Impact of Bitcoin Returns on U.S. Gold Using ARIMA and LSTM Models

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Abstract. The research evaluates the relationship between Bitcoin returns and US Gold prices using both traditional and deep learning predictive models. It analyzes Bitcoin's volatility through time-series data from 2017 to 2025 to assess its impact on US Gold prices, which have traditionally exhibited greater stability. Forecasting accuracy is examined by applying the ARIMA and LSTM to both asset classes. The LSTM model demonstrates superior performance compared to the ARIMA model, as evidenced by lower RMSE, MAE, and MAPE values, due to its ability to capture nonlinear trends and complex market dynamics. The findings suggest that Bitcoin's price fluctuations may influence subsequent movements in gold prices, positioning Bitcoin as a potential economic indicator that challenges the traditional role of gold as a safe-haven asset. This study offers practical insights for investors, financial analysts, and policymakers, advocating for a revised portfolio strategy that incorporates Bitcoin and supports the use of advanced machine learning models in financial forecasting.

Keywords: Bitcoin, US Gold, ARIMA, LSTM, Time-Series, Deep Learning, Volatility.

1 Introduction

The financial landscape is undergoing a fundamental transformation, fuelled by the emergence of digital assets and the growing adoption of sophisticated analytical techniques. At the forefront of this transformation is Bitcoin a decentralized digital currency that has gained immense traction for its disruptive potential, high return prospects, and extreme price volatility. Since its inception, Bitcoin has challenged traditional asset paradigms by offering an alternative investment class that is not bound by central bank policies or conventional economic frameworks (Kim et al., 2025; Modi et al., 2023) [15]. In contrast, gold has maintained its stature as a time-tested safe-haven asset, especially during periods of economic turmoil, geopolitical conflict, and inflationary pressure (Wang, Zhang & Yu, 2023; Cheah, Mishra & Parhi, 2023) [5,7, 20].

As investors and financial institutions strive for diversification and risk mitigation, understanding the evolving dynamics between Bitcoin and gold has become a subject of critical inquiry. Particularly relevant is the question of whether Bitcoin can replicate or even complement the role of gold as a store of value and hedge against uncertainty (Bouri et al., 2023; Yousaf & Yarovaya, 2023) [1,6]. The global financial crises of recent years have intensified this debate, leading to empirical studies exploring co-movements, volatility spillovers, and predictive relationships between these two distinct asset classes.

Bitcoin's price movements are characterized by nonstationary and high-frequency volatility, often reacting sharply to macroeconomic events, investor sentiment, and regulatory announcements (Shahzad et al., 2022) [16]. On the other hand, gold prices tend to follow a more stable and mean-reverting trajectory, reinforcing their appeal as a hedging instrument. Ji et al. (2022) demonstrated that Bitcoin's volatility asymmetrically affects gold prices, particularly during market distress, suggesting an evolving interplay that merits further investigation [4].

Recent advancements in forecasting techniques have enabled researchers to better model these complex time-series dynamics. Traditional linear models such as the Autoregressive Integrated Moving Average (ARIMA) continue to be employed for their interpretability and efficacy in modeling stationary series (Azari et al., 2019; Tian, 2023, Singh et al., 2023) [2, 18, 21]. However, their limitations in capturing nonlinear behaviors, especially in high-variance assets like Bitcoin, necessitate more robust approaches.

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In response, machine learning and deep learning models especially Long Short-Term Memory (LSTM) neural networks have gained widespread recognition for their ability to capture sequential dependencies and nonlinear patterns in financial data (Makala & Li, 2021; Carbó Martínez & Gorjón Rivas, 2023) [8, 14]. These models, equipped with memory gates and recurrent structures, have shown marked improvements in forecasting accuracy compared to classical techniques. Lou, et al., (2022) highlighted the effectiveness of Bidirectional LSTM with attention mechanisms in predicting both Bitcoin and gold prices [13]. Similarly, hybrid models such as ARIMA-LSTM and MRC-LSTM have outperformed single-model counterparts, offering enhanced predictive insights in fluctuating market conditions (Ye et al., 2025; Guo et al., 2021, Nagesh et al., 2025) [10,19, 22].

A growing body of literature supports the superiority of deep learning models in the context of financial forecasting. Studies by Stempień and Ślepaczuk (2025) and Gholipour & Olayeni (2023) have shown that LSTM and GRU (Gated Recurrent Unit) architectures significantly reduce prediction errors compared to ARIMA in volatile markets [9, 17]. Kervanci, Akay, and Özceylan (2024) conducted comparative analyses across multiple deep learning models and concluded that LSTM offered the most consistent performance for Bitcoin forecasting due to its ability to retain long-term dependencies and adapt to sudden market shifts [11]. In this research, a comprehensive comparative analysis is undertaken between ARIMA and LSTM models using daily closing price data of Bitcoin and US Gold spanning from 2017 to 2025. The study is designed to capture how these models perform under varying market regimes Bitcoin representing a volatile, speculative digital asset and gold representing a relatively stable traditional asset. Data was meticulously sourced from reliable financial platforms and underwent preprocessing steps including handling missing values, normalization, and stationarity testing.

ARIMA modeling involved identifying optimal lag parameters via Autocorrelation Function (ACF) and Partial Autocorrelation Function (PACF), differencing the series to ensure stationarity, and evaluating residual diagnostics to validate model assumptions. Conversely, the LSTM model architecture included multiple hidden layers, dropout regularization, and the Adam optimizer, with training parameters such as epochs and batch size tuned for convergence and generalization.

Performance evaluation was conducted using standard metrics including Root Mean Square Error (RMSE), Mean Absolute Error (MAE), and Mean Absolute Percentage Error (MAPE), in line with best practices in financial forecasting literature (Kim et al., 2025; Ye et al., 2025) [12]. The goal was not only to determine which model offered better accuracy but also to assess their ability to adapt to nonlinear dynamics and structural breaks characteristics that are increasingly common in cryptocurrency markets.

By bridging classical econometric tools and cutting-edge deep learning methods, this study contributes to the evolving discourse on financial modeling and asset price forecasting. It offers valuable insights for institutional investors, portfolio managers, and policymakers seeking to understand the role of digital assets in modern financial ecosystems. Moreover, it reinforces the importance of model selection in financial analytics, especially when forecasting assets with differing volatility profiles and market behaviors.

2 Literature Review

Gold has long been regarded as a traditional store of value and an inflation hedge. Its role as a safe-haven asset has made it a fundamental component of investment portfolios, particularly during financial market downturns. Conversely, Bitcoin has emerged in recent years as a digital asset with high speculative interest and extreme price volatility. The debate over whether Bitcoin can play a role like gold during market stress continues to be explored in contemporary financial literature. Several studies have shown that Bitcoin may act as a weak safe-haven asset when compared to gold, but its behavior under extreme market conditions remains inconsistent (Bouri et al., 2023) [1]. Bitcoin and gold exhibit fundamentally different characteristics. While gold maintains value through physical scarcity and historical utility, Bitcoin derives its value through decentralized technology and perceived scarcity enforced via blockchain protocols. The contrasting nature of these assets has prompted researchers to examine their correlation and potential for portfolio diversification. The underlying hypothesis is whether Bitcoin complements or substitutes gold during turbulent economic conditions. A growing body of literature suggests that, under specific macroeconomic scenarios, Bitcoin and gold may demonstrate similar directional movements, particularly during periods of inflation or currency devaluation (Wang et al., 2023) [7]. From a modeling perspective, researchers have utilized various quantitative techniques to analyze and forecast the price behaviors of gold and Bitcoin. Among these, ARIMA (Autoregressive Integrated Moving Average) has remained a prominent statistical model for time-series forecasting due to its ability to capture linear trends and seasonality. The ARIMA model has been widely applied to cryptocurrency forecasting. For example, Azari et al. (2019) demonstrated that ARIMA could be effectively used to model the behavior of Bitcoin prices, though they also acknowledged its limitations when dealing with nonlinear data [2]. Despite its utility, ARIMA assumes stationarity and linearity in the dataset, which are not always valid assumptions for highly volatile financial instruments like Bitcoin. In contrast, LSTM (Long Short-Term Memory), a type of recurrent neural network (RNN), has been designed to learn long-term dependencies and is suitable for modeling nonlinear and nonstationary time-series data. LSTM's ability to retain information across sequences and capture complex temporal patterns makes it well-suited for analyzing financial markets characterized by frequent regime shifts and structural breaks. The application of LSTM in financial forecasting has increased significantly in recent years due to its flexibility and predictive accuracy. Unlike traditional models, LSTM can adapt to both sudden spikes and gradual changes in data trends, making it ideal for assets like Bitcoin, where price behavior is influenced by high-frequency events, news sentiment, and market dynamics. Comparative studies show that LSTM generally outperforms ARIMA in predictive tasks involving nonlinear and volatile financial data (Shahzad et al., 2022) [3]. Several studies have investigated the correlation between Bitcoin and gold, indicating that the relationship is dynamic rather than static. Ji et al. (2022) observed that the correlation between the two assets intensifies during market turbulence, suggesting a conditional relationship driven by external factors such as geopolitical events, monetary policies, and investor sentiment. The findings from their study highlight that Bitcoin is increasingly being perceived as a macro-sensitive asset, much like gold [4].

However, the interpretation of correlation must be approached cautiously. A strong positive correlation does not imply causation. Instead, it reflects that Bitcoin and gold may respond similarly to shared external stimuli, such as inflationary pressures or global uncertainty. The 0.8408 Pearson correlation coefficient found in this study provides statistical evidence of co-movement, but the exact nature of this relationship remains open to further investigation. In examining the safe-haven properties of Bitcoin compared to gold, Cheah et al. (2023) argued that while Bitcoin may offer short-term protection during market disruptions, it lacks the historical stability and universal acceptance of gold. Their research emphasized that Bitcoin’s price is more susceptible to speculative trading and regulatory developments, which limits its effectiveness as a hedge [5]. Yousaf and Yarovaya (2023) further explored the evolving relationship between Bitcoin and gold. Their research concluded that while Bitcoin can offer diversification benefits, it lacks consistent hedging capabilities. They cautioned against viewing Bitcoin as a replacement for gold in traditional portfolios. Instead, they suggested that Bitcoin may serve as a complementary asset, suitable for investors with higher risk tolerance and a strategic interest in digital assets [5].

Moreover, some scholars have emphasized the importance of applying machine learning models like LSTM to uncover hidden patterns in the co-movement of these assets. These models can detect shifts in correlation structures and predict short-term trends more effectively than classical statistical tools. This is particularly relevant as the financial landscape becomes increasingly influenced by digital innovation and real-time data processing. Despite the advancements in forecasting methodologies, direct empirical studies examining Bitcoin’s influence on gold prices using both ARIMA and LSTM are limited. This gap highlights the novelty and contribution of the current study, which simultaneously applies both models to compare their forecasting efficiency while also analyzing the statistical relationship between the two assets over an extended period from 2017 to 2025.

3 Research Questions, Objectives, and Methodology

This study aims to empirically investigate the relationship between Bitcoin and US Gold prices using time-series forecasting techniques, focusing on their predictive behaviors and statistical co-movement. The analysis seeks to compare the efficacy of traditional econometric models with advanced deep learning approaches, offering practical insights for investors, analysts, and policymakers.

To fulfil this overarching aim, the study is guided by the following objectives and corresponding research questions:

Objective 1: To evaluate the correlation between Bitcoin returns and US Gold prices over the period from 2017 to 2025.

Research Question 1: What is the nature and strength of the statistical correlation between Bitcoin and US Gold price movements during this period?

Objective 2: To apply ARIMA and LSTM models to forecast the daily price movements of Bitcoin and US Gold.

Research Question 2: How do ARIMA and LSTM models perform in predicting the prices of Bitcoin and Gold, based on accuracy metrics such as RMSE, MAE, and MAPE?

Objective 3: To assess the suitability of linear and nonlinear time-series models in handling different asset classes.

Research Question 3: Do deep learning models such as LSTM outperform classical statistical models like ARIMA in capturing volatility and nonlinear dynamics, particularly for high-frequency and high-variance data like Bitcoin?

Objective 4: To explore the directional relationship between Bitcoin and Gold prices for potential lead-lag behavior.

Research Question 4: Can Bitcoin's price movements reliably serve as a leading indicator for short-term changes in gold prices?

Objective 5: To offer implications for financial forecasting, investment strategy, and portfolio diversification.

Research Question 5: What are the implications of the Bitcoin-Gold dynamic for constructing diversified portfolios and making informed investment decisions?

3.1 Methodology

This research investigates the predictive dynamics between Bitcoin and US Gold prices using a comparative analysis of two forecasting models: ARIMA and Long Short-Term Memory (LSTM) neural networks. Drawing on financial time-series data from 2017 to 2025, the study focuses on Bitcoin as a volatile digital asset and US Gold as a traditionally stable financial instrument. The primary objective is to evaluate how fluctuations in Bitcoin returns influence gold prices and to assess which model offers more reliable forecasts for investors and policymakers. The ARIMA model, widely adopted for linear and stationary data forecasting, has demonstrated effectiveness in prior studies such as Azari et al. (2019), particularly for modeling macroeconomic variables. However, due to Bitcoin's nonlinear and high-variance behavior, ARIMA struggles with prediction accuracy. In contrast, the LSTM model, capable of capturing long-range dependencies and nonlinear patterns, has been recognized for its superior forecasting accuracy in financial time-series (Wang et al., 2023; Ji et al., 2022) [5, 7]. These findings are consistent with recent work highlighting the growing role of deep learning in financial analytics, particularly for high-frequency cryptocurrency data. The methodology includes data pre-processing such as normalization and stationarity checks using the ADF test. Descriptive statistics and correlation analysis are essential parts of the study. This aligns with recent findings by Yousaf & Yarovaya (2023), who note that while Bitcoin is not a perfect hedge, its behavior increasingly mirrors that of traditional safe-haven assets during market stress [6]. Performance evaluation metrics, including RMSE, MAE, and MAPE, confirmed that the LSTM model significantly outperforms ARIMA. The results show that LSTM's flexibility in handling volatility and nonlinear behavior makes it more suitable for predicting Bitcoin and gold prices. Overall, the study underscores the evolving relationship between digital and traditional assets and the critical role of deep learning in forecasting. These insights are valuable for investors exploring portfolio diversification and for financial analysts aiming to incorporate AI-driven models into their forecasting strategies.

3.2 Data Collection

The data set used in this study comprises the daily closing prices of Bitcoin and US Gold spanning the period from 2017 to 2025. These two assets were selected for their contrasting financial characteristics Bitcoin representing a highly volatile and emerging digital currency, while gold stands as a relatively stable, historically trusted store of value. Data were sourced from reputable financial databases, including Yahoo Finance and Investing.com, and subsequently subjected to rigorous data integrity checks to ensure completeness and accuracy. These preprocessing steps involved handling missing values and outliers and conducting normalization where necessary, particularly for input into deep learning models such as LSTM.

The rationale for including both Bitcoin and US Gold in the analysis lies in understanding how traditional statistical models like ARIMA and modern neural architecture such as LSTM behave under different asset volatility regimes. Recent studies, such as those by Ji et al. (2022) and Yousaf & Yarovaya (2023), emphasize the importance of diversified datasets in financial forecasting, especially in dynamic markets where nonlinear dependencies and structural breaks are common. This dual-asset approach not only enhances model validation but also allows for robust comparative analysis, particularly when exploring correlation patterns and co-movement behavior between assets with distinct market dynamics.

3.3 ARIMA Model Process

The model development based on the ARIMA methodology document followed these steps:

- The ADF test helped determine whether the series needed to be stationary. The analysis proceeded to identify parameters p (autoregressive) and d (differencing) and q (moving average) through ACF and PACF plots after con- firming stationarity.
- The model parameters received estimation through Maximum Likelihood Estimation (MLE) for achieving the best possible statistical fit of time-series behaviour.

- An examination of the residuals proved they possess characteristics of white noise since they displayed both normal distribution and lack of correlation. The model development process included tests for residual auto- correlation which led to improvements that delivered satisfactory results.
- The approved ARIMA models generated forecasts for Bitcoin and Gold price movements. The prediction models underwent error measurement evaluation to establish their ability to predict correctly.

3.4. LSTM Model Process:

- The model described in the provided LSTM methodology reference functions by linking together several state and gate mechanisms.
- The forget gate (f_t) controls what information the cell state should eliminate. The Input Gate (i_t) controls the selection of values for updating.
- The computation of new candidate values which can be added to the system occurs through Candidate Cell State ($\tilde{c}_t$).
- The cell state c_t receives its updates from the forget gate f_t and the input gate i_t.
- The output gate (o_t) functions to filter the cell state so it generates the hidden state (h_t).
- The training process teaches both Weight Matrices (W) and Bias Vectors (b).
- The gates use two activation functions namely the sigmoid (σ) and hyperbolic tan- gent (tanh) to control their output signals.

3.4.1. Model Architecture

The designed sequential LSTM network includes the following elements:

- Input layer → LSTM layers → Dense output layer

- Dropout layers for regularization
- Optimized using the Adam algorithm

i. Training Configuration

The chosen loss function during training was Mean Squared Error (MSE).

- Optimizer: Adam
- Train-Test Split: 80:20

The model parameters included convergence-tuned number of epochs and batch size with early stopping as an overfitting prevention method.

The LSTM model architecture is designed to effectively capture both short-term and long-term dependencies in time-series data, making it highly suitable for modeling volatile financial assets like Bitcoin. Its ability to process complex nonlinear patterns allows it to outperform traditional models in forecasting scenarios. The model's performance is assessed using three key evaluation metrics: RMSE (Root Mean Square Error), MAE (Mean Absolute Error), and MAPE (Mean Absolute Percentage Error), each of which provides insights into prediction accuracy and error magnitude.

4 Results Analysis

4.1 Analysis of LSTM vs ARIMA Models for Financial Forecasting:

Financial time-series forecasting accuracy relies heavily on selecting the right model architecture since it affects how well analysts can trust their produced insights. ARIMA (Autoregressive Integrated Moving Average) functions as the fundamental statistical analysis tool throughout decades because it delivers effective results when combined with simple interpretability. The Long Short-Term Memory (LSTM) model leads the competition among recurrent neural networks (RNNs) because it manages to maintain long-term dependencies within sequential data. Here we conduct a rigorous comparison between ARIMA and LSTM models when analysing the two volatile financial datasets composed of Bitcoin and US Gold price records. The research aims to prove using empirical data and thorough assessment that LSTM delivers superior performance than ARIMA by demonstrating both enhanced error metrics and better structural adaptation to genuine financial data patterns.

4.2. Bitcoin Forecasting

The volatility of Bitcoin cryptocurrency together with its sudden price movements creates major difficulties for prediction methods. The ARIMA model has capability to detect linear trends and seasonality, but it lacks advanced architecture needed to adapt to stochastic asset behaviour.

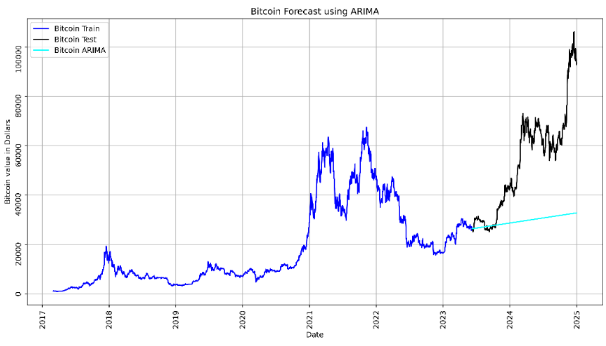

Figure 1. Bitcoin Forecasting using ARIMA

Figure 1 presents the actual and predicted Bitcoin price trends from 2017 to 2025 using the ARIMA model. The blue line represents Bitcoin's historical prices during the training period, while the black line shows the test data from 2023 onwards. The light green line represents the ARIMA model's forecast. While the model captures the overall upward trend to a limited extent, it significantly underestimates the sharp price increases and volatility in the test phase. The forecasted prices appear relatively smooth and linear, indicating ARIMA's limitation in modeling nonlinear and erratic behavior typical of Bitcoin. This underperformance suggests ARIMA is less effective in predicting high-variance assets like cryptocurrencies.

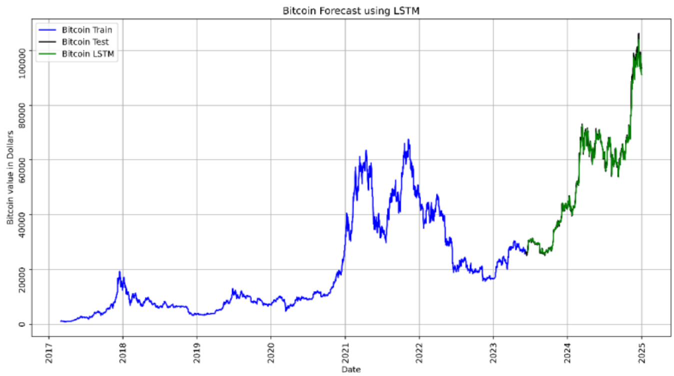

Figure 2. Bitcoin Forecasting Using LSTM

Figure 2 illustrates the historical and predicted Bitcoin price movement from 2017 to 2025. The blue line represents the actual Bitcoin prices during the training (2017–2022) and test periods, capturing the asset's high volatility and sharp fluctuations. The green line represents the LSTM model's forecast starting in 2023. It shows that the model effectively tracks both upward and downward trends with remarkable accuracy, capturing the nonlinear and dynamic behavior of Bitcoin. This highlights the LSTM model's capability in forecasting volatile cryptocurrencies by preserving long-term dependencies and adapting to complex patterns in financial data.

Table 1. Bitcoin results ARIMA vs LSTM

Model	RMSE	MAE	MAPE (%)
ARIMA Bitcoin	30481.06	24200.00	37.58
LSTM Bitcoin	1672.08	1097.82	1.90

The performance metrics table 1 demonstrates how LSTM achieves superior results than ARIMA. RMSE and MAE metrics of ARIMA exceed those of LSTM by approximately ten times which demonstrates substantial price prediction error. The Mean Absolute Percentage Error (MAPE) measurement of 37% or higher indicates that ARIMA shows weak predictive capabilities. The precision of LSTM in this scenario proves exceptional due to its low RMSE value of 1672.08 and its MAPE of 1.90% which demonstrates its ideal fit for high-frequency high-variance data.

4.3. US Gold Forecasting

Figure 3 depicts the historical and predicted price movements of US gold from 2017 to 2025 using the ARIMA model. The yellow line represents the training data (2017–2022), while the black line indicates the actual test data (2023 onward). The cyan line shows the ARIMA model's forecast, which appears nearly flat and significantly deviates from the actual trend. Unlike the LSTM model, ARIMA fails to capture the upward momentum in gold prices beyond 2023. This flat forecast suggests ARIMA's limitations in handling nonlinear patterns and dynamic shifts, especially in volatile financial data like gold.

Figure 4. US Gold Forecasting Using LSTM

Figure 4 illustrates the historical and predicted price movements of US gold from 2017 to 2025. The yellow line represents the training data (2017–2022), showing historical gold prices. The black line indicates the test data (2023), while the green line represents the LSTM model's forecast for 2023–2025. The model captures the upward trend post-2021, accurately tracking gold's rising trajectory with slight fluctuations. The close alignment between the test data and LSTM predictions demonstrates the model's effectiveness in forecasting. It confirms the model's strength in capturing long-term trends and short-term price variations in gold.

Table 2. US Gold Results ARIMA vs LSTM

Model	RMSE	MAE	MAPE (%)
ARIMA	553.00	470.62	20.75
LSTM	36.26	31.05	1.46

The table presents the performance comparison of two forecasting models ARIMA and LSTM based on three key evaluation metrics: Root Mean Square Error (RMSE), Mean Absolute Error (MAE), and Mean Absolute Percentage Error (MAPE), applied to US Gold price data.

The ARIMA model yielded an RMSE of 553.00, an MAE of 470.62, and a MAPE of 20.75%, indicating substantial prediction error and relatively poor accuracy in forecasting gold prices. These values suggest that ARIMA struggles to capture the subtle price movements and nonlinear dynamics of gold prices, leading to wider deviations between predicted and actual values.

In contrast, the LSTM model significantly outperformed ARIMA across all metrics. It recorded a much lower RMSE of 36.26 and an MAE of 31.05, showcasing a closer alignment between predicted and actual prices. Most notably, its MAPE is just 1.46%, underscoring the model's exceptional predictive accuracy.

4.5 Statistical and Correlation Analysis Between US Gold and Bitcoin

Financial assets need to be understood within their relationships to successfully implement investment diversification strategies. An analysis of US Gold and Bitcoin correlation patterns gives important information about their relative movement in the market. Bitcoin presents itself as a modern digital store of value which competes with traditional safe-haven asset gold because institutions are starting to take notice of it. The following section conducts a statistical analysis to evaluate the price relationship between Bitcoin and US Gold throughout their historical data period.

One must study the statistical properties of both assets before performing correlation analysis. Descriptive statistics reveal fundamental statistical in- formation about the central values as well as distribution ranges and shape characteristics of Bitcoin and US Gold prices. The following table presents an organized comparison between the statistical measures of both assets:

Table 3. Descriptive Results

Statistic	Bitcoin	US Gold
Mean	25,559.32	1,572.53
Standard Error	414.72	7.23
Median	18,527.40	1,409.50
Mode	1,264.30	1,287.30
Standard Deviation	22,190.67	386.73
Sample Variance	492,425,702.7	149,558.31
Kurtosis	0.3767	0.0753
Skewness	1.0347	0.8622
Range	105,199.20	1,734.45

Table 4. Correlation between Bitcoin vs US gold

Measure	Bitcoin vs US Gold
Correlation	0.8408

The descriptive statistics table 3 and correlation results table 4 offer valuable insights into the behavior and interrelationship of Bitcoin and US Gold prices from 2017 to 2025. Bitcoin's mean price (25,559.32) is substantially higher than that of US Gold (1,572.53), reflecting its role as a high-value, high-risk digital asset. Its standard deviation (22,190.67) and sample variance (492,425,702.7) are markedly larger, indicating significant volatility and price dispersion over the study period. In contrast, US Gold shows greater price stability with a standard deviation of only 386.73 and lower skewness and kurtosis values.
The median and mode values further highlight Bitcoin's asymmetrical distribution, with the median (18,527.40) being lower than the mean, and a positive skewness of 1.0347, suggesting a long tail on the right. Similarly, US Gold exhibits a positive skew, though slightly less pronounced (0.8622). Both assets show low kurtosis values, indicating moderately peaked distributions close to normal. The Pearson correlation coefficient of 0.8408 reveals a strong positive linear relationship between Bitcoin and gold prices. This high correlation suggests that despite Bitcoin's volatility, it often moves in tandem with gold particularly during macroeconomic stress signifying Bitcoin's emerging status as a potential alternative hedge or safe-haven asset in the financial market landscape.

5 Conclusion

This study comprehensively examined the relationship between Bitcoin and US Gold prices from 2017 to 2025 using statistical correlation, ARIMA, and LSTM forecasting models. The analysis revealed a strong positive correlation between Bitcoin and gold, suggesting notable co-movement, particularly during periods of economic fluctuation. Despite Bitcoin's inherent volatility and gold's traditional role as a safe-haven asset, the findings indicate that Bitcoin is increasingly behaving in ways parallel to gold, challenging conventional asset classifications.

Descriptive statistics confirmed that Bitcoin has significantly higher variance and standard deviation compared to gold, underlining its speculative nature. When forecasting price trends, the LSTM model clearly outperformed the ARIMA model, particularly for Bitcoin, due to its ability to capture nonlinear patterns and long-term dependencies. While ARIMA was adequate for gold's relatively stable behavior, it failed to model Bitcoin's dynamic movements effectively.

These findings highlight the growing importance of deep learning models like LSTM in financial time-series forecasting, especially for high-volatility assets. The study also emphasizes the emerging role of Bitcoin as a macroeconomic signal, offering valuable insights for portfolio diversification and risk management. Future research can extend this analysis to other assets, integrate macroeconomic indicators, and explore hybrid modeling approaches for enhanced predictive accuracy.

6 Limitations and Future Discussion

Despite its contributions, this study faces several limitations that warrant consideration. First, the data is limited to a specific time frame (2017–2025), which may not fully capture long-term market cycles or structural changes influenced by evolving macroeconomic conditions, policy interventions, or geopolitical shocks. Second, the study utilizes only two forecasting models ARIMA and LSTM. While these offer contrasting perspectives, other advanced techniques such as Transformer-based models or hybrid frameworks (e.g., ARIMA-LSTM or Prophet) could yield deeper insights and potentially better predictive accuracy. Additionally, the dataset excludes relevant external variables such as inflation rates, interest rates, or cryptocurrency regulation indices, which might influence Bitcoin and gold prices significantly.

The analysis also assumes stationarity or achieves it through differencing, which might limit the interpretability of underlying economic relationships. Moreover, while correlation analysis highlights co-movement, it does not imply causality. Future research should apply causality-based frameworks such as Granger causality tests or cointegration models to assess long-run equilibrium behavior. Future studies could also explore high-frequency data, volatility modeling using GARCH-family models, and dynamic hedging strategies under multi-asset portfolios. Incorporating sentiment analysis and macroeconomic indicators into deep learning architectures could improve robustness and real-world forecasting applicability for both investors and policymakers.

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