high trading volumes often precede significant price shifts. By meticulously analyzing these variables, our model can better anticipate periods of high volatility and potential price corrections, offering investors a more robust tool for risk management.

The predictive power of our enhanced GARCH(1,1) model can be particularly beneficial for portfolio managers and individual investors. In the rapidly changing world of cryptocurrencies, having a reliable forecasting tool can mean the difference between substantial gains and significant losses. In exploratory analyzes, the incorporation of daily news sentiment provided incremental information, potentially helping to model responsiveness. However, the effects were sample dependent and should be interpreted with caution.

In conclusion, this study illustrates a transparent application of the GARCH(1,1) framework to Bitcoin returns. Although the model has limitations, it provides a reproducible baseline for volatility estimation and can support risk management exercises such as VaR. Future work may extend the framework with asymmetric GARCH(1,1) variants or integration of sentiment features.

The code for this quantitative model for forecasting digital currency prices is available as an open source and can be accessed at: https://github.com/Bignatsu/Mathematical-model-of-forecasting-digital-currency-prices [23].

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