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# An Empirical Analysis of Forecasting Bitcoin and Gold Price Using ARIMA Model

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***Abstract:*** The autoregressive integrated moving average (ARIMA) model is a widely used technique for capturing past dependencies and trends in order to generate future predictions. This study presents a comparative analysis of the ARIMA model's forecasting capabilities as applied to gold and Bitcoin prices. The methodology employed consists of obtaining historical price data, implementing machine learning techniques, fitting the ARIMA model, then validating its predictive ability using multiple error metrics. Our results indicated that the optimal ARIMA parameters for Bitcoin and gold are different, which emphasizes their different price behaviors. Additionally, the study examined implications for policy, including issues such as prices for CPUs and GPUs, the role of market dynamics, as well as the possibility for price manipulation, which is of special relevance for cryptocurrencies that exist outside the mainstream. The study also suggests potential directions for future research, such as applying advanced machine-learning techniques and adopting cross-validation. This research offers important insights regarding Bitcoin and gold price dynamics and demonstrates the applicability of the ARIMA model for financial forecasting while demonstrating the necessity of further investigation into more refined predictive models.

***Keywords:*** ARIMA model, Bitcoin, gold price

## 1. Introduction

The introduction of Bitcoin in 2009 began a new era in digital finance which continues to evolve and grow, attracting investors at all levels worldwide. Since it first emerged, Bitcoin has generated fiery debate concerning its role in financial markets and the potential that it, as a decentralized digital currency, may transform traditional investment portfolios. By contrast, gold, which has historically been treasured for its stability and hedging value during periods of financial turmoil, remains the go-to option for investors seeking to mitigate risk. The existing literature on the topic has presented various viewpoints which are often at odds with each other. Urquhart and Zhang, in examining the hedge and safe-haven properties of Bitcoin, gold, and commodities found that Bitcoin acts as a diversifier, balancing out risks in investment portfolios, and may serve as a hedge in some circumstances [1]. Bouri et al. go further in arguing that Bitcoin and gold are essentially similar in terms of their financial role, yet also take the view that both are, at best, weak safe havens [2]. By contrast, Madani and Fitti reaffirm the conventional wisdom which considers gold to be the go-to hedge for reducing portfolio risk across all agent types [3].

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This paper analyzes the relationship between Bitcoin and gold prices, treating Bitcoin as a high-risk investment and gold as a risk-hedging investment, especially in regard to periods of high economic instability such as the ongoing banking crisis which began in 2022. It will further delve into whether Bitcoin and gold can serve as hedging assets vis-à-vis each other, exploring the factors which drive their respective prices, and assessing whether Bitcoin acts like a traditional asset or whether its properties are unique. Likewise, it will examine how changes in the stock market predict changes in Bitcoin and gold prices, and vice versa, providing implications for portfolio diversification, financial risk management, and market efficiency. The study employs the ARIMA model, a robust forecasting technique commonly used in time-series analysis. Drawing upon the research of Ayaz et al., which utilized ARIMA to predict Bitcoin prices, this study utilized an extensive dataset of Bitcoin and gold prices between January 2020 and May 2023 [4]. The selected timeframe, which, it should be noted, includes the current banking crisis, offers a chance to analyze how these two assets react to major market events.

Via an empirical examination of Bitcoin and gold prices, this study illuminates the factors which influence investors' preference for Bitcoin over gold or vice versa, exploring claims that Bitcoin is the new gold – a safe haven for investors in the digital age. On this note, it will discuss the observed negative correlation between Bitcoin and gold prices. This paper offers a fresh contribution to the existing literature by combining traditional financial analysis with cutting-edge cryptocurrency studies, taking lessons from the recent banking crisis, and utilizing comprehensive data and robust methods to demonstrate the revolutionary dynamics between Bitcoin and gold. The insights revealed by this paper have profound implications for individual and institutional investors, as well as for the policymakers who must navigate the complex environment of a rapidly digitalizing financial system.

The study is organized as follows: the methodology section describes the data acquisition and analytical approaches; the results section presents the findings, along with a comparison of the forecasts; the discussion section reviews the implication of the study's findings. Finally, the Conclusion summarizes the research, listing key takeaways and future possibilities for this area of study.

## 2. Methodology

### 2.1. Data Preprocessing

The initial stage began with sourcing Bitcoin and gold price data from Yahoo Finance and importing it into R using the quantmod package. The quantmod package is widely recognized for its ability to manage, analyze, and model financial data. After the data was compiled, it was converted into time series objects, thereby facilitating sequential analysis.

### 2.2. Modeling

#### 2.2.1. Durbin-Watson Test and Autocorrelation Function Analysis

Prior to fitting the model, the Durbin-Watson test was applied to the residuals from regression analysis. The DW statistics yielded 0.0399 for Bitcoin and 0.1374 for gold, which indicated positive autocorrelation, thereby confirming the appropriateness of time-series analysis. The DW value ranges from 0 to 4, with a value between 0 to 1.5 or 2.5 to 4 indicating that the data is dependent on time, whereas a value between 1.5 to 2.5 suggests that data is cross-sectional or independent of time. Accordingly, the DW values obtained for Bitcoin and gold demonstrate the longitudinal nature of the data, which is to say that the data is dependent on time. In order to better understand autocorrelation, Autocorrelation Function (ACF) plots were analyzed (see Figure 1 and Figure 2). Cyclical patterns from both the ACF plots of Bitcoin and gold indicate that the time series data are not random white

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noise, but rather have an underlying structure that can potentially be modeled. The DW test formula was displayed as set out below:

$$d = \frac{\sum_{t=2}^{T} (e_t - e_{t-1})^2}{\sum_{t=1}^{T} e_t^2} \tag{1}$$

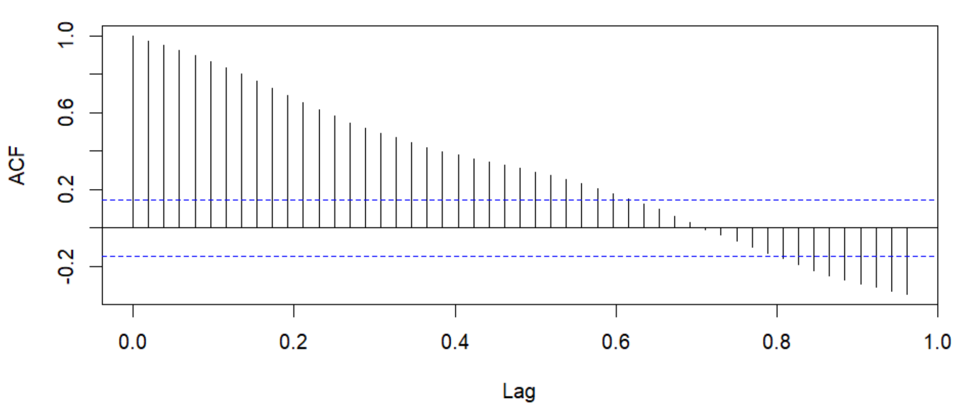


Figure 1: ACF for Bitcoin Price from January 2020 to May 2023.

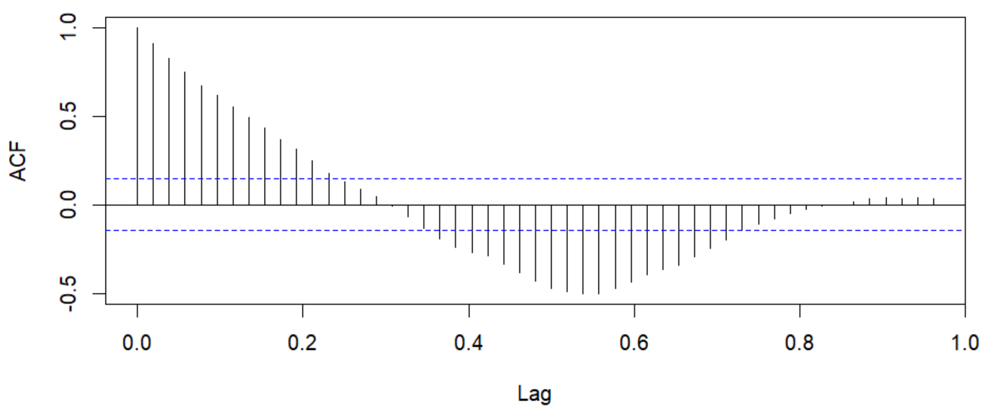


Figure 2: ACF for Gold Price from January 2020 to May 2023.

### 2.2.2. ARIMA Model Procedure

Subsequently, the ARIMA model was applied to predict Bitcoin and gold prices. ARIMA is a class of models that explains a given time series based on its own past values and lagged forecast errors, in order that one can use the equation to forecast future points in the series. The model is characterized by three parameters: (p, d, q). The mathematical representation of an ARIMA model is as follows:

$$y'_t = c + \phi_1 y'_{t-1} + \cdots + \phi_p y'_{t-p} + \theta_1 \varepsilon_{t-1} + \cdots + \theta_q \varepsilon_{t-q} + \varepsilon_t \tag{2}$$

After conducting the Durbin-Watson test and determining the configuration of the ARIMA model parameters, the process proceeds to coding, model fitting, and the accuracy metrics assessment. The

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dataset was divided into two segments: the training set and the test set. The training set contained gold and Bitcoin price data from January 2020 through December 2022, while the test set involved data from January 2023 to May 2023. This partitioning permitted the application of the model to unseen data, which was a vital step for affirming the model's predictive efficacy.

### 2.2.3. Evaluation Metrics and Tuning

Following this, the next step consisted of fitting the ARIMA model with various parameter combinations of p, d, and q. A triple loop function was used to iterate across diverse combinations, with parameters p and q ranging from 0 to 10, and parameter d from 0 to 2. This range was selected because high values of p, d, or q can result in model overcomplexity and overfitting. Moreover, time series data usually requires low levels of differencing (d) to attain stationarity. One or two levels are typically sufficient for this purpose. Thus, to avoid overfitting and to diminish computational complexity, we capped the parameters at these levels. In each iteration, the ARIMA model was trained on the training set, while its forecast accuracy was measured on the test set using multiple error metrics – the Root Mean Square Error (RMSE), Mean Absolute Error (MAE), Mean Absolute Percentage Error (MAPE), Corrected Akaike Information Criterion (AICc), and Bayesian Information Criterion (BIC). RMSE, MAE, and MAPE are popular metrics for quantifying the difference between values predicted by a model and the observed values. AICc and BIC are measured for the relative quality of a statistical model for a given data set. They address the trade-off between the goodness-of-fit of the model versus its complexity.

Afterwards, these error metrics were normalized and amalgamated, yielding a composite score for each combination. The combination resulting in the smallest composite score was deemed the optimal parameter set for the ARIMA model. For each error metric M - RMSE, MAE, MAPE, AICC, BIC:

$$M_{\text{Normalized}} = \frac{(M-\mu_M)}{\sigma_M} \tag{3}$$

A composite score for each model parameter combination is then computed as:

$$Score = RMSE_{Normalized} + MAE_{Normalized} + MAPE_{Normalized} + AICc_{Normalized} + BIC_{Normalized} \tag{4}$$

The model parameter combination with the smallest composite score is selected as optimal for the ARIMA model. When the optimal parameters were identified, the final model was fitted to the complete dataset (combining training and test sets) to make forecasts. This rigorous procedure, involving training, testing, model selection based on multiple error metrics, and eventual fitting of the selected model to the whole dataset, ensured a robust methodology.

## 3. Results

### 3.1. Training and Testing Results

As regards gold price data, the best score came from the ARIMA model with parameters (6,2,0) - indicating an autoregressive order of 6, a differencing order of 2, and a moving average order of 0.

Table 1: Error metrics table for Gold price testing.

| p | d | q | RMSE | MAE | MAPE | AICc | BIC | Score |
|---|---|---|---|---|---|---|---|---|
| 6 | 1 | 8 | 10.5627 | 9.167713 | 869.4528 | 872.4106 | 915.2007 | -0.94365 |
| 6 | 1 | 9 | 10.82649 | 9.382416 | 870.0576 | 873.4619 | 918.8553 | -0.38498 |
| 6 | 1 | 10 | 11.37218 | 9.678482 | 868.6365 | 872.5222 | 920.484 | 0.215124 |
| **6** | **2** | **0** | **4.467366** | **3.70186** | **882.2076** | **882.7676** | **903.5115** | **-9.78337** |
| 6 | 2 | 1 | 10.21562 | 8.914516 | 867.8269 | 868.5786 | 892.1743 | -2.49729 |
| 6 | 2 | 2 | 10.3538 | 9.049768 | 869.8202 | 870.7932 | 897.211 | -1.97379 |

For Bitcoin data, the best score came from the ARIMA model with parameters (8,2,9), which indicates an autoregressive order of 8, a differencing order of 2, and a moving average order of 9.

Table 2: Error metrics table for Bitcoin price testing.

| p | d | q | RMSE | MAE | MAPE | AICc | BIC | Score |
|---|---|---|---|---|---|---|---|---|
| 8 | 2 | 7 | 3769 | 3329.2 | 12.746 | 2985.7 | 3031 | -6.965 |
| 8 | 2 | 8 | 9445.4 | 8792 | 33.358 | 2982.8 | 3030.6 | 0.9057 |
| **8** | **2** | **9** | **3056.4** | **2664.2** | **10.232** | **2985.1** | **3035.5** | **-7.855** |
| 8 | 2 | 10 | 9776.6 | 9178.8 | 34.924 | 2993.6 | 3046.4 | 2.0879 |
| 9 | 0 | 0 | 6671.8 | 6264.4 | 23.9 | 3016.7 | 3048.8 | -1.575 |
| 9 | 0 | 1 | 6600.7 | 6152.9 | 23.381 | 3014.5 | 3049.4 | -1.77 |

Based on the forecast results and test data, it can be seen that the ARIMA model generated fairly accurate predictions for future Bitcoin and gold prices. Within the testing dataset, the model successfully captured the upward trend in Bitcoin and gold prices (see Figure 3 and Figure 4).

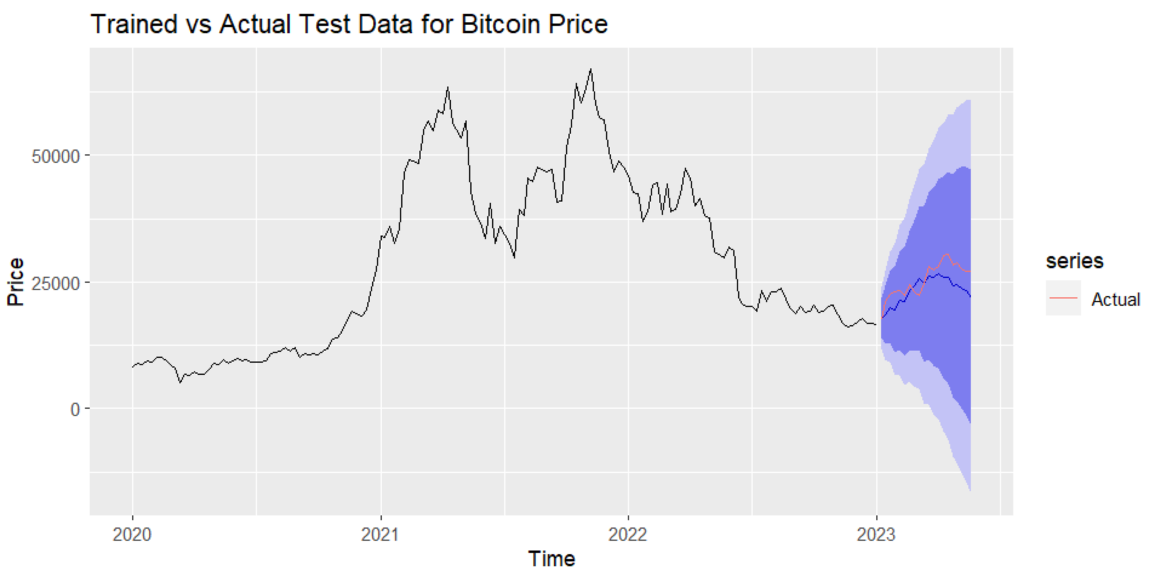


Figure 3: Trained vs Actual test Data for Bitcoin Price.

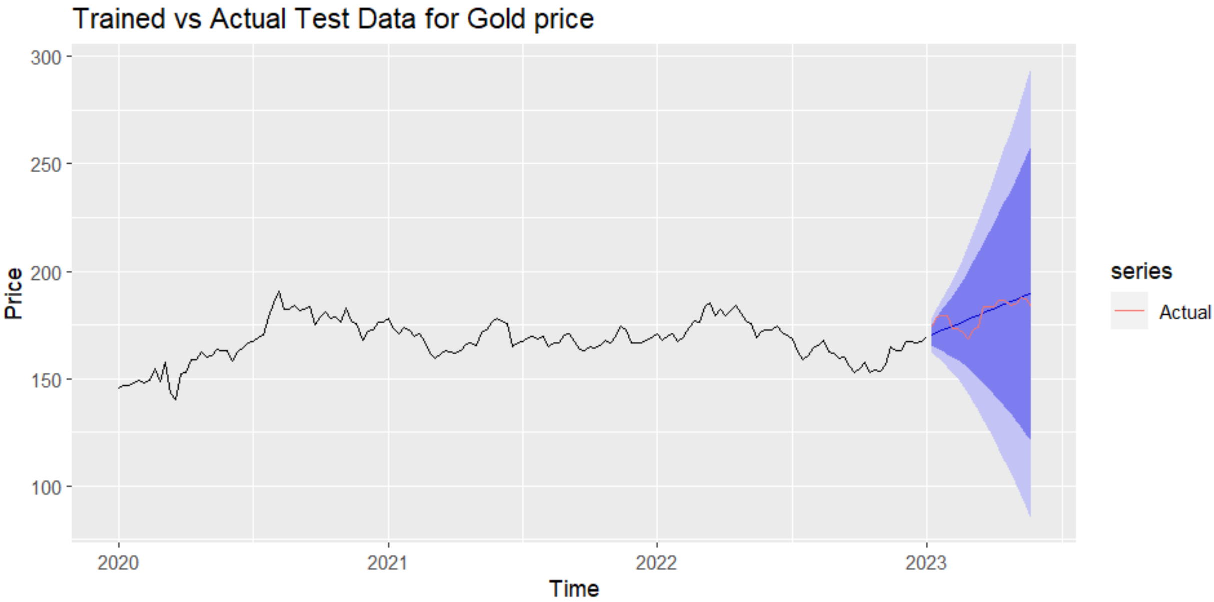


Figure 4: Trained vs Actual test Data for Gold Price.

As Figure 5 and Figure 6 shown, the ARIMA model trained on the dataset achieved a high degree of fit between its predictions and the actual data. This can be seen from the closeness of the fitted line to the original training data, illustrating the model's accuracy in capturing the underlying trend and dynamics of the dataset.

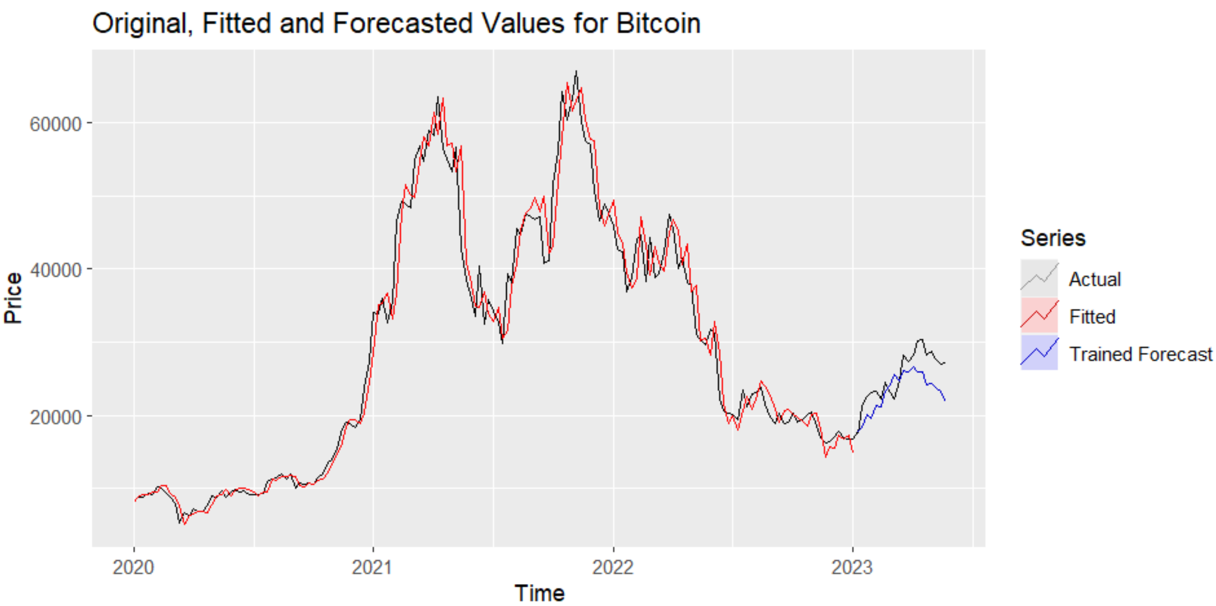


Figure 5: Fitting ARIMA on original Bitcoin price training set.

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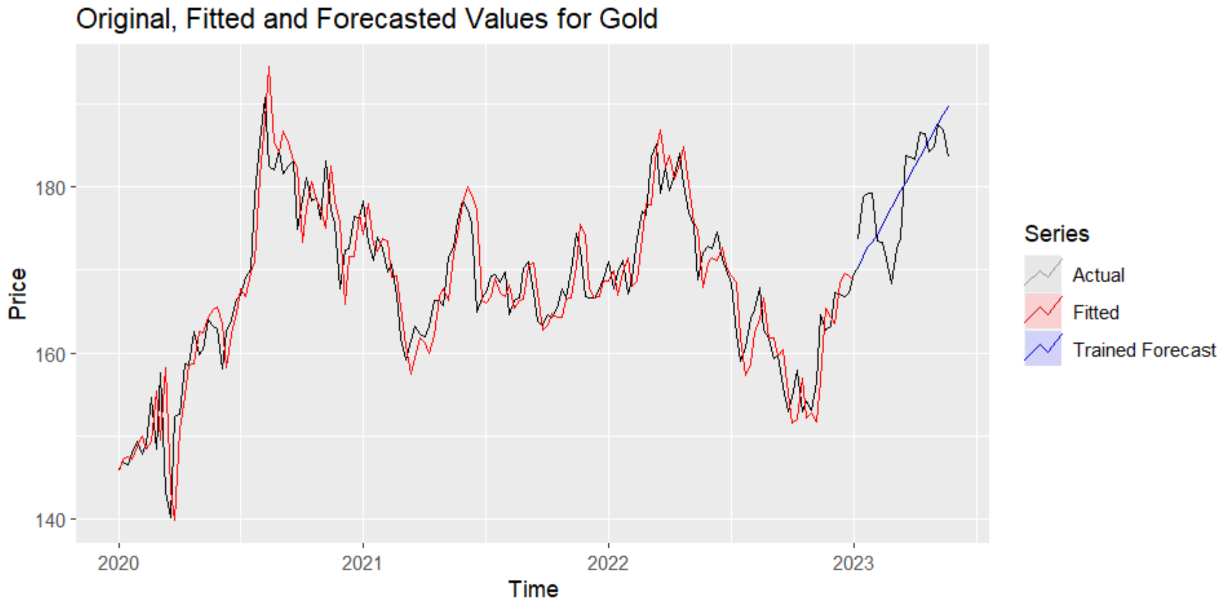


Figure 6: Fitting ARIMA on original Gold price training set.

Additionally, it applied the checkresiduals function (see Figure 7 and Figure 8) to both models and observed that all the Ljung-Box test results were greater than 0.05, which indicates that the residuals were independent and identically distributed, and, therefore, our models were well-specified. The Ljung-Box test yielded a p-value of 0.4055 for the gold training forecast and 0.1157 for the Bitcoin training forecast.

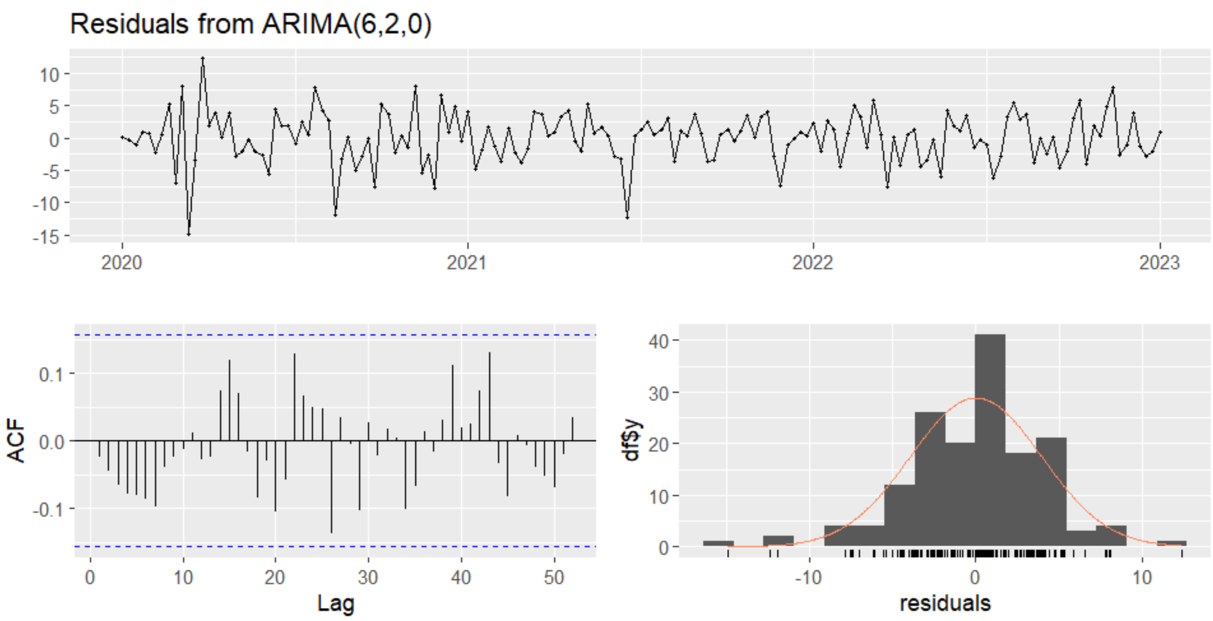


Figure 7: Result of checkresiduals function on testing data forecast for Gold price.

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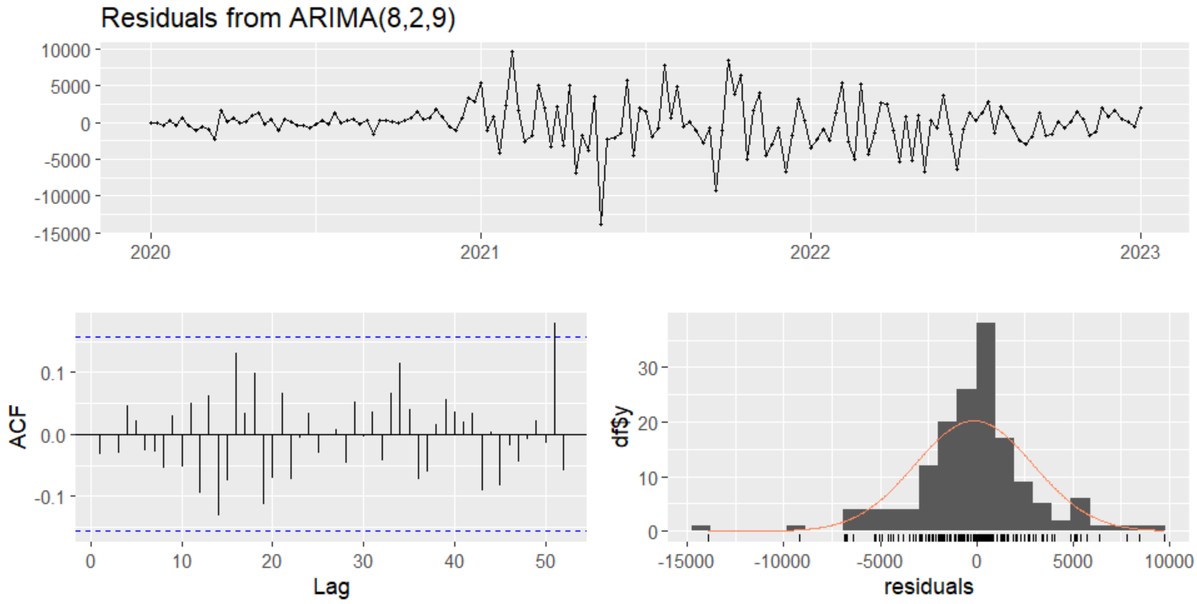


Figure 8: Result of checkresiduals function on testing data forecast for Bitcoin price.

## 3.2. Forecast Results

After the rigorous methodology described in the preceding section was implemented, it obtained forecast results for both Bitcoin and gold prices. Specifically, the ARIMA models, which were optimized for each dataset, were employed to make predictions 13 weeks forward from the beginning of June 2023 (see Figure 9 and Figure 10). Regarding gold prices, the point forecasts decline gradually over the 13-week period. From a starting price of approximately \$184, they fell to about \$179. Over time, the 80% confidence intervals widen as a consequence of increasing uncertainty in the more distant future, which is a normal attribute of time series forecasts. Aligning with the historic performance of gold as a steady, safe-haven asset, the pattern portrays a potential downward trend in gold prices within a relatively stable boundary.

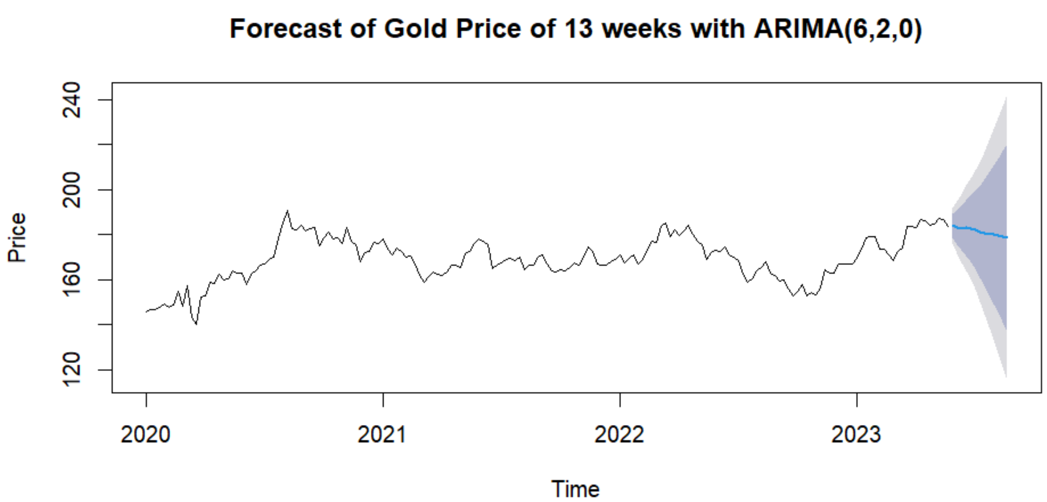


Figure 9: Forecast of Gold price for 13 weeks from May 22, 2023.

Regarding Bitcoin, the point forecasts exhibit noticeably greater fluctuations over the 13-week period than were seen with gold. Forecasts for Bitcoin prices range from approximately $26,672 to $32,971. The 80% confidence intervals expand dramatically through the forecast period, indicative of the well-established volatility of Bitcoin prices.

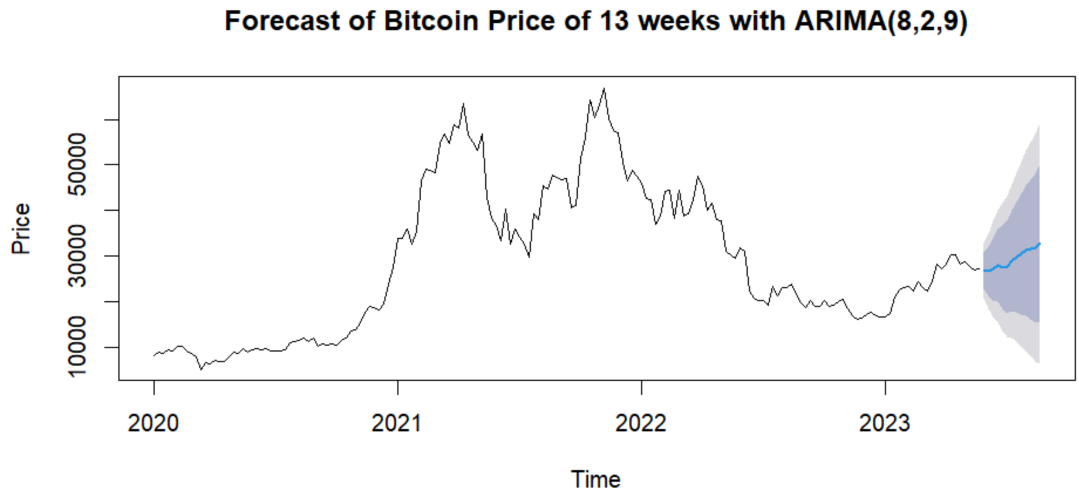


Figure 10: Forecast of Bitcoin price for 13 weeks from May 22, 2023.

In spite of the robust statistical foundation of the ARIMA models, when interpreting these predictions, it is important to bear in mind the overall context, in which a multiplicity of factors influence asset prices. The notoriously unpredictable and highly volatile character of Bitcoin exacerbates this inherent uncertainty. Comparing our results to other predictions and studies in the literature, the forecast aligns with the commonly posited future trajectory of Bitcoin described by: continued growth interspersed with significant volatility [5]. The results do not support the confidence that Bouri et al., as well as Urquhart and Zhang, place in Bitcoin as serving a similar hedge and safe-haven role to gold [1, 2]. On the gold side, our predictions also align with conventional wisdom: a mostly steady value with minor fluctuations. In accordance with this paper's original objectives, these forecasts give us a quantitative basis for understanding future price dynamics for Bitcoin and gold, highlighting the fundamental differences between the two assets: gold, the traditional safe-haven asset, being relatively stable and Bitcoin is volatile, but possessing the potential for high returns. This stark contrast presents opportunities for strategically combining the different assets to diversify portfolios.

The method used and the findings obtained provide direction for future research on cryptocurrencies and their relationship with traditional markets. Our ARIMA-based approach could be applied to other cryptocurrencies or other traditional assets. Similarly, it may be modified with different parameter selections or supplementary datasets. Cryptocurrency markets will inevitably continue to evolve and expand. Therefore, this sort of quantitative analysis will be of paramount importance for both investors and researchers.

## 4. Discussion

The contrast between the forecasted price trends of Bitcoin and gold, as well as each asset's risk profile, reveals something of the broader economic and policy factors affecting their valuation. Our study appears to confirm the common perception that Bitcoin, which is frequently hyped as 'digital gold', in fact, exhibits dynamics that are vastly different from gold and which are driven by factors inherent in Bitcoin's digital nature. Unlike gold, Bitcoin is not a tangible asset, essentially complete

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in itself. Bitcoin's valuation is massively affected by the availability and cost of computational resources, including central processing units (CPUs) and graphics processing units (GPUs). Hayes emphasized that the price of Bitcoin is closely related to the cost of producing it: a process known as 'mining', which demands enormous amounts of computational power [5]. As the prices of semiconductors and GPUs continue to rise, the cost of mining Bitcoin increases, indirectly driving up Bitcoin's price [6]. These industrial dynamics, which are themselves highly volatile, are absent in gold valuation, which is mainly dependent on macroeconomic factors and the supply-demand balance.

Price manipulation is another factor that differentiates the valuation of Bitcoin and gold. Notwithstanding the fact that Bitcoin and other mainstream cryptocurrencies like Ethereum are relatively immune to price manipulation, non-mainstream cryptocurrencies are often subject to manipulative practices. The investigation by Glaser et al. found substantial evidence of speculative behavior and a large number of pump-and-dump schemes in the cryptocurrency market, with both developers and major stakeholders manipulating prices in pursuit of quick profits [7]. These circumstances are utterly alien to the gold market, where price manipulation is infinitely more challenging due to the market's sheer size, the intrinsic nature of gold as a scarce tangible asset, and regulatory oversight. Cryptocurrency is also set apart from traditional assets like gold by its unique relationship to artificial intelligence (AI). AI and machine learning are important tools for predicting cryptocurrency price movements [8]. Via techniques such as sentiment analysis, transaction pattern recognition, and complex predictive models, AI can significantly influence cryptocurrency trading strategies and market dynamics [9].

In addition to this, taking into account the role of interest rates and financial stability, it ought to be noted that sharp interest rate hikes have historically been linked to banking crises [10]. The relationship between interest rates and the price dynamics of Bitcoin and gold presents yet another layer of complexity. Gold is regarded as a safe-haven asset during such crises. However, the behavior of Bitcoin is much less predictable and may be influenced by a wide range of external factors, including technological advancements and regulatory changes. In terms of policy, our findings indicate a need for stricter regulation of the cryptocurrency market. In particular, there must be legal and regulatory interventions targeting market manipulation and the dramatically uneven distribution of gains in smaller cryptocurrencies. Additionally, policymakers will need to take into account how AI-driven trading might influence market dynamics and whether regulations are required to prevent AI-driven market manipulation. Despite the promotion of the idea of Bitcoin as 'digital gold,' the characteristics and dynamics driving Bitcoin and gold prices are fundamentally different, and this difference is inevitable owing to their different nature and market structures. These individual asset-specific factors are of vital relevance for investors, as well as for regulators creating policies that will regulate these assets.

## 5. Conclusion

Our research demonstrated the utility of the ARIMA model for predicting Bitcoin and gold prices, contributing helpful insights as to the price dynamics of traditional assets as compared to cryptocurrency. A promising area of future research would involve a more robust validation approach, such as cross-validation, which would strengthen the reliability of our model's parameters. The employment of advanced machine learning algorithms and the incorporation of additional variables, such as economic indicators and sentiment analysis data, may also be explored to improve the model's forecasting ability. In the course of this study, challenges associated with computational resource limitations and the complex nature of time-series data were encountered. These were addressed by capping the ARIMA parameters and adopting rigorous statistical tests. Contrary to our initial expectations, it was found that despite being labeled as 'digital gold', Bitcoin and gold exhibit vastly different price behaviors and risk profiles. This is neither a positive nor a negative trait of Bitcoin,

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but it does show that investors and regulators should not treat cryptocurrency in the same way as traditional assets.

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