Analysis of the Prediction and Influencing Mechanism for Bitcoin Price

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Abstract: As a matter of fact, with the rapid development of information technology, cryptocurrency has become a common tool for investment. Under the dramatically fluctuations markets globally, the cryptocurrency prices have been changed with a huge volatility. Among which, Bitcoin is the currency with the largest assets, also fluctuate significantly. With this in mind, this study will evaluate and estimate the influencing factors for Bitcoin prices. To be specific, the hedge and support mechanism for price of Bitcoin will be discussed and evaluated. In the meantime, the Autoregressive Integrated Moving Average (ARIMA) model is adopted in order to show the price trend prediction. In addition, the correlation analysis is adopted in order to find the intrinsic connections between other issues and cases. At the same time, the limitations and prospects will be demonstrated as well according to the analysis. Overall, these results shed light on guiding further exploration of Bitcoin pricing as well as provide a guideline for analysis of the inherit price for Bitcoin.

1 INTRODUCTION

Cryptocurrency, including Bitcoin, is constructed based on the blockchain system, and the blockchain system has also evolved since its inception, now serving as the foundation of various decentralized applications beyond cryptocurrency. Blockchain is a distributed and decentralized ledger technology (DLT) to record and memorize the transactions across networks, in a transparent, secure, and immutable way. Every block inside the blockchain system contain a series of transactions, these blocks are cryptographically linked, ensuring its data integrity. This contributes to the protection of information transactions' confidentiality and integrity, which form the basis of the Blockchain system. Because blockchain systems are inherently decentralized, there is no longer a need for middlemen, which lowers costs and improves transaction efficiency and speed (Wang et al., 2019).

Blockchain's progress has improved its adaptability to smart contract applications in recent years, this ensures the possibility of decentralized autonomous organizations (DAOs), which function without centralized control (Buterin, 2014). This development highlights blockchain's potential in trust less settings, where codes take the role of conventional centralized organizations (Swan, 2015). A sketch is shown in Figure. 1 (Santander, 2015). Blockchain is therefore developing into the essential infrastructure for the digital economy, driving innovation in fields that demand efficiency, safety, and transparency (Yermack, 2017). This accelerates the application of blockchain technologies.

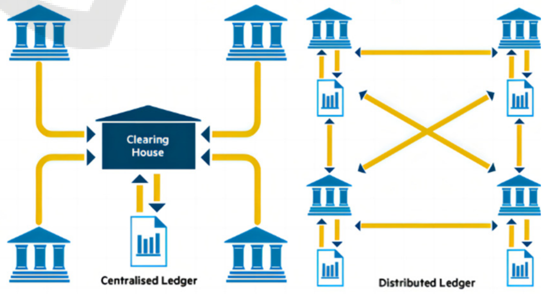

Figure 1: Blockchain Operation Process (Santander, 2015).

Web3 is the next generation of the internet, transitioning from centralized control to a decentralized and user-centric model. In this system, the users can control their digital identities, assets and data facilitated by decentralized applications (dApps). The fundamental principles of Web3 include decentralization, privacy, and interoperability, which

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is highly connected to the spirit of blockchain. Web3 is the future shape of internet, breaking the monopoly of information and resources, fostering, and promoting a more inclusive and equitable internet where the users are the core of this system.

Bitcoin operates on blockchain, consensus mechanisms such as Proof of Work (PoW) or Proof of Stake (PoS) are utilized to validate transactions. PoW, particularly, is important to Bitcoin's operation, as it requires miners to solve mathematical puzzles to validate transactions, known as mining for this process. The miners compete to solve the puzzles and the first to do so will be rewarded newly minted Bitcoin. This process requires energy especially electricity, so the costs of mining may fluctuate significantly. The fluctuations in mining costs could be affected by energy cost and technology advancement, the overall changes directly impact the prices of Bitcoins. So, knowing exactly how mining costs evolve is crucial for analysing Bitcoin's cost-support price.

This study is based on the existing research, using the Bitcoin mining output model to forecast the future mining cost and its impacts for Bitcoin's pricing. The halving event of Bitcoin mining output in 2024 is a pivotal moment in the cryptocurrency's economic cycle. The Block Reward for miners will be reduced from 6.25 per block to 3.125 per block. Historically, each halving event can cause significant increase in Bitcoin's price, driven by the reduction in supply and increase in demand (Narayanan et al., 2016). For instance, in 2012, the first halving caused a price increase of 8000% in a span of 12 months, while the second and third halving led to price increases of 2900% and 600%, respectively. These trends demonstrated the robust relationship between Bitcoin price increases and halving, which gave this study considerable inspiration. By examining the potential changes in mining output and costs, this study aims to make contribution to the existing literature on Bitcoin's economic model. In addition, this study similarly seeks to explore the correlation between Bitcoin and traditional assets such as stocks and gold, and thus explore the broader implications of these changes to provide more informed recommendations for diversification and asset allocation in conjunction with changes in the cost of Bitcoin.

The framework for this study will involve two key analytical approaches. First, an Autoregressive Integrated Moving Average (ARIMA) time series model is employed to predict future bitcoin mining output, considering factors such as network difficulty and hash rates. The model is well suited to capturing the temporal dynamics of bitcoin mining and provides a solid basis for predicting future changes in output. Second, Spearman rank correlation coefficients will be used to assess the relationship between Bitcoin and traditional assets, providing more insight into how Bitcoin's price movements align or deviate from more mature markets. By integrating these methods and validating the data, this study aims to comprehensively analyse the future status and role of Bitcoin, especially in the context of 2024 halving event.

2 DATA AND METHOD

This part illustrates all the models used in this paper, including Bitcoin mining output model; ARIMA model and Spearman's rank correlation coefficient. Previous scholars have developed a model of Bitcoin mining output, his research established a model of Bitcoin mining output (Hayes, 2015). By measuring the relationship between various factors and time that affect Bitcoin mining output, a more accurate cost-support price could be predicted:

$$BTC\ mining\ output\ /\ Day = \theta\left(\frac{\beta\rho}{\delta}\right) \quad (1)$$

Here, β is the block reward in BTC/block; δ is the mining difficulty in GH/block; ρ is the hash rate used by miners in TH/s and θ is a constant used to convert hash arithmetic to expected daily bitcoin production.

This model takes Block reward, mining difficulty and hash rates as the factors of Bitcoin mining production, these factors serve as vital tools for understanding the dynamic nature of Bitcoin mining, especially in a volatile market environment. In the following calculation process, this study will use this model to estimate the daily output of Bitcoin mining, then calculate and fit the future change in mining support costs with the Bitcoin halving cycle. The ARIMA model, is a commonly used in time featured analysis. Its general form can be expressed as:

$$Y_t = c + \varphi_1 Y_{t-1} + \varphi_2 Y_{t-2} + \cdots + \varphi_p Y_{t-p} + \theta_1 \epsilon_{t-1} + \theta_2 \epsilon_{t-2} + \cdots + \theta_q \epsilon_{t-q} + \epsilon_t \quad (2)$$

This research uses an ARIMA model to analyze datasets on Bitcoin mining costs. The model is used to understand historical trends and make predictions about future mining costs. The model using process involves:

- Selecting a simplified ARIMA model based on data characteristics and preprocessing results
- Determining model parameters through analysis of ACF and PACF
- Estimating parameters using maximum likelihood and confirming significance through statistical tests

- Assessing model fit using AIC and BIC criteria
- Verifying residual white noise properties with the Ljung-Box Q test
- Generating forecasts for future Bitcoin mining output

The Spearman's rank correlation coefficient, denoted by the Greek letter ρ, is a non-parametric measure used to assess the strength and direction of association between two ranked variables. The formula can be expressed as:

$$\rho_{xy} = 1 - \frac{6\Sigma d_i^2}{n(n^2-1)} \quad (3)$$

Spearman's correlation is chosen for its ability to capture monotonic relationships without assuming linearity. So, this research utilizes Spearman's rank correlation coefficient to assess the relationship between Bitcoin and traditional assets (NASDAQ and Gold). This analysis is conducted over the entire study period and examine how correlations evolve over time.

This study collected two distinct datasets to investigate Bitcoin mining costs changes through time and the relationship between Bitcoin prices with traditional assets like gold and stocks. The quarterly data from January 2016 to July 2024 are collected, containing 35 datasets spanning 8 years. For each quarterly data, there is less variation in internal changes, so one collects data every three months to ensure the continuity and reliability of the relevant data. The datasets include the following variables including block reward; Hash Rate (TH/S); Mining Difficulty (GH/S); Bitcoin price ($); Actual Mining cost of Bitcoin ($); Actual Total Cost; Estimated Mining Cost; Ratio (Mining cost/Price) and Error Ratio (Estimated/Real Cost). Data sources include coinwards.com for hash rate, mining difficulty and block reward, Binance.com for Bitcoin price, and macromicro.com for actual mining cost of Bitcoin and the actual mining output of Bitcoin. This dataset will be used to examine the model of (Hayes, 2015), and then to predict the Bitcoin mining cost in the future, trying to provide supportive data for Bitcoin price analysis.

To analyze the relationship between Bitcoin and traditional assets, one collected weekly data from January 2015 to July 2014, encompassing Bitcoin Price ($); NASDAQ Composite Index and Gold Spot Price ($/oz). The data was sourced from Yahoofinance.com for Bitcoin/USD prices and NASDAQ Composite Index and World Gold Council for Gold prices. These datasets comprise approximately 500 weekly observations. Figure. 2 and Figure. 3 show the normalized weekly price trends of Bitcoin, NASDAQ, and Gold, sourced from Tradingview.com. These datasets will be used for Spearman correlation analysis to find the relationship of Bitcoin and traditional assets and trying to find opportunities for Bitcoin to hedge and to inform asset allocation recommendations.

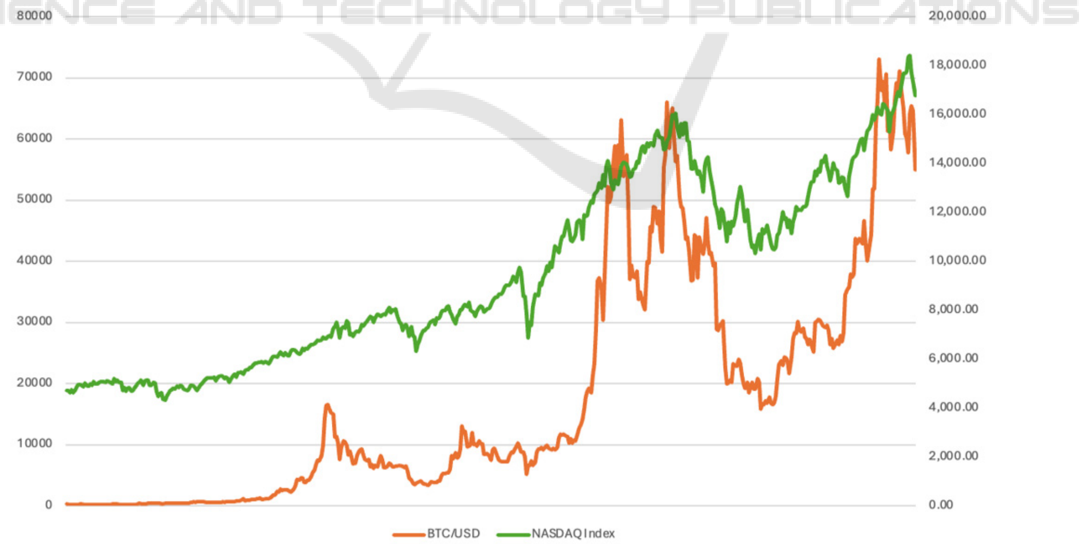

Figure 2: BTC & NASDAQ (Photo/Picture credit: Original).

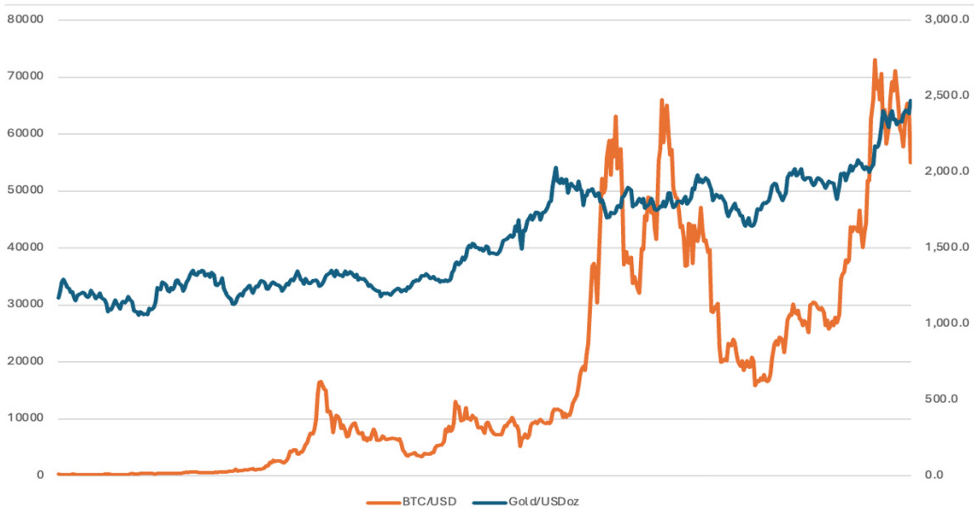

Figure 3: BTC&GOLD (Photo/Picture credit: Original).

3 RESULTS AND DISCUSSION

3.1 ARIMA MODEL

This part will present the results of the ARIMA model applied to the quarterly Bitcoin mining output data collected from January 2016 to July 2024. Then examine and compare it with the real mining cost and output. Using the estimated mining output and real total mining cost, one could get the estimated mining cost of each Bitcoin. Then, this study will divide the estimated mining cost by real mining cost to get the error ratio, which could test the accuracy of the prediction of the model.

In this research, an ARIMA (0,1,1) model was selected on the data characteristics, which shows a noticeable trend without a clear seasonal pattern. When determining the values of p and q, one analyzed the ACF and PACF plots of the post differential data. The ACF plots showed a rapid decay after lagging by order 1, while the PACF plots did not show a clear truncated tail pattern. These features suggest that the MA (1) term may be suitable for the data without the AR term. Therefore, one chose the ARIMA (0,1,1) model, and preprocessing results with the following specific formula:

$$Y_t = -53.822 - 0.411\epsilon_{t-1} \tag{4}$$

The ARIMA model parameters were determined through the analysis of the ACF and PACF. Model selection was based on minimizing the AIC and BIC. These parameters were obtained by maximum likelihood estimation and their significance was confirmed by statistical tests. The specific significance test results are as shown in Table 1.

One used a significance level of 0.05. The p-value of 0.047 for the constant term is just below the 0.05 level of significance, which suggests that this parameter may have some importance in the model, but its effect may not be as significant as that of the MA parameter. The p-value of 0.013 for the MA parameter is significantly lower than 0.05, which suggests that this parameter plays an vital role in the model. The goodness of fit of the model was assessed by AIC and BIC with the following values: Akaike Information Criterion (AIC): 471.355 and Bayesian Information Criterion (BIC): 475.934. The AIC and BIC values were minimized, further supporting the model's adequacy.

The model Q statistic data, namely the Ljung-Box Q test statistic, is displayed in Table 2 together with the p-value and statistic value. The Q statistic test for white noise may be used to verify if the model residuals are white noise, the original hypothesis is: the residuals are white noise). Q6 will be used to test the residuals of the first 6 orders to meet the white noise, commonly, the p-value is greater than 0.1 means it meets the white noise test. Usually, only Q6 need to be examined. The p-value of Q6 is larger than 0.1, so the original hypothesis cannot be rejected, at the significance level of 0.1, so these residuals are white noise, the model could meet the requirements. Then, using the fitted ARIMA (0,1,1) model, forecasts for Bitcoin mining output were generated for the period from Q3 2024 to Q1 2026, the forecasts indicate a continuous decreasing trend in mining output. The results are shown in Figure. 4 and Figure. 5.

Table 1: ARIMA prediction results.

ARIMA (0,1,1) Model Parameter List						
Term	Symbol	Coefficient	Standard Error	*z-value*	*p-value*	95% CI
Constant Term	c	-53.822	27.112	-1.985	0.047	-106.960 ~ -0.684
MA parameters	β_1	-0.411	0.165	-2.489	0.013	-0.734 ~ -0.087
AIC value = 471.355						
BIC value = 475.934						

Table 2: Q statistical Table.

Item	Statistic	p-value
Q6	0.561	0.454
Q12	0.735	0.693
Q18	0.740	0.864
Q24	2.922	0.571

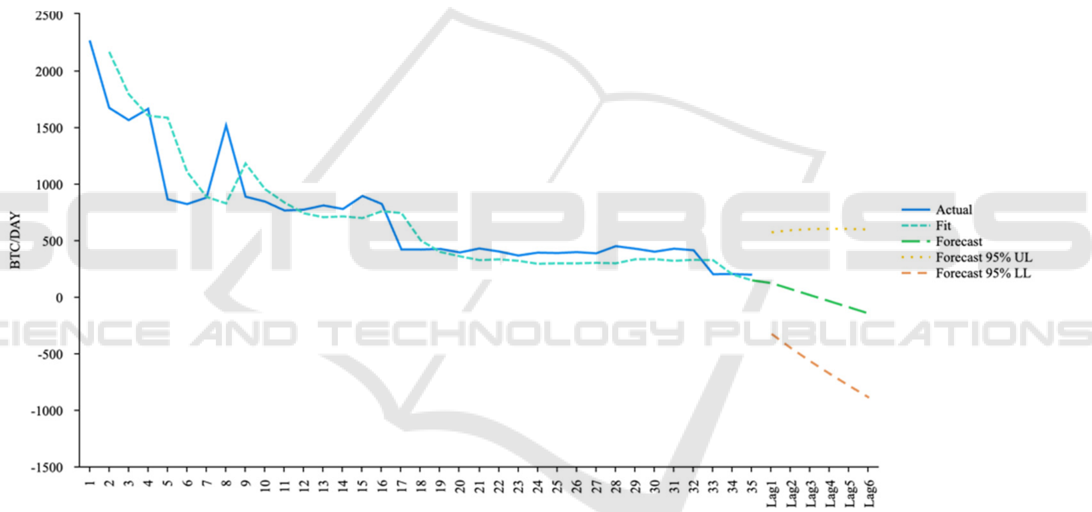

Figure 4: Bitcoin Mining Output Forecast (Photo/Picture credit: Original).

Figure 5: Error Ratio Normal Distribution (Photo/Picture credit: Original).

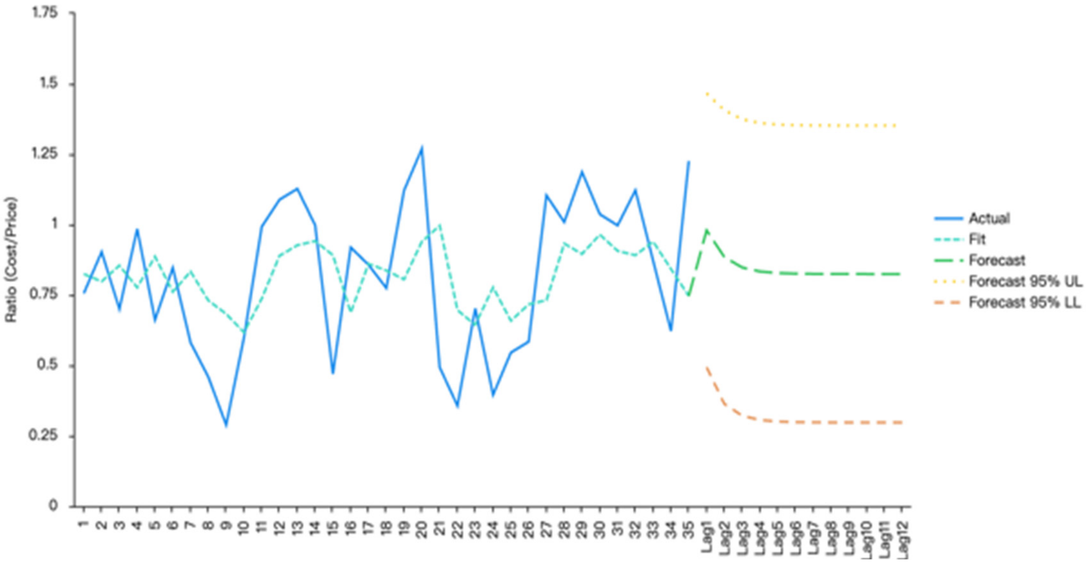

Figure 6: Ratio Forecast (Photo/Picture credit: Original).

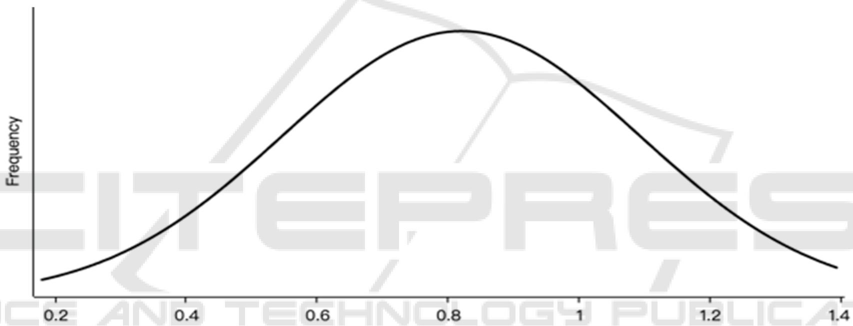

Figure 7: Ratio Normal Distribution (Photo/Picture credit: Original).

The data visualization in Figure. 6 and Figure. 7 shows the data for Error Ratio (Estimated mining cost/Real Cost), examining the last 35 issues of the dataset: The 35 measurements of accuracy on the dataset consistently centered around 0.85, with a distribution that closely follows a normal distribution. The distribution is bell-shaped, which is approximately normal, with the mean around 0.85, which demonstrate the accuracy of the model's predictions.

Reviewing historical data, the ratio of bitcoin mining costs to the true price of bitcoin ranges from 0.5 to 1.2, which shows the profitability of miners as well as the volatility of the bitcoin price. Based on this data and the multiplier relationship with the mining price, over a four-year timeframe (the timeframe of each halving) after the 2024 Bitcoin mining halving event, one can get the critical support price on Bitcoin as presntend in Table 3.

Table 3: Price supporting analysis.

Important Support Price	Explanation
$30000 Shutdown Price	Historically, there has been no instance where mainstream or flagship models have shut down under relatively moderate electricity prices.
$48000 Black Swan Support Price	(Shutdown price * 160%) No Black Swan events have ever occurred where the market price fell below 160% of the electricity cost during the current cycle.
$52000 Cost Support Price	When the price falls below this level, the risk of buying a BTC on the secondary market is significantly lower than the risks undertaken by miners who invest tens of millions or more to mine.
$60000 Bear Market Support Price	In most cases during a bear market, the market price fluctuates around 200% of the shutdown price, which is around $60,000.

Table 4: Spearman correlation analysis.

		BTC/USD	
Gold/USDoz	Coefficient	0.882**	
	p value	0.000	
NASDAQ INDEX	Coefficient	-0.489**	
	p value	0.000	
Spearman Correlation Matrix			
	BTC/USD	Gold/USDoz	NASDAQ Index
BTC/USD	1		
Gold/USDoz	0.882**	1	
NASDAQ INDEX	-0.489**	-0.571**	1
* p<0.05 ** p<0.01			

3.2 Correlation Analysis

The Spearman correlation analysis was conducted to assess the relationship between Bitcoin (BTC/USD) Gold (Gold/USD per oz) and NASDAQ Index. The results are given in Table 4. The BTC/USD and Gold/USD per oz correlation coefficient is 0.882, and it is at the 0.01 significance level, meaning that there is a significant positive correlation between the two. The NASDAQ INDEX and BTC/USD have a -0.489 correlation coefficient, at the 0.01 significance level. The value of correlation coefficient between BTC/USD and NASDAQ INDEX is -0.489 and shows 0.01 level of significance, thus indicating that there is a moderate negative relationship Between BTC/USD and NASDAQ Index.

The result for Bitcoin and gold demonstrates a strong positive correlation suggests that Bitcoin and gold tend to move in the same direction, which means the price of Bitcoin could possibly increase while the price of gold increasing. This implies that Bitcoin may be seen as a digital store of value by investors, which is like gold (Dyhrberg, 2016). However, a moderate negative correlation between Bitcoin and NASDAQ Index are found, this negative relationship means potential hedging opportunity against stock market movements may exist, by using Bitcoin as a tool, particularly in the tech-heavy NASDAQ.

Although Bitcoin and gold price is strongly correlated, the unique risk-return features and the negative correlation with the stock market shows its possibility to play a role in portfolio diversification. Brière et al. found that including even a small proportion of Bitcoin in a diversified portfolio significantly improved its risk-return characteristics (Brière et al., 2015). The negative correlation with the NASDAQ Index suggests that Bitcoin could potentially server as a hedge against downturns in the technology sector. This aligns with findings by Guesmi et al., who found that Bitcoin can perform effective diversifier in various financial markets (Guesmi et al., 2019). During stock market downturns, one needs to increase Bitcoin allocation to potentially offset losses in equity positions.

During periods of economic uncertainty: Consider allocating both Bitcoin and gold, as they showed similar features, but also takes a dynamic hedging strategy, the investors could adjust the proportion of Bitcoin and other assets in their portfolios. One research stressed that dynamic strategies involving Bitcoin outperformed static approaches. (Platanakis et al., 2020)

4 CONCLUSIONS

To sum up, this study investigates the price prediction of bitcoin and analyse the inherit influencing mechanisms. While this study provides valuable insights into the measurement and prediction of bitcoin mining costs, as well as exploring the relationship between bitcoin and traditional assets, there are undeniably still some limitations. Bitcoin's time horizon as a mainstream investment target is less than ten years, and the amount of historical data is relatively limited, so this may limit the reliability of back testing based on Bitcoin's historical data. The cryptocurrency market is in a state of rapid change and development, so limited historical data is one of the major limitations of this paper. The mining cost model used in this study, although validated by data back testing and highly accurate, may not fully capture the latest technological advances in mining equipment and technology. Therefore, more accurate and efficient mining-related models are necessary. The correlation analysis does not analyse global macroeconomic factors much, but only price movements, which may miss the impact of some policy shifts and major economic events. Future research could improve these limitations in these ways, i.e., using more accurate models of bitcoin mining output and costs; analysing the impact of specific macro policy and regulatory changes in conjunction with the bitcoin and cryptocurrency markets in a more comprehensive manner.

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