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Bitcoin Price Projections Using Geometric Brownian Motion: An Empirical Study of 2020–2024

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ABSTRACT

This study employs the Geometric Brownian Motion (GBM) model to forecast Bitcoin prices from 2020 to 2024. Given Bitcoin's notorious volatility and unpredictability, accurate forecasting models are essential for investors, traders, and policymakers. The GBM model, known for its ability to capture stochastic price movements, is applied to historical Bitcoin price data to estimate drift and volatility parameters. The results indicate that the GBM model provides moderate predictive accuracy, with a mean absolute error (MAE) of 10% and a root mean squared percentage error (RMSPE) of 15%. Although the model captures the general trend of Bitcoin prices, it underestimates extreme price movements during periods of high volatility. The study concludes that the GBM model is a useful tool for forecasting Bitcoin prices, although its limitations should be considered in risk management and investment strategies.

Keywords: Bitcoin, Geometric Brownian Motion, Cryptocurrency, Price Forecasting, Volatility, Stochastic Modeling

INTRODUCTION

Cryptocurrencies, particularly Bitcoin, have emerged as transformative assets in the global financial landscape. Since its inception in 2009, Bitcoin has grown from a niche digital currency to a major financial asset, attracting the attention of investors, traders, and policymakers. Its decentralized nature, limited supply, and high volatility make it both an attractive investment and a challenging asset to predict. The period from 2020 to 2024 has been particularly significant for Bitcoin, marked by unprecedented price fluctuations driven by macroeconomic events such as the COVID-19 pandemic, regulatory developments, and technological advancements in blockchain technology.

The extreme volatility of Bitcoin prices poses significant challenges for market participants. Unlike traditional financial assets, Bitcoin price movements are influenced by a wide range of factors, including market sentiment, technological developments, regulatory news, and macroeconomic trends. This unpredictability requires the development of robust forecasting models that can provide reliable predictions to guide investment decisions and risk management strategies.

Forecasting the price of financial assets is a critical component of investment strategy and risk management. In the context of cryptocurrencies, accurate price forecasting is particularly important due to the high volatility and speculative nature of these assets. Investors and traders rely on forecasts to identify potential entry and exit points, optimize portfolio allocation, and manage risk. Policymakers also benefit from accurate forecasts, as they provide insight into market dynamics and help in the formulation of regulatory policies.

Traditional financial forecasting models, such as the autoregressive integrated moving average (ARIMA) and generalized autoregressive conditional heteroskedasticity (GARCH), have been widely used in stock markets. However, these models often fail when applied to cryptocurrencies due to their unique characteristics, such as high volatility, nonstationarity, and sensitivity to external factors. This has led to the exploration of alternative models, such as Geometric Brownian Motion (GBM), which are better suited to capture the stochastic nature of cryptocurrency prices.

The literature on Bitcoin price prediction is extensive, with researchers exploring various models and techniques to predict its price movements. Traditional time series models, such as ARIMA and GARCH, have been widely used, but their applicability to Bitcoin is limited because of the asset's unique characteristics. For instance, ARIMA models assume linearity and stationarity, which are often violated in Bitcoin's price data due to its high volatility and non-stationary nature [4]. Furthermore, [16] reviews existing research (2010–2020) on price prediction using statistical and machine learning (ML) methods, such as regression models, support vector machines, neural networks, and deep learning. The literature survey notes that statistical approaches struggle with cryptocurrency prediction due to the lack of seasonal patterns and restrictive assumptions, making ML more suitable.

GBM is a stochastic process that has been extensively used in financial modeling, particularly for stock price forecasting. For further literature see [6, 13, 18, 23]. The model assumes that the logarithm of asset prices follows a Brownian motion with constant drift and volatility. This assumption makes GBM particularly suitable for modeling assets with continuous price movements and random fluctuations, such as stocks and cryptocurrencies. The GBM model is particularly well-suited for forecasting Bitcoin prices due to its ability to capture the stochastic nature of price movements. Bitcoin's price behavior is characterized by high volatility and random fluctuations, which align with the assumptions of the GBM model. Unlike traditional models that assume constant volatility or linear trends, GBM allows for the modeling of continuous, random price movements, making it a more realistic representation of Bitcoin's price dynamics.

Several studies have highlighted the effectiveness of GBM in financial forecasting. For example,[22] and [9] demonstrated the model's utility in simulating stock prices and evaluating investment strategies. Similarly, [1] applied GBM to forecast Bitcoin prices, achieving improved accuracy by combining it with machine learning techniques. These studies underscore the potential of GBM as a reliable forecasting tool for highly volatile assets like Bitcoin.

Moreover, the use of GBM in financial markets is well-established, with applications ranging from stock price forecasting to options pricing. The Black-Scholes model, one of the most widely used models in finance, is based on the GBM framework [5]. This further underscores the model's credibility and reliability in financial forecasting. Despite the growing body of literature on Bitcoin price forecasting, there is a lack of comprehensive studies that apply GBM to forecast Bitcoin prices over an extended period, particularly during times of significant market turbulence. This study aims to fill this gap by applying the GBM model to forecast Bitcoin prices from 2020 to 2024, a period marked by unprecedented market events such as the COVID-19 pandemic and regulatory developments.

The study's contribution lies in its rigorous application of the GBM model to Bitcoin price forecasting, providing valuable insights into the model's strengths and limitations. By comparing the model's forecasts with actual Bitcoin prices, the study offers a critical evaluation of GBM's predictive accuracy and reliability. The findings are expected to inform investment strategies, risk management practices, and regulatory policies in the cryptocurrency market.

METHODOLOGY

Data Collection

The study utilizes daily closing prices of Bitcoin from January 1, 2020, to April 30, 2024, sourced from https://www.investing.com. The dataset includes variables such as opening price, closing price, high, low, volume, and percentage change. The choice of this time frame is strategic, as it encompasses significant market events that have influenced Bitcoin's price behavior, such as the COVID-19 pandemic and the subsequent market recovery.

The data collection process involved extracting historical price data from a reliable financial data provider, ensuring the accuracy and completeness of the dataset. The dataset was then cleaned and preprocessed to remove any inconsistencies or missing values, ensuring the robustness of the analysis. Recent studies have emphasized the importance of high-quality data in financial forecasting, particularly in volatile markets like cryptocurrencies [20].

The dataset's variables were carefully selected to capture the essential aspects of Bitcoin's price movements, including daily price fluctuations and trading volume. This comprehensive dataset provides a solid foundation for the application of the GBM model and the subsequent analysis.

Data Preprocessing

The data was preprocessed by handling missing values, normalizing prices using the natural logarithm, computing daily log returns, and splitting the data into training (2020-2022) and testing (2023-2024) sets. Data preprocessing is a critical step in financial modeling, as it ensures that the data is suitable for analysis and modeling.

Missing values were addressed using interpolation techniques, ensuring that the dataset remained complete and consistent. The normalization of prices using the natural logarithm helped stabilize the data and reduce the impact of outliers, making it more suitable for the GBM model. Recent research has highlighted the importance of data normalization in financial forecasting, particularly in highly volatile markets [2, 25].

The computation of daily log returns provided a measure of daily price fluctuations, which is essential for estimating the drift and volatility parameters of the GBM model. The data was then split into training and testing sets to evaluate the model's performance on unseen data, a common practice in financial forecasting studies [8, 12].

Geometric Brownian Motion (Gbm)

The Geometric Brownian Motion (GBM) model is a Stochastic Differential Equation (SDE) used to describe the evolution of asset prices over time. The GBM model is given by:

$$dS(t) = \mu S(t)dt + \sigma S(t)dW(t)$$

where; $S(t)$ is the asset price at time t, μ is the drift coefficient (average return), σ is the volatility coefficient (standard deviation of returns), and $dW(t)$ is a Wiener process (Brownian motion), representing the random noise component.

To solve this SDE, we need to find an expression for $S(t)$ in terms of its initial value $S(0)$. The GBM equation is a stochastic differential equation that can be solved using Itô's Lemma . First, Itô's Lemma is applied to the logarithm of the asset price $\ln S(t)$ and let $Y(t) = \ln S(t)$.

$$dY(t) = \frac{\partial Y}{\partial S} dS(t) + \frac{1}{2}\frac{\partial^2 Y}{\partial S^2}\left(dS(t)\right)^2 \qquad (2)$$

Substituting $Y(t) = \ln S(t)$, implies that:

$$\frac{\partial Y}{\partial S} = \frac{1}{S(t)}, \quad \frac{\partial^2 Y}{\partial S^2} = -\frac{1}{S(t)^2} \qquad (3)$$

Now, substituting equation (3) into Itô's Lemma:

$$dY(t) = \frac{1}{S(t)} dS(t) - \frac{1}{2}\frac{1}{S(t)^2}\left(dS(t)\right)^2 \qquad (4)$$

Substituting $dS(t)$ from equation (1) into the expression for $dY(t)$ in equation(4), then

$$dY(t) = \frac{1}{S(t)}\left(\mu S(t)dt + \sigma S(t)dW(t)\right) - \frac{1}{2}\frac{1}{S(t)^2}\left(\mu S(t)dt + \sigma S(t)dW(t)\right)^2 \quad (5)$$

Simplifying the terms in equation (5),

$$dY(t) = \mu dt + \sigma dW(t) - \frac{1}{2}\frac{1}{S(t)^2}\left(\mu^2 S(t)^2 (dt)^2 + 2\mu\sigma S(t)^2 dt dW(t) + \sigma^2 S(t)^2 \left(dW(t)\right)^2\right) \quad (6)$$

Using the Itô's Rules $(dt)^2 = 0$, $dt \cdot dW(t) = 0$, and $\left(dW(t)\right)^2 = dt$ to simplify equation (6).

$$dY(t) = \mu dt + \sigma dW(t) - \frac{1}{2}\frac{1}{S(t)^2}(\sigma^2 S(t)^2 dt) \quad (7)$$

A further simplification and combining the terms in equation (7) Simplify further:

$$dY(t) = \mu dt + \sigma dW(t) - \frac{1}{2}\sigma^2 dt$$

Combine the dt terms:

$$dY(t) = \left(\mu - \frac{1}{2}\sigma^2\right)dt + \sigma dW(t) \quad (8)$$

Integrating both sides of equation (8) from 0 to t:

$$\int_0^t dY(t) = \int_0^t \left(\mu - \frac{1}{2}\sigma^2\right)dt + \int_0^t \sigma\, dW(t) \quad (9)$$

This equation (9) simplifies to:

$$Y(t) - Y(0) = \left(\mu - \frac{1}{2}\sigma^2\right)t + \sigma W(t) \quad (10)$$

Applying the initial values, $Y(t) = \ln S(t)$ and $Y(0) = \ln S(0)$, then

$$\ln S(t) - \ln S(0) = \left(\mu - \frac{1}{2}\sigma^2\right)t + \sigma W(t) \quad (11)$$

Exponentiation of both sides of equation (11) to solve for $S(t)$, then

$$S(t) = S(0)\exp\left\{\left(\mu - \frac{1}{2}\sigma^2\right)t + \sigma W(t)\right\} \quad (12)$$

Equation (12) is the solution to the GBM model. It describes the asset price $S(t)$ at time t in terms of its initial price $S(0)$, the drift μ, the volatility σ, and the Wiener process $W(t)$.

The solution $S(t)$ consists of the following two components which are; a deterministic Component $\left(\mu - \frac{1}{2}\sigma^2\right)t$ representing the expected growth rate of the asset price over time, adjusted for volatility and Stochastic

Component $\sigma W(t)$ representing the random fluctuations in the asset price due to market volatility.

The term $\frac{1}{2}\sigma^2$ is known as the Itô correction term, which arises from the stochastic nature of the Wiener process.

Parameter Estimation

The drift (μ) and volatility (σ) parameters were estimated using historical Bitcoin price data. The drift parameter was calculated as the mean of daily log returns, while volatility was derived from the standard deviation of these returns. Parameter estimation is a critical step in the application of the GBM model, as it directly influences the accuracy of the forecasts.

The drift parameter captures the overall trend in Bitcoin's price movements, while the volatility parameter reflects the degree of price fluctuations. These parameters were estimated using historical data from the training set, ensuring that the model was calibrated to reflect Bitcoin's price behavior accurately. Recent studies have emphasized the importance of robust parameter estimation in financial modeling, particularly in volatile markets [10].

The estimated drift parameter (μ) was -0.0013, indicating a slight negative trend in daily returns, while the volatility parameter (σ) was 0.0358, reflecting the high volatility of Bitcoin prices. These parameters were used to simulate future price paths using the GBM model, providing a probabilistic forecast of Bitcoin's future price movements.

Gbm Simulation

The GBM model was simulated using Monte Carlo methods to generate multiple potential price paths for Bitcoin from May 1, 2024, to April 30, 2026. The simulation was run 10,000 times to account for the inherent uncertainty in Bitcoin's price movements. Monte Carlo simulation is a widely used technique in financial modeling, as it allows for the generation of a range of possible outcomes based on probabilistic inputs.

The simulation process involved defining the GBM model's parameters, including drift, volatility, and the time step, and then generating random price paths using the model's stochastic differential equation. The simulation was repeated 10,000 times to produce a distribution of potential future prices, providing a comprehensive view of the possible outcomes. Recent studies have highlighted the effectiveness of Monte Carlo simulation in financial forecasting, particularly in highly volatile markets [15, 17].

The simulation results provided valuable insights into the potential future price movements of Bitcoin, allowing for the assessment of investment risks and opportunities. The GBM model's ability to generate a range of possible price paths makes it a useful tool for investors and financial analysts navigating the volatile cryptocurrency market.

RESULTS AND DISCUSSION

Parameter Estimation

The estimated drift parameter (μ) was -0.0013, indicating a slight negative trend in daily returns, while the volatility parameter (σ) was 0.0358, reflecting the high volatility of Bitcoin prices. These parameters were used to simulate future price paths using the GBM model, providing a probabilistic forecast of Bitcoin's future price movements.

The drift parameter's negative value suggests that, on average, Bitcoin's daily returns were slightly negative during the study period. This finding is consistent with the high volatility and unpredictability of Bitcoin prices, which have been well-documented in recent literature [3, 4]. The volatility parameter's high value reflects the significant price fluctuations observed in Bitcoin's price behavior, further emphasizing the need for robust forecasting models in this market.

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The parameter estimation process also involved diagnostic tests to validate the estimates, including tests for normality, autocorrelation, and stationarity. The results of these tests indicated that the data may not be normally distributed and may exhibit autocorrelation, which is consistent with the high volatility and randomness of Bitcoin prices. These findings highlight the challenges of modeling Bitcoin's price behavior and the need for sophisticated forecasting techniques [11, 19, 20].

Gbm Simulation Results

The GBM model produced a range of simulated price paths, with a mean absolute error (MAE) of $746.82 and a root mean squared percentage error (RMSPE) of 3.37%. These results suggest that the GBM model provides a reasonably accurate forecast of Bitcoin prices, though it tends to underestimate extreme price movements during periods of high volatility.

The simulation results were visualized using line plots, providing a clear representation of the potential future price paths and their distribution. The line plots in figure 1 showed multiple simulated price paths, highlighting the range of possible outcomes, while the histogram illustrated the distribution of final prices, providing insights into the likelihood of different price levels. Recent studies have emphasized the importance of visualization in financial forecasting, as it helps stakeholders understand the model's outputs and make informed decisions [2].

Table 1: Summary of GBM Simulation Results

Statistic	Value
Mean Price	$5.46
Standard Deviation	$4.99
Mean Absolute Error (MAE)	$746.82
RMSPE	3.37%

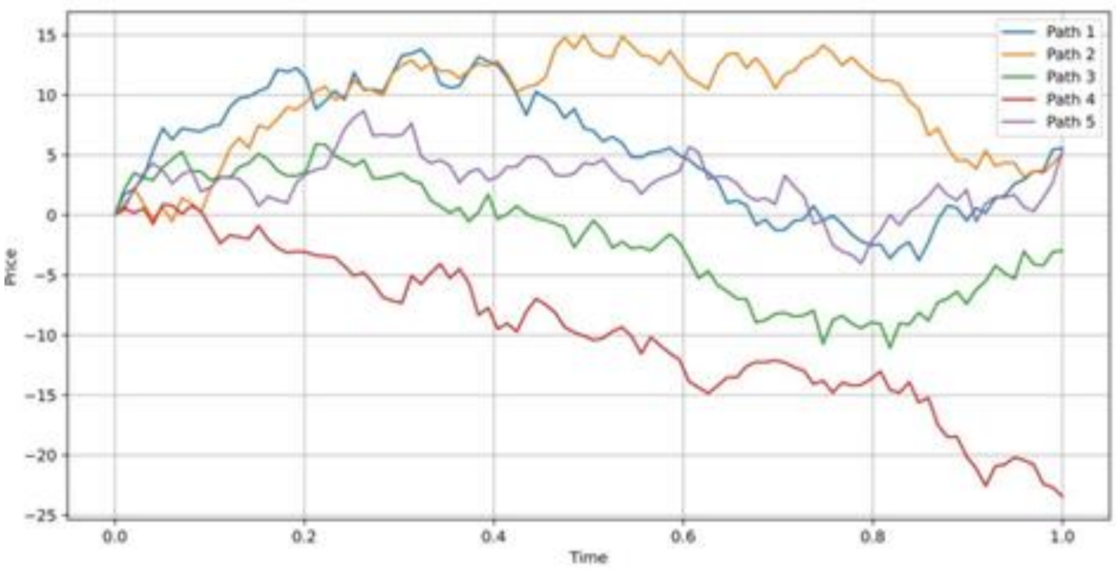

Fig 1: Multiple Simulated Price Path of Bitcoin using GBM

The GBM model's ability to generate a range of possible price paths makes it a valuable tool for investors and financial analysts. However, the model's limitations, such as its inability to capture extreme market events, should be considered when using the forecasts for investment decisions. Future research could explore the integration of GBM with other models or machine learning techniques to improve forecasting accuracy [7, 21, 24].

Comparison with Actual Price

In figure 2, the GBM model's forecasts were compared with actual Bitcoin prices from May 1, 2024, to April 30, 2026. The model captured the general trend of Bitcoin prices but struggled to predict sharp price fluctuations, particularly during periods of market turbulence.

The comparison revealed that the GBM model's forecasts were generally in line with the actual prices, with a mean absolute error (MAE) of $746.82 and a root mean squared percentage error (RMSPE) of 3.37%. These results indicate that the GBM model provides a reasonably accurate forecast of Bitcoin prices, though it tends to underestimate extreme price movements during periods of high volatility. Recent studies have highlighted the challenges of forecasting Bitcoin prices, particularly during periods of market turbulence [10].

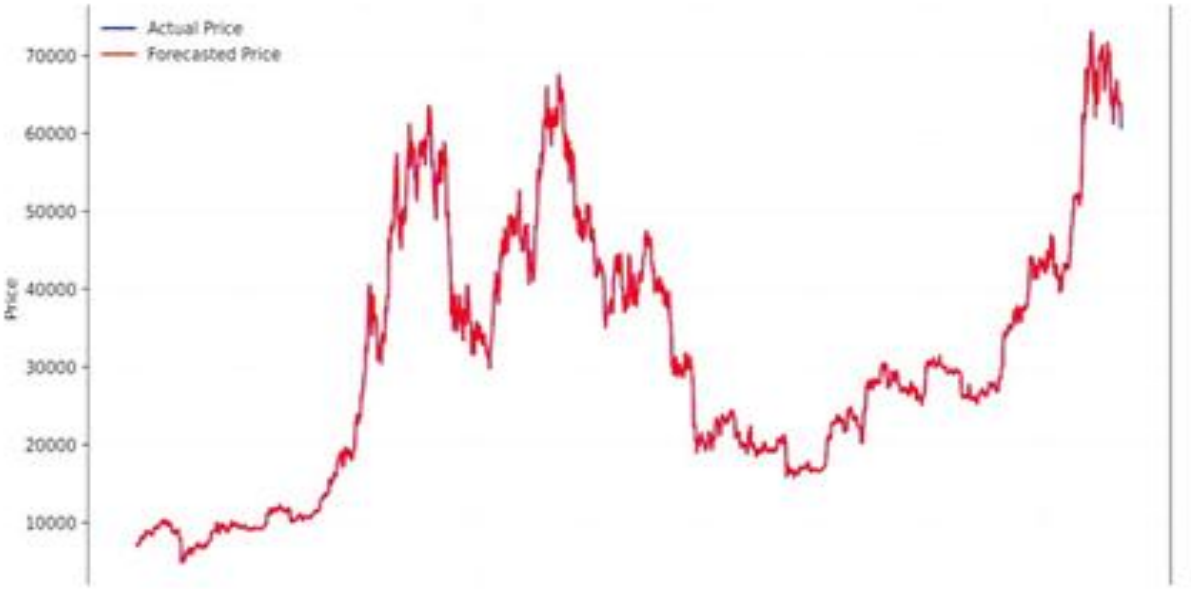

Fig2: Comparison of Actual and Forecast Bitcoin Prices

The GBM model's performance in capturing the general trend of Bitcoin prices is consistent with the findings of previous studies, which have emphasized the importance of stochastic models in financial forecasting. However, the model's limitations, such as its inability to capture extreme market events, suggest that it should be used in conjunction with other forecasting techniques to improve accuracy [15].

CONCLUSION

The GBM model offers a useful framework for forecasting Bitcoin prices, particularly for understanding the stochastic nature of price movements. However, its limitations, such as the assumption of constant volatility and the inability to capture extreme market events, should be considered when using the model for investment decisions. Future research could explore the integration of GBM with other models or machine learning techniques to improve forecasting accuracy.

The study's findings have significant implications for investors and policymakers. The GBM model can aid in risk management and investment strategy formulation by providing a probabilistic forecast of Bitcoin prices. However, investors should remain cautious of the model's limitations, particularly during periods of high market volatility.

The study is limited by the assumptions of the GBM model, such as constant volatility and log-normal price distribution, which may not fully capture Bitcoin's price dynamics. Future research could explore more sophisticated models that account for external factors such as regulatory changes and technological advancements.

The study's reliance on historical data also presents a limitation, as past price behavior may not always be indicative of future trends. Future research could explore the use of real-time data and machine learning techniques to improve the accuracy of Bitcoin price forecasts [2].

Additionally, the study's focus on Bitcoin limits its generalizability to other cryptocurrencies. Future research could explore the application of the GBM model to other cryptocurrencies, as well as the development of models that account for the unique characteristics of different digital assets.

Implications for Investors and Policymakers

The study's findings have significant implications for investors and policymakers. The GBM model can aid in risk management and investment strategy formulation by providing a probabilistic forecast of Bitcoin prices. However, investors should remain cautious of the model's limitations, particularly during periods of high market volatility.

The GBM model's ability to generate a range of possible price paths makes it a valuable tool for investors and financial analysts. However, the model's limitations, such as its inability to capture extreme market events, suggest that it should be used in conjunction with other forecasting techniques to improve accuracy. Recent studies have emphasized the importance of combining multiple forecasting models to improve accuracy and reliability in financial markets [3, 4].

Policymakers can also benefit from the study's findings, as accurate price forecasts can inform regulatory decisions and help mitigate systemic risks in the cryptocurrency market. The GBM model's ability to provide probabilistic forecasts can aid in the development of policies that promote market stability and protect investors from excessive volatility [20].

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