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The Influence of Virtual Currencies on Conventional Currencies

A Case Study on the Bitcoin and the Price of Gold

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Abstract

This research investigates the growing impact of virtual currencies, with a specific focus on how Bitcoin, a leading digital currency, influences gold prices. It delves into the evolving role of Bitcoin in the traditional financial sphere, examining its effect on gold, a classical asset and a benchmark of economic stability. Through this study, we aim to understand the nuances of this unique interaction and its implications for the broader financial landscape. This paper presents an in-depth case study that examines the correlations and potential causal relationships between the volatility in virtual currency markets and gold price fluctuations, a traditional indicator of economic stability and a renowned safe-haven asset, with a particular focus on the period encompassing the COVID-19 pandemic. Using a range of econometric methods, including time-series analysis and the Autoregressive Integrated Moving Average (ARIMA) model, this research analyzes historical price data from the past decade, with a special emphasis on the impact of the COVID-19 pandemic alongside other key geopolitical events and macroeconomic factors, to elucidate the interplay between these distinct asset classes.

Keywords: Cryptocurrency Market, Investment Strategy, Economic Impact, Gold price, Market Dynamics.

1. Introduction

1.1 background

The financial landscape has been revolutionized by the emergence of virtual currencies, such as Bitcoin, Ethereum, and various other cryptocurrencies (Wang et al., 2023). Anchored by blockchain technology, these digital assets signify not only technological progression but also a fundamental shift in the mechanisms of value exchange, storage, and perception within the global economy. This transition represents a notable divergence from traditional financial systems, heralding a new era in digital financial transactions (Aliu et al., 2023).

As virtual currencies gain increasing traction, attracting interest from both retail and institutional investors, their influence extends beyond mere market scope. These currencies are redefining the concept of money and challenging the long-standing dominance of fiat currencies and regulated financial institutions (Prasad, 2023). This burgeoning digital asset class presents complex questions for traditional financial markets, particularly concerning conventional fiat currencies and established commodities such as gold (Jafari, 2018).

The intersection of cryptocurrencies and traditional financial instruments is both intriguing and pivotal, offering a unique lens to examine how digital assets interact with and potentially transform established financial markets (Nam, 2023). This interplay may reshape investment strategies, risk management, and the dynamics of financial markets, necessitating a reevaluation of traditional financial theories and practices (Majeed & Mohammed, 2023).

This essay examines the substantial influence of the COVID-19 pandemic on the field of research, emphasising the unparalleled economic changes that have had a dramatic impact on worldwide financial markets. The current moment of increased volatility and uncertainty is crucial for examining the price swings of gold and Bitcoin. This essay analyses the significant influence of the COVID-19 pandemic on financial markets, specifically focusing on the increased instability and its effect on the prices of gold and Bitcoin. This study examines the ability of these resources to withstand and respond to economic pressures, aiming to get a more profound comprehension of the interplay between conventional and digital financial industries in times of crisis.

Furthermore, the research specifically examines the correlation between gold and Bitcoin, intentionally disregarding other assets to solely analyse this particular link. This technique seeks to offer comprehensive understanding of their interaction during the epidemic, so contributing to the advancing field of finance.

1.2 The Nature and Classification of Bitcoin

Bitcoin, existing at the intersection of a currency and an asset class, is a paradigm of cryptoassets. It functions as a decentralized exchange medium, distinct from traditional banking structures and powered by blockchain technology(Buchwalter, 2019). Its market-driven valuation diverges from fiat currencies, which are underpinned by physical commodities or government endorsement. As an investment asset, Bitcoin is marked by significant volatility and liquidity, with its valuation susceptible to technological, regulatory, and market sentiments. This dualistic role of Bitcoin spurs theoretical debates on the integration and impact of such digital assets in the wider financial system, thereby challenging established financial norms (Alandjani, 2023).

2. Methodology

2.1ARIMA Model Setting

The ARIMA (Autoregressive Integrated Moving Average) model, which combines elements of the autoregressive (AR) and moving average (MA) models, is represented by the notation ARIMA(p, d, q). Here, 'p' denotes the order of the autoregressive component, 'd' signifies the degree of differencing required to achieve stationarity, and 'q' indicates the order of the moving average component(Arumugam & Natarajan, 2023).. The construction of the ARIMA model involves a systematic approach, including establishing time series stationarity, estimating parameters, verifying the model's adequacy, and applying it in forecasting.

$$\mathrm{Return}_t = \alpha + \theta_1 \mathrm{Return}_{t-1} + \theta_2 \mathrm{Return}_{t-2} + \ldots + \theta_p \mathrm{Return}_{t-p} + \varphi_1 \varepsilon_{t-1} + \varphi_2 \varepsilon_{t-2} + \ldots \varphi_p \varepsilon_{t-q} + \varepsilon_t \quad (1)$$

This model is designed to deepen the comprehension of underlying patterns and facilitate the forecasting of outcomes resulting from fluctuations in gold prices.

2.2 Weak Stationarity Test

In this study, the Augmented Dickey-Fuller (ADF) test was utilized to assess stationarity within the dataset. The null hypothesis of the ADF test asserts the presence of a unit root, indicative of non-stationarity in the series. In contrast, the alternative hypothesis proposes the absence of a unit root, implying stationarity. The ADF test was conducted on the daily data series, and it yielded the following results:

Table 1 Result of weak stationarity test

	t	p
Daily		
Raw	-1.722	0.7409
1st order difference	-31.428	0.0000
2nd order difference	-55.697	0.0000

The results presented in Table 1 reveal nonstationarity in the raw data for daily observations, as the p-values exceed the 5% significance threshold, thereby failing to reject the null hypothesis. However, the application of first and second order differencing to these data series indicates stationarity, as reflected by significantly lower p-values, below the significance level. Notably, the second order of differencing was particularly effective in enhancing the stationarity of data series.

2.3 Data Source

In this study, we conducted an exhaustive analysis of international gold prices, denominated in US Dollars, over a prolonged period from January 2, 2016, to December 1, 2023. The data was meticulously sourced from the esteemed “Investing” statistical website, renowned for its accuracy and comprehensive coverage of global financial markets.

To assess the predictive capability of the ARIMA model, a forecast horizon was set from January 1, 2023, to December 1, 2023. This methodology permitted an evaluation of the model's precision in projecting future trends based on historical data, an essential component in confirming the model's practicality for real-world financial forecasting.

2.4 Stationarity Test

The application of the ARIMA model necessitates verifying the stationarity of the dataset, achieved through the Augmented Dickey-Fuller (ADF) test. This critical step ensures that the time series data does not exhibit time-dependent structures, which is essential for the validity of any subsequent ARIMA analysis.

2.4.1 Autocorrelation and Partial Autocorrelation Analysis

The analysis of log-differentiated data presented in Figure 1 confirms the stationarity of gold prices. Additionally, this study involves an examination of the autocorrelation function (ACF) and partial autocorrelation function (PACF) across various lags to ascertain the optimal selection of model variables. This comprehensive approach aids in identifying the most relevant lags for the time series analysis, ensuring the robustness and accuracy of the predictive model.

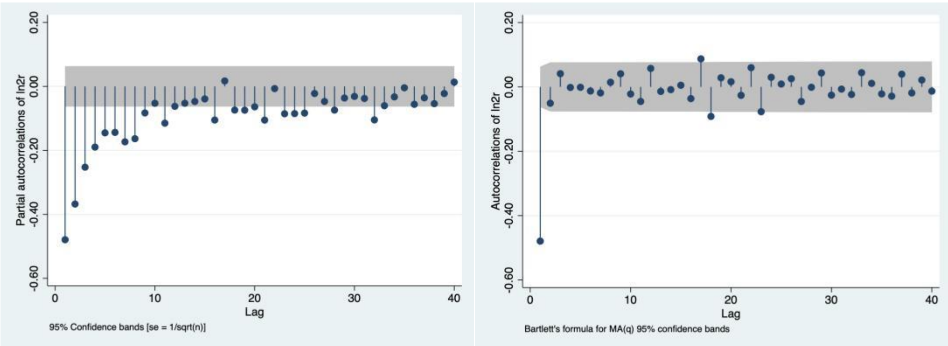

Figure 1 Daily ACF & PACF Graph

In this study, the graph's Y-axis shows the values of the autocorrelation function (ACF) and partial autocorrelation function (PACF) for logarithmic returns of international gold prices, while the X-axis represents time lag. The 95% confidence interval for the Autoregressive (AR) and Moving Average (MA) components is marked between y = -2 and y = 2, aiding in identifying white noise in model residuals. The residuals, as per the Box-Jenkins methodology, align with a normal distribution, consistent with the zero mean and constant variance R, as corroborated by Nyongesa and Wagala's findings. This succinct representation is crucial for analyzing serial correlation in the data.

2.4.2 Constructing Potential Models

Subsequent to a thorough analysis of the PACF and ACF criteria, an ARIMA (1, 1, 0) model is identified as the most appropriate. This conclusion is drawn from the examination of varying p and q values, as detailed in Table 1, coupled with the analysis of corresponding PACF and ACF values. The model exhibiting the lowest information criteria is deemed optimal for predicting daily fluctuations. In conclusion, the ideal parameters for daily forecasting are determined to be p=1, d=1, and q=0.

1. Empirical Results and Analysis

Upon selection, the models were operationalized using datasets segmented into daily intervals. The ensuing stage involved a critical assessment of the residuals for each model to evaluate the validity of the regression analyses performed. In this context, the Portmanteau test was utilized as the primary diagnostic tool. Table 2 delineates the results of this residual analysis.

Table 2 Residual test

Model	Portmanteau (Q) statistic	Prob > chi2
Daily-ARIMA(1,1,0)	18.7297	0.9983

In the context of this study, the Portmanteau test, a rigorous statistical procedure, was employed to validate the residuals of the proposed time series models. This test is predicated on the null hypothesis, which posits that the residuals are devoid of autocorrelation and hence conform to a white noise process. Such an attribute is crucial for the reliability of any time series model, as it ensures that the model errors are random and not influenced by systematic patterns or trends. For the purpose of this analysis, a conventional threshold of statistical significance was established at the level of 0.05.

The results of the Portmanteau test, as presented in Table 2, indicate that the probabilities associated with each of the tested models significantly exceed the set threshold. This finding implies that there is insufficient statistical evidence to reject the null hypothesis for any of the models under consideration. Such an outcome is indicative of the absence of autocorrelation in the residuals, thereby reinforcing the validity and robustness of the models.

Subsequent to the testing phase, the study progressed into a phase of in-depth analysis, utilizing advanced visualization techniques. This phase was pivotal in offering a more intuitive and graphical representation of the models' performance. By juxtaposing the observed data, referred to as the "actual value," against the predicted values for the treatment group, termed as the "fitted value," a comparative analysis was conducted. This approach not only highlighted the discrepancies between the observed and predicted values but also provided valuable insights into the predictive accuracy and efficacy of each model. Such a comparative visual analysis is instrumental in assessing the practical applicability of the models, especially in terms of their forecasting capabilities and reliability in real-world scenarios.

In conclusion, the comprehensive validation and analysis phases underscore the methodological rigor and the analytical depth of the study, affirming the reliability and applicability of the time series models in capturing and forecasting complex patterns in the data.

1.1 Comparison of predicted and actual values

In this section, primary objective of the study is to compare the performance of a predictive model against real-world data. The graph below visually compares and helps assess the accuracy of a forecast model in duplicating real market behaviours.

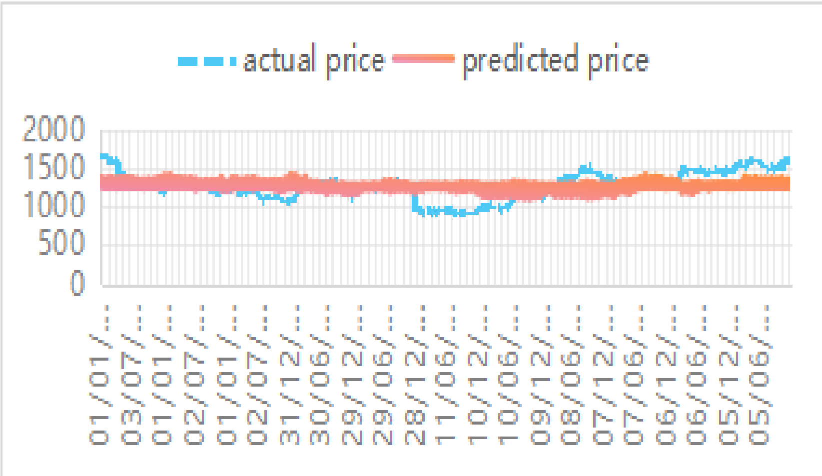

Figure 2 Comparison of predicted and actual value

The given graphical depiction is a line chart illustrating two significant data series: the real prices and projected prices, spanning a particular duration. The x-axis is partitioned chronologically, displaying dates in a day/month/year format, commencing with 01/01/2019 and concluding on 18/08/2023. The y-axis depicts the prices, which span from 500 to more than 1800 units.

The pricing data is represented by two separate lines: a dashed blue line represents the actual prices, while a solid orange line represents the forecast values. Both lines show variations over time, with the actual price line experiencing a significant decrease in the middle of the timeframe. The forecasted price line seems to follow this pattern, although with a delay. The close proximity of the two lines implies a correlation between the expected and actual values, indicating that the predictive model may have successfully caught the overall trend of the actual prices.

The provided graphical representation is a line chart that displays two important data series: actual prices and forecasted prices, over a specific time period. The x-axis is divided chronologically, showing dates in a day/month/year format, starting with 01/01/2019 and ending on 18/08/2023. The y-axis represents the prices, ranging from 0 to over 1800 units, without specifying the exact currency unit.

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The scientific community frequently utilises this chart to visually and quantitatively evaluate the performance of prediction models in comparison to observed data. This allows researchers to effectively examine the effectiveness of their predictive algorithms and models. The graph's structure enables quick visual assessment of the model's predictive accuracy over time, while it does not include statistical markers that would offer a more comprehensive examination of the model's performance, such as error margins or confidence intervals.

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The time series graph displays two kinds of data: the actual prices and the expected prices during a specified time period. The horizontal axis represents a chronological timeline from 2019 to 2021, following the day/month/year format. The vertical axis is scaled to represent pricing values, ranging from around 500 to a maximum of 1800. The specific money denomination is unspecified.

The current financial valuations are represented by a red line, while the predicted valuations are represented by a blue line. Every dataset exhibits prominent oscillations, which indicate the presence of volatility within the studied time period. Despite the lack of clear trends or cyclical patterns, the red and blue lines on the graph indicate a correlation, as the predicted price consistently falls below the actual figures but closely follows its fluctuations.

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3.2 Daily Result

The analytical model revealed a pronounced negative correlation between fluctuations in gold prices and virtual currencies. Specifically, on a daily basis, it was observed that a 15.7% surge in gold prices corresponded to a 9.14% decline in daily revenues for bitcoin, highlighting a significant inverse relationship between these two economic indicators.

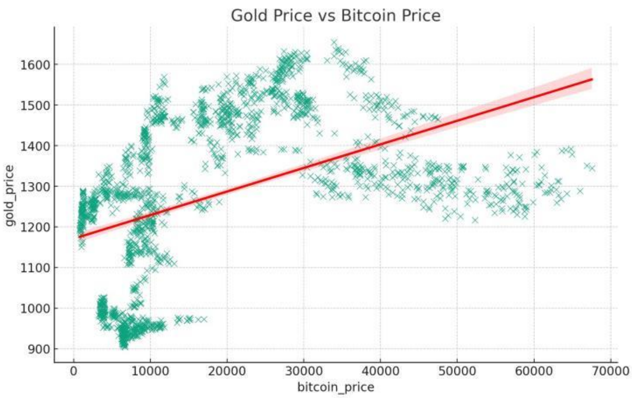

Figure 3 Relationship between gold and bitcoin price

In this study, we present a scatter plot graph to elucidate the correlation between the prices of gold and Bitcoin. This graph includes empirical data points, each representing a specific instance of observed prices. A red regression line is plotted to represent the trend in the relationship between the two variables.

Our regression analysis reveals a statistically significant coefficient of 0.0058, indicating the extent to which Bitcoin prices influence gold prices. This coefficient suggests that for every unit increase in Bitcoin prices, there is a corresponding increase of approximately 0.0058 dollars in gold prices. This positive correlation implies that as Bitcoin prices rise, there is a marginal but consistent increase in the price of gold.

Further analysis reveals that this relationship, while statistically significant, suggests a relatively modest impact of Bitcoin price fluctuations on gold prices. This finding contributes to the broader understanding of how emerging digital assets, such as cryptocurrencies, can influence traditional investment commodities like gold. The implications of this relationship are particularly relevant in the context of diversifying investment portfolios and understanding the dynamics between traditional and digital asset markets.

4. Conclusion

Our analysis employing the ARIMA (1,1,0) model clearly demonstrates its superiority in predicting future gold prices, particularly when incorporating the most recent four days of pricing data and news. This finding underscores a significant correlation between recent market events and gold price trends.

This investigation delineates the heightened sensitivity of traditional currency markets, particularly the gold market, to the dynamics of virtual currencies, accentuated notably in the milieu of the COVID-19 pandemic. Empirical data revealed a pronounced correlation between the fluctuations in virtual currency valuations, exemplified by Bitcoin, and the market price of gold. This correlation signifies an escalating influence of digital currencies on established financial assets, a trend that has become increasingly evident subsequent to the COVID-19 outbreak. The findings suggest that variations in virtual currency values exert a considerable impact on the gold market, potentially affecting investment strategies and overall market stability, particularly within the volatile economic landscape engendered by the pandemic. The proliferation of virtual currency investments in the COVID-19 era may precipitate a reevaluation of gold as a safe-haven asset, thereby influencing its demand and market value.

In light of these insights, future research endeavors should be directed towards three critical areas to deepen the understanding of this nexus, especially in the post-pandemic context:

The development and integration of advanced, hybrid ensemble forecasting models to accurately predict the impact of virtual currency trends on gold prices, addressing the unique volatility introduced by the pandemic.

The proposal of innovative metrics for assessing the predictive accuracy of these models, extending beyond traditional frameworks such as the Root Mean Square Error (RMSE), to better encapsulate the complexities and nuances introduced by the pandemic.

Future study could be focus on the in-depth examination of the scalability and applicability of analytical models, particularly the Autoregressive Integrated Moving Average (ARIMA) model, in scrutinizing the interplay between virtual currencies and gold prices across various temporal dimensions, including weekly and monthly data series. This examination should consider diverse data volumes and be contextualized within the economic disruptions precipitated by COVID-19.

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