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Evaluating the Efficiency of Financial Assets as Hedges against Bitcoin Risk during the COVID-19 Pandemic

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Abstract: In the turbulent landscape of financial markets, Bitcoin has emerged as a significant focus for investors due to its highly volatile returns. However, the risks and uncertainties associated with it necessitate effective hedging strategies. This paper explores the potential of various financial assets, including interest rates, stock markets, commodities, and exchange rates, as dynamic hedges against Bitcoin's risk. Utilizing a DCC-GARCH model, we construct a dynamic hedging model to analyze the viability of these financial assets as hedges. The data is categorized into pre-pandemic and pandemic periods to assess any change in hedging performance due to the outbreak of COVID-19. Our empirical findings suggest that the dynamic DCC-GARCH model outperforms the static OLS model in this context. During the pandemic period, a diverse set of financial assets demonstrated enhanced efficiency in hedging Bitcoin risk compared to the pre-pandemic phase. Among the hedging commodities, stock market indices, the US dollar index, and commodity futures displayed superior performance.

Keywords: cryptocurrency risk; financial volatility; dynamic hedging; COVID-19 impact; DCC-GARCH model

MSC: 32K99

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1. Introduction

The advent of Bitcoin dates back to 2008, with the inaugural Bitcoin block's genesis in 2009. The promotion and popularization of blockchain technology fostered the first public transaction, interchanging Bitcoin for physical goods, in May 2010. In July the same year, Tokyo-based online trading platform Mt. Gox emerged, becoming the pioneer in employing Bitcoin as a trading tool, with its value approximating US$0.08. The establishment of the maiden cryptocurrency exchange in July 2017 marked a significant surge in Bitcoin prices, albeit with inherent instability influenced by policy changes and market news. The notorious COVID-19 pandemic, commencing from October 2019, catalyzed considerable fluctuations in Bitcoin prices during 2020.

The pandemic instigated substantial morbidity and mortality globally, impelling governments to implement lockdown measures to curb viral spread. This enforced stasis critically hampered the global economy and supply chains, instigating market instability, evidenced by stock market downturns, futures liquidation, reduced demand for air travel, and an oil price war. These cascading effects incited investor panic, leading to sharp market variations. Governments responded with various relief and revitalization schemes, albeit unable to address the inflation and market instability issues, thereby exacerbating national government debt problems.

In 2020, the US Federal Reserve announced interest rate cuts and implemented an unlimited quantitative easing policy. The resulting overcirculation of money stimulated asset and commodity price surges, leading to global inflation. Subsequent tightening policy, designed to control inflation by raising interest rates and redirecting funds from risky assets back to the banking system, invited pessimistic economic outlooks from scholars.

In light of the evolving economic climate and market instability, exacerbated by COVID-19, investors turned towards innovative financial products such as Bitcoin to offset losses. As widely acknowledged by previous studies [1,2], Bitcoin presents a highly volatile investment opportunity, but this volatility also offers substantial speculative potential. As the pandemic unfolded, numerous investigations explored Bitcoin's role, analyzing its relationship with traditional financial markets [3–5] and its impact on market efficiency [6].

A closer examination of Bitcoin's trends in recent years, as depicted in Figure 1, corroborates its inherent volatility and sensitivity, manifested through dramatic price fluctuations. In this context, Ederington (1979) seminal work highlighted the pronounced relevance of futures contracts as a hedge against market risk [7]. However, he pointed out that the efficacy of such a strategy could vary across different markets. This underscores the necessity of customizing risk management tactics to suit particular market dynamics.

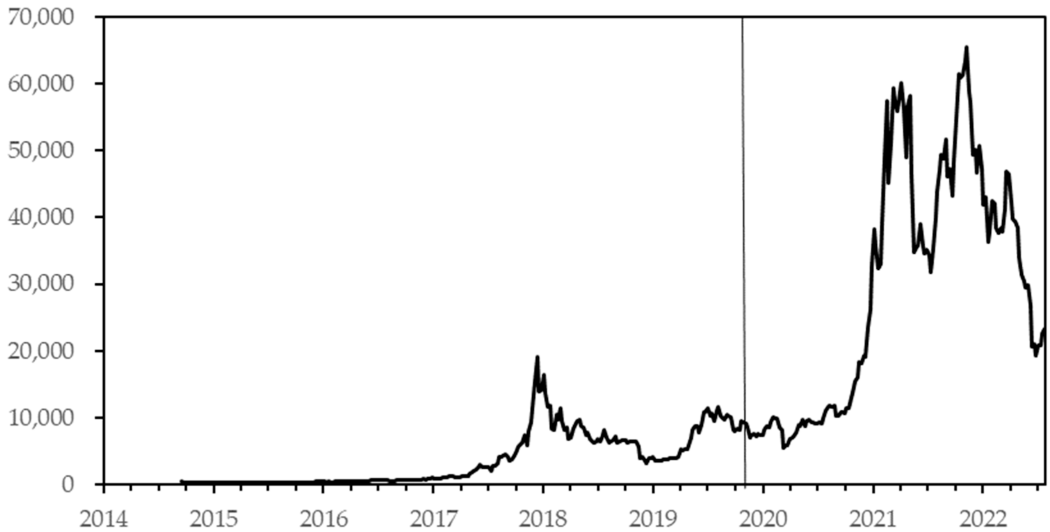


Figure 1. Trend of weekly closed prices of Bitcoin. Data source: Yahoo! Finance.

Bitcoin's rapid ascent began in November 2020, quadrupling in a brief period. This growth trajectory took a pivotal turn on 7 September 2021, when El Salvador recognized Bitcoin as legal tender, a first in global history. Despite this significant advancement, Bitcoin's peak unit price at $68,925 on 10 November 2021, brought a slew of challenges, such as high transaction prices, excessive volatility, and increased scrutiny from global regulators. These factors combined with negative market news led to a sharp plunge in Bitcoin prices, which dipped over 30% in just two months. The situation further worsened in 2022 when the second-largest cryptocurrency exchange, FTX, filed for bankruptcy, leading to a mass exodus of market speculators.

In the realm of the cryptocurrency market, significant price fluctuations amplify investment risks while accelerating market fund flows. Thus, adopting an active investment approach becomes essential for investors to mitigate losses in high-volatility markets and navigate the uncertainties associated with passivity. During dramatic market adjustments, stable assets such as gold, precious metals, government bonds, or the US dollar, which do not follow significant fluctuations, are often employed as hedging tools for investors seeking risk diversification.

Wijk (2013) demonstrated the impact of several financial assets like the US Dow Jones Index, the USD-Euro exchange rate, and oil prices on Bitcoin [8], highlighting potential avenues for hedging Bitcoin-related risks. Further, Dyhrberg (2016) and Klabbers (2017) established Bitcoin's hedging potential against the FTSE 100 Index, USD, and its role in diversifying portfolio risks [9,10]. Yet, Balcilar et al. (2017) and Wang et al. (2019) [11,12] emphasized the challenges in predicting Bitcoin prices due to its high volatility.

This study seeks to bridge the existing gap in literature pertaining to the hedging properties of Bitcoin during unprecedented crises such as the COVID-19 pandemic. In contrast to the conclusion drawn by Choi & Shin (2022), who dismissed Bitcoin as the "new gold" for hedging during the pandemic [13], our perspective posits Bitcoin not as a hedging asset but as an investment tool. With the escalating interest in cryptocurrencies, a comprehensive understanding of Bitcoin's risks and the development of suitable hedging strategies are of paramount importance for investors.

Our study centers on Bitcoin due to its prominent role in the cryptocurrency market. We investigate potential financial assets that may act as effective hedges against Bitcoin's volatility. To this end, we utilize the DCC-GARCH model to scrutinize the correlation between Bitcoin and these assets, both before and after the COVID-19 pandemic. Our objective is to illuminate how the hedging value of these assets against Bitcoin's volatility risk may have altered amidst the turmoil of the pandemic. By offering an empirical analysis that acknowledges both the currency-like and asset-like characteristics of cryptocurrencies, our study enriches the current body of literature and provides critical insights for market participants and policymakers.

The DCC-GARCH model is integral to our methodology as we apply it to probe the correlation between Bitcoin and the aforementioned financial assets. Our chief aim is to analyze and compare the hedging ratio of these assets pre- and post-COVID-19. This comparative analysis is intended to reveal if and how the hedging value of these assets against Bitcoin's volatility risk evolved during the upheaval triggered by the pandemic.

The rest of this paper is organized as follows. Section 2 describes the data while Section 3 introduces the econometric model used in the study. Section 4 discusses the empirical findings. Section 5 presents the conclusions by summarizing our primary findings and insights. Lastly, Section 6 provides a discussion on the limitations of our study and outlines potential directions for future research.

2. Data

The variables collected in this study include eight items, namely the weekly closing prices of Bitcoin (BTC), the 10-year U.S. Treasury bond yield (TNX), the Vanguard S&P 500 Growth ETF (VOOG), the Nasdaq Composite Index (IXIC), the Standard & Poor's 500 Volatility Index (VIX), West Texas Intermediate crude oil futures (WTI), the Chicago Mercantile Exchange gold futures (GC), and the U.S. Dollar Index (USDX). The sample period was from 15 September 2014 to 31 July 2022, with a total of 411 weekly data points obtained from Yahoo! Finance. Given that the World Health Organization recognized the virus in early 2020, but research on the epidemic indicates that COVID-19 began to spread in human society from October to November 2019, this paper uses the end of October 2019 as the boundary to observe the structure and changes of variables in two sub-periods, before and after the occurrence of the epidemic.

The decision to use weekly data instead of daily data for our GARCH models is supported by several key considerations that we should have elaborated on in our original manuscript. Firstly, the volatility of Bitcoin and other financial assets can be quite high on a day-to-day basis. Weekly data helps smooth out some of this volatility and provide a more extended view of trends in the data, a beneficial approach when considering Bitcoin as a potential hedging instrument. Secondly, while daily data provides more granular detail, it can often introduce noise into the model. This noise, arising from non-market factors such as individual investor behavior, rumors, or news events, may not significantly impact the longer-term trend. Weekly data helps mitigate some of these short-term fluctuations and focuses on underlying patterns and relationships. Lastly, unlike traditional financial markets, Bitcoin markets operate 24/7. Continuous trading can sometimes lead to anomalies in daily data due to factors such as low liquidity during certain times. Using weekly data helps overcome this problem, as it considers the aggregated effect over the week, thereby reducing the impact of such anomalies.

To increase the diversification of Bitcoin hedging performance and spread risk, comparative hedging was carried out with financial assets that correspond to or are relatively representative of each market. Representative commodities in each market and Bitcoin were included in the hedging portfolio. The reasons for selecting the variables are described as follows. First, the yield of the ten-year US Treasury note (TNX) reflects market expectations of inflation and Federal Reserve policy, and is also an important indicator of investor expectations of corporate earnings. Secondly, this paper chooses three hedging targets related to the stock market, namely Vanguard S&P 500 Growth ETF (VOOG), Nasdaq Composite Index (IXIC), and Standard & Poor's 500 Volatility Index (VIX). Considering the cost of investor funds, this paper chooses Vanguard S&P 500 Growth ETF (VOOG) as the stock market hedging target with low investment threshold and tracking error less than 0.04%. The Nasdaq Composite Index (IXIC) uses all listed companies on the NASDAQ weighted by market capitalization, which also reflects the situation of the US stock market. The Standard & Poor's 500 Volatility Index (VIX) is an index of market volatility in the Chicago Options Exchange, representing the implied volatility of the S&P 500 Index in the next month, reflecting the confidence of the investing public in the economic outlook during that period. The value of VIX is positively related to investors' expected volatility in the stock market, and it is also known as the "panic index".

For commodity markets, the focus is on the most active trading of WTI crude oil futures and gold futures (GC). West Texas Intermediate (WTI) crude oil is commonly used in the production of gasoline and fuel, and is one of the indispensable raw materials in daily life. Its spot and futures prices are also representative of the scale. The Commodity Exchange (COMEX) gold futures are an important means of hedging and value preservation against market uncertainty and inflation, and are often included in discussions on hedging issues. Finally, the US Dollar Index (USDX) in the foreign exchange market is selected as the hedging target. The US dollar is the main settlement currency for global commodity trade, and exchange rates are extremely important. The US Dollar Index is a number obtained by weighting the exchange rate between the US dollar and other currencies, and the value of the US Dollar Index can observe the trend of the US dollar against world currencies.

Descriptive Statistics

Tables 1 and 2 provide descriptive statistics of the original prices and rates of change before and during the pandemic, respectively. Observing both tables in conjunction, it is clear that the VIX index, a measure of market sentiment, has the largest standard deviation. This value exceeds 17 in both the pre- and post-pandemic periods, indicating significant volatility in investor sentiment throughout the sample period. A closer look at the VIX values reveals that the maximum VIX reached 66.04 after the outbreak of COVID-19, significantly higher than the pre-outbreak maximum of 30.11. This significant increase highlights the heightened sense of fear and uncertainty in the financial market during the pandemic. The standard deviation of BTC, both before and during the pandemic, was also significantly higher than other assets, reaching 10.6828 and 9.9314, respectively. Furthermore, BTC had the highest average return among all assets, with 1.1769 and 0.6482 before and during the pandemic, respectively. As shown in Figure 1, BTC has increasingly attracted investor attention, especially from 2017 onwards, when price fluctuations began to intensify. This volatility became even more pronounced following the outbreak of the pandemic in late 2019.

Table 1. Descriptive Statistics Before COVID-19.

	Mean	Std. Error	Max.	Min.	Skewness	Excess Kurtosis
	Panel A. Price					
BTC	3651.01	3963.45	19,140.80	210.34	1.07	0.43
TNX	2.28	0.42	3.23	1.37	0.12	−0.64
VOOG	124.54	22.51	166.22	91.30	0.36	−1.38
IXIC	6136.59	1249.66	8386.40	4258.44	0.25	−1.48
VIX	15.04	4.20	30.11	9.14	1.24	1.42
WTI	54.01	10.69	93.54	29.42	0.55	0.85
GC	1255.36	91.89	1526.60	1056.20	0.59	1.06
USDX	95.54	3.39	103.00	84.87	−0.68	0.77
	Panel B. Return					
BTC	1.1769	10.6828	34.7021	−35.3456	−0.2100	1.1175 [a]
TNX	−0.1511	4.7231	20.5177	−11.9298	0.8140 [b]	2.2236 [a]
VOOG	0.1978	1.9233	5.6618	−7.8728	−0.8066 [b]	2.0566 [a]
IXIC	0.2266	2.1912	5.4894	−8.7293	−0.7973 [b]	1.6102 [a]
VIX	0.0058	17.1583	78.1489	−55.6225	0.7519 [b]	2.3285 [a]
WTI	−0.1839	4.6597	11.5126	−14.5497	−0.2469 [b]	0.2728 [a]
GC	0.0808	1.8000	6.7864	−6.3184	−0.0167	1.0334 [a]
USDX	0.0502	0.9826	3.0960	−2.6417	0.1648	0.2356 [a]

Note: The weekly data, spanning from 29 October 2019 to 31 July 2022, were sourced from Yahoo! Finance. These data form the basis for all tables in this study, analyzed utilizing the DCC-GARCH model. The respective variable codes are as follows: Bitcoin (BTC), US 10-year Treasury bond yield (TNX), Vanguard S&P 500 Growth ETF (VOOG), NASDAQ Composite Index (IXIC), Standard & Poor's 500 Volatility Index (VIX), West Texas Intermediate crude oil futures (WTI), Chicago Mercantile Exchange gold futures (GC), and US Dollar Index (USDX). The superscript 'a' signifies significant excess kurtosis at the 5% level, while 'b' represents significant skewness at the same level.

Table 2. Descriptive Statistics during COVID-19.

	Mean	Std. Error	Max.	Min.	Skewness	Excess Kurtosis
	Panel A. Price					
BTC	29,178.03	18,287.55	65,466.84	5392.32	0.23	−1.35
TNX	1.48	0.69	3.24	0.54	0.79	0.08
VOOG	228.84	41.73	302.96	132.17	−0.16	−0.94
IXIC	12,198.66	2330.15	16,057.44	6879.52	−0.33	−1.02
VIX	23.76	9.06	66.04	12.05	1.99	6.36
WTI	64.49	24.90	120.67	16.94	0.39	−0.53
GC	1781.46	126.74	2010.10	1459.10	−0.91	0.49
USDX	95.78	4.23	107.91	89.89	0.72	−0.04
	Panel B. Return					
BTC	0.6482	9.9314	22.4951	−40.7891	−0.8420 [b]	2.0768 [a]
TNX	0.2969	9.6628	33.2939	−46.7699	−0.5300 [b]	5.0349 [a]
VOOG	0.2756	3.4753	10.4523	−15.5328	−0.5998 [b]	3.5006 [a]
IXIC	0.2730	3.4965	10.0622	−13.5129	−0.4280 [b]	2.0694 [a]
VIX	0.3850	17.0259	85.3718	−49.5296	0.9011 [b]	4.7045 [a]
WTI	0.3087	7.9188	27.5756	−34.6863	−0.5969	4.5164 [a]
GC	0.1092	2.3941	9.0090	−9.7425	−0.2240	2.7891 [a]
USDX	0.0603	1.0575	4.6858	−4.9159	−0.0454	4.9421 [a]

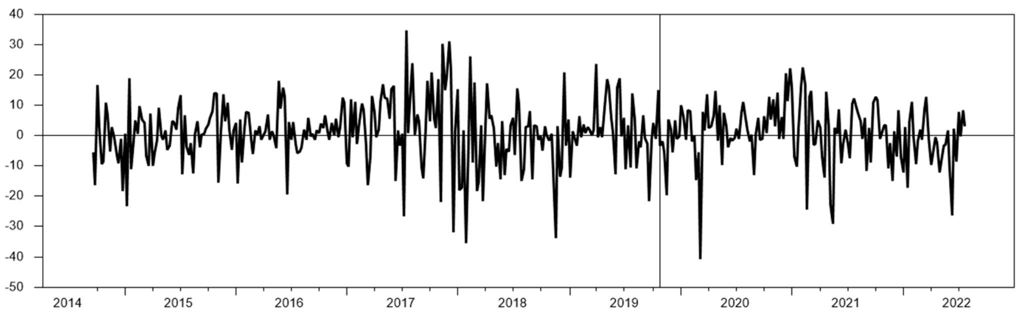
Note: The sample period for the weekly data, obtained from Yahoo! Finance, extends from 29 October 2019 to 31 July 2022. These data underpin all tables showcased in this study, analyzed using our DCC-GARCH model. The variable codes are as follows: Bitcoin (BTC), US 10-year Treasury bond yield (TNX), Vanguard S&P 500 Growth ETF (VOOG), NASDAQ Composite Index (IXIC), Standard & Poor's 500 Volatility Index (VIX), West Texas Intermediate crude oil futures (WTI), Chicago Mercantile Exchange gold futures (GC), and US Dollar Index (USDX). The superscript "a" indicates significant excess kurtosis at the 5% level, and the superscript "b" indicates significant skewness at the 5% level.

Looking at other financial assets, the standard deviations of these assets significantly increased during the pandemic compared to pre-pandemic levels. In terms of skewness, stock market indices exhibit greater asymmetry in their performance compared to other assets, with VOOG and IXIC showing significant negative skewness, and the VIX volatility index demonstrating significant positive skewness. The TNX interest rate index displayed significant positive skewness before the pandemic and significant negative skewness during the pandemic, indicating a reversal in market interest rates. The average rate of change for the TNX index was −0.1511 before the pandemic, turning to 0.2969 during the pandemic. This shift reflects adjustments to Federal Reserve policy in response to the pandemic. Particularly, as inflation escalated in the latter stages of the pandemic, the Federal Reserve was compelled to gradually increase interest rates.

Among the commodities, the volatility of WTI crude oil futures significantly exceeds that of gold futures (GC), both pre- and post-pandemic. The oil prices underwent major downturns in 2015 and 2019 due to geopolitical conflicts, economic sanctions, and market oversupply, which resulted in the lowest average return rate of −0.1839 among all assets. However, this downward trend reversed in 2020 when the average return rate shifted into positive territory. This transformation is also evident from the skewness coefficient of WTI returns, which shifted from significant negative skewness pre-pandemic to non-significant skewness post-pandemic.

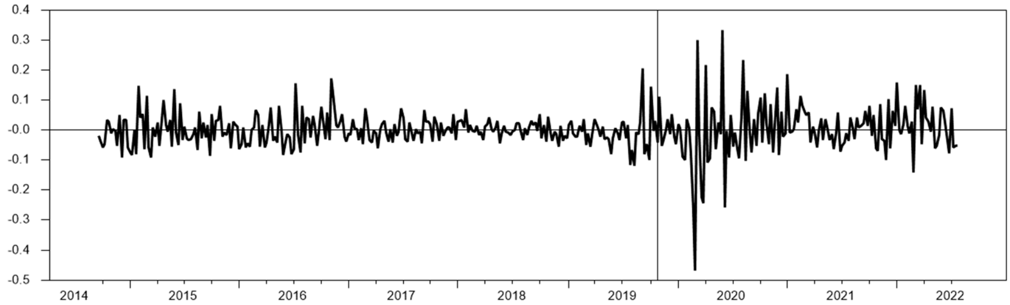
The US Dollar Index (USDX), which represents exchange rates, has the lowest standard deviation both before and after the pandemic. However, its average return rate remains positive, indicating the relative strength and stability of the US dollar during the sample period. Finally, all financial assets exhibit significant excess kurtosis at the 5% level. As a result, this study employed the T-distribution for dynamic estimation, given its ability to account for the heavy-tailed characteristics of financial asset returns.

Figure 2a–h show the changes in the returns of all financial assets, with the vertical solid line indicating the point of the COVID-19 outbreak. We can observe that, except for BTC (a) and VIX (e), all financial assets experienced larger fluctuations during the pandemic period, especially in the first half of 2020 before the outbreak, reflecting the extreme instability of the financial market due to external uncontrollable factors. In comparison, the impact of the pandemic on Bitcoin seems relatively low, as the fluctuations before the outbreak were not inferior to those during the pandemic. However, we cannot ignore the risks associated with Bitcoin, as it has maintained a highly volatile state since 2017, with the highest volatility among all financial assets. While investors may rejoice in Bitcoin's high return, they should not overlook the frequent and rapid price drops that often occur.



(**a**)

Figure 2. *Cont.*



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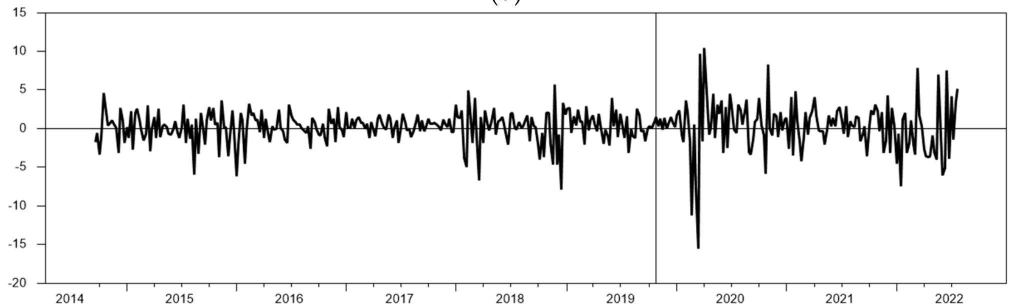

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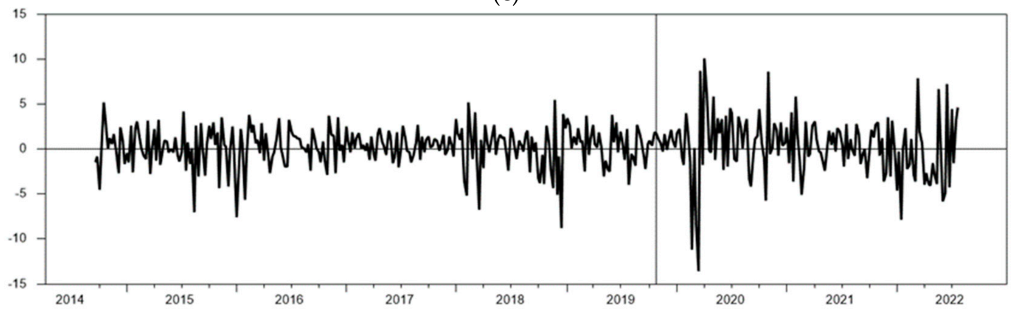

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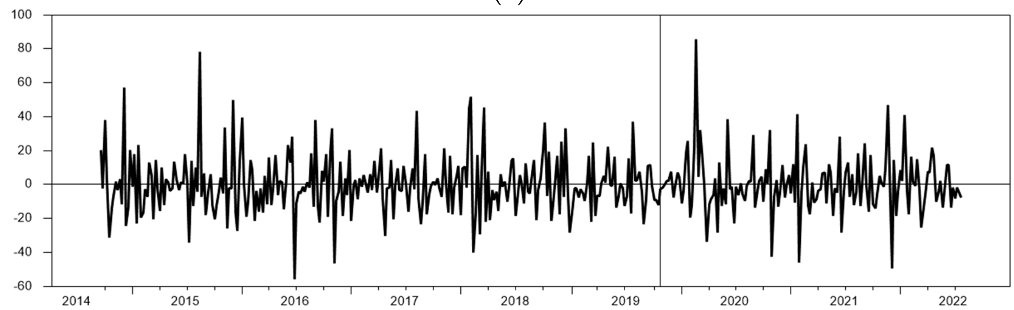

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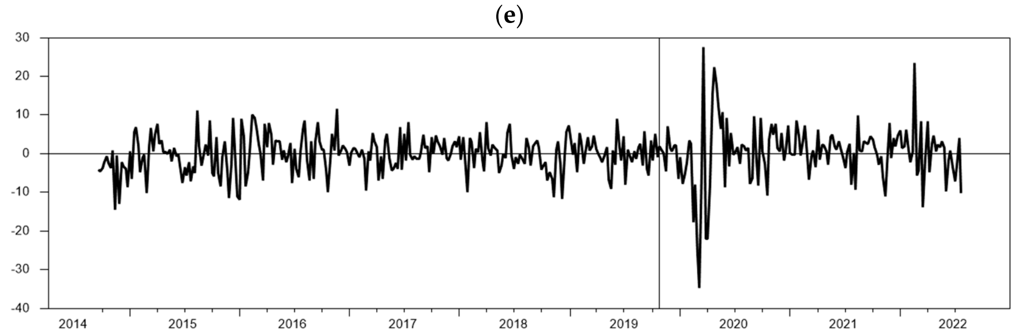

(**f**)

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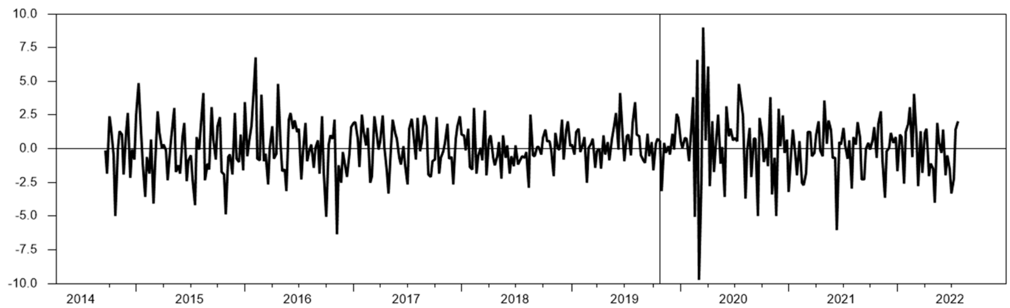

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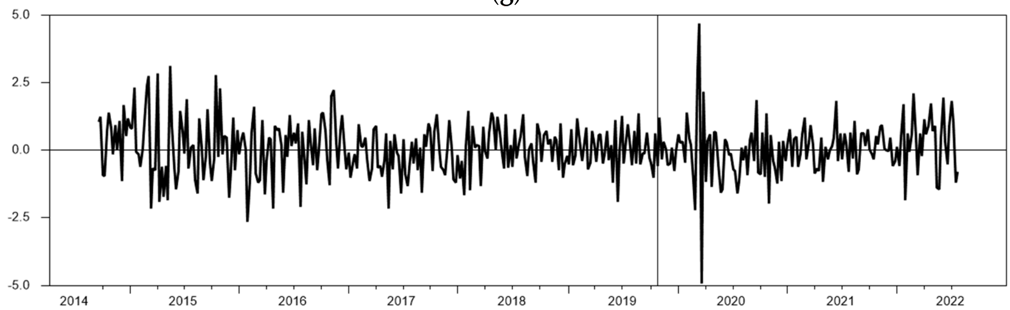


(**h**)

Figure 2. Weekly Returns of Financial Assets. (**a**) BTC weekly returns; (**b**) TNX weekly returns; (**c**) VOOG weekly returns; (**d**) IXIC weekly returns; (**e**) VIX weekly returns; (**f**) WTI weekly returns; (**g**) GC weekly returns; (**h**) USDX weekly returns. Data source: Yahoo! Finance.

In 2019, the uncertainty of financial assets increased due to political and economic events such as the US-China trade war, Hong Kong protests, Middle East conflicts, and specific economic sanctions. At the end of 2019, the outbreak of COVID-19 and subsequent inflation concerns led to a high demand for safe-haven assets, with cryptocurrencies attracting market investors' attention as a tax haven, and even persistently breaking the daily closing price record in 2020. Given the highly volatile behaviour of Bitcoin, investors must make moderate hedging arrangements. This article selects various financial asset indicators or commodities from different perspectives for hedging analysis, and the results help investors reduce investment risks.

3. Econometric Model

This study focuses on the hedging relationship between Bitcoin and other financial indicators and commodities. Our empirical analysis employs both a traditional static Ordinary Least Squares (OLS) model and a dynamic Dynamic Conditional Correlation Generalized Autoregressive Conditional Heteroskedasticity (DCC-GARCH) model. These methods are used to estimate the minimum variance optimal hedge ratio and the hedge effectiveness relationship between Bitcoin and other assets, as well as to test the correlation between variables. All empirical tasks are performed using the RATS (Regression Analysis of Time Series) statistical software.

3.1. Traditional of Regression Hedge Model (Ordinary Least Squares, OLS)

According to Edgerington (1979), the OLS return hedging model is used to estimate the minimum variance hedging ratio [9]. The equation is then applied to the variables of Bitcoin and other financial assets, and the research model is as follows:

$$Bitcoin_t = \alpha + \beta \times Asset_t + \varepsilon_t \tag{1}$$

where, $Bitcoin_t$ is the bitcoin return rate, $Asset_t$ is the return rate of other financial assets, α is the intercept term, β is the slope, and ε_t is the residual. To minimize the variance of the expected return of the hedging portfolio, we can derive the minimum variance hedge ratio of β^*, which is:

$$\beta^* = \frac{Cov(\Delta Bitcoin_t,\ \Delta Asset_t)}{Var(\Delta Asset_t)} \tag{2}$$

Myers and Thompson (1989) showed that the OLS model was found to have a flaw where unconditional sample moments replaced conditional sample moments [14]. Myers (1991) argued that in the case of unconditional OLS, the estimated hedging ratio of the model would overlook situations where hedgers achieve hedging with new information [15]. On the other hand, Lien (2005) held the opposite opinion and believed that the effect of the hedging ratio calculated by the OLS model was the best in hedging performance [16]. The hedging ratio provided by the OLS model is usually better than that in the error correction model, and any errors in the calculation results may be due to insufficient sample size for estimation and testing, or structural changes occurring between estimation samples that would lead to opposite results in model performance.

3.2. Dynamic Conditional Correlation GARCH Model (DCC-GARCH)

Traditional time series and econometric models often presume the error term to be homoscedastic. However, this assumption does not hold for the most real-world financial asset time series data. To address this, Engle (1982) proposed Autoregressive Conditional Heteroskedasticity (ARCH), which dispenses with the assumption of homoscedasticity, thereby ackling the problem of fixed conditional variance [17]. Within a specific interval, the volatility in the ARCH model is premissed on historical volatility. Should the random error term escalate, subsequent volatility will follow suit, and vice versa. This attribute aligns with the financial volatility clustering phenomenon frequently observed in markets. However, a significant drawback of the ARCH model is its extensive linear lag structure.

Bollerslev (1986) introduced the Generalized Autoregressive Conditional Heteroskedasticity (GARCH) model, offering a solution to the ARCH model's limited portrayal for conditional variance [18]. In contrast to ARCH, GARCH considers the conditional variance as a function of both past squared errors and past conditional variances. This adjustment allows for smoother variance evolution and has demonstrated improved performance in practical applications.

However, GARCH mode traditionally scrutinizes the static relationship between the covariances of two time series, which can be biased during structural changes in the series. To counter this, Engle (2002) presented the Dynamic Conditional Correlation (DCC) model to estimate the conditional correlation coefficients, primarily focusing on each GARCH model's univariate parameters, and computes the variance of the univariate model throughout the research period [19]. This innovation allows for a more nuanced understanding of financial data behavior.

Many scholars have empirically demonstrated the improvement of GARCH hedging performance. Baillie and Myers (1991) studied financial data from 1985 to 1986, finding that the distribution of commodity prices is not completely normal, and that besides the variance being non-constant, there is also high autocorrelation [20]. Therefore, they used univariate and bivariate GARCH models to test hedging on six futures daily data against a large number of stock index trading data. They compared four methods, including OLS, bivariate GARCH, conventional hedging strategies, and found that even after taking into account trading costs, GARCH model outperformed the other three. Kroner and Sultan (1993) observed that most hedging studies ignored the long-term cointegration relationship and dynamic allocation between assets [21]. Therefore, they proposed an alternative model using GARCH error correction model to hedge spot and futures exchange rates for pound, Canadian dollar, yen, German mark, and Swiss franc in the foreign exchange market. The results showed that regardless of whether trading costs were considered, the hedging performance of GARCH was superior to other models. The DCC model retains the concise estimation method of Bollerslev's (1990) CCC (Constant Conditional Correlation) and the characteristic of dynamic changes in correlation coefficient [22]. Its features are summarized as follows:

It adopts a two-stage estimation method, where the first stage calculates the individual estimation results of the univariate GARCH model, and the second stage estimates the dynamic correlation coefficients. The calculation speed is fast and concise. The correlation coefficients between multiple variables are not fixed constants and reflect the true situation of the correlation coefficients between general assets. The dynamic covariance matrix can be obtained. The number of multivariate variables can be increased to hundreds, making it applicable to general investment portfolio management, large-scale vector autoregression, and other volatility estimation and risk management. The conditional covariance matrix is guaranteed to be positive definite. The application of the DCC model first involves setting a 2×1 vector of $y_t = [y_{1t}, y_{2t}]$ where y_{1t} and y_{2t} represent Bitcoin and other financial assets, respectively. The conditional mean equations are set as followed:

$$y_t = \mu + \varepsilon_t / \Psi_{t-1} \sim t(0, V_t) \tag{3}$$

where y_t is time series data of GARCH model, the expected return of μ is a constant vector of 2×1, and $\varepsilon_t = [\varepsilon_{1t},\ \varepsilon_{2t}]$ is a vector of conditional unexpected changes at time at $\mathrm{t} - 1(\Psi_{t-1})$. Holmes (1996) found that the GARCH(1,1) model can fully describe the phenomenon of heterogeneous variation in asset returns, so a GARCH(1,1) model is used to build the hedging model [23]. The conditional mean equation is mainly used to generate the residual term (white noise), and GARCH(1,1) is found in empirical research to exhibit the phenomenon of volatility clustering, which refers to the clustering of variations in regression residuals, consistent with the description of the GARCH model. The conditional variance in the current period is affected by the errors and variances in the previous period, and if the volatility was high in the previous period, there will be a correspondingly high volatility in the current period. The thick-tailed and high-peaked characteristics of GARCH(1,1) can improve the explanatory power of the model and reduce errors. The residual term is assumed to be multivariate normal with a mean of 0, and the variance is a covariance matrix (V_t).

$$V_t = \mathrm{D_t C_t D_t} \tag{4}$$

where $\mathrm{D_t}$ is the diag $\sqrt{\mathrm{v_{11,t}}} \ldots \sqrt{\mathrm{v_{22,t}}}$ of 2×2 diagonalized matrix of V_t, $\mathrm{C_t}$ is the correlation matrix. The model's conditional variance is related to the covariance matrix as follows:

$$\mathrm{H_{ii,\ t}} = \mathrm{c_i} + \alpha_\mathrm{i} \varepsilon^2_{\mathrm{i,\ t-1}} + \beta_\mathrm{i} \mathrm{h_{i,\ t-1}} \tag{5}$$

$$\mathrm{H_{ij,\ t}} = \rho_{\mathrm{ij,t}} \sqrt{\mathrm{H_{ii} H_{jj,t}}} \tag{6}$$

$\mathrm{H_{ii,\ t}}$ denotes as the conditional variance at time t for an asset, $\mathrm{c_i}$ is a constant term, α_i is a measure of how much the variance is influenced by the squared error of the previous period, capturing the ARCH effect. β_i denotes as the measure of how much the variance is influenced by the variance of the previous period represents the persistence effect of the variable's volatility. $\mathrm{H_{ij,\ t}}$ represents as the conditional covariance at time t between Bitcoin and other assets is also included. After modeling the correlation matrix, $\mathrm{C_t}$ can be expressed as follows:

$$\mathrm{C_t} = \mathrm{diag}\{\mathrm{Q_t}\}^{\frac{1}{2}} \mathrm{Q_t} \mathrm{diag}\{\mathrm{Q_t}\}^{\frac{-1}{2}} \tag{7}$$

$\mathrm{Q_t}$ is a dynamic correlation structure, which is the conditional correlation matrix at time t, and $\mathrm{Q_t}$ is modeled as a function following the GARCH form. The settings are as follows:

$$\mathrm{q_{ij,\ t}} = (1 - \mathrm{q_a} - \mathrm{q_b}) \overline{\rho}_{\mathrm{ij}} + \mathrm{q_a} \varepsilon_{\mathrm{i,\ t-1}} \varepsilon_{\mathrm{j,\ t-1}} + \mathrm{q_b} \mathrm{q_{ij,\ t-1}} \tag{8}$$

The parameters of $\mathrm{q_a}$, $\mathrm{q_b} > 0$ and $(\mathrm{q_a} + \mathrm{q_b}) < 1$ are in line with the stationary conditions of the GARCH model. $\mathrm{q_{ij,\ t}}$ represents the conditional correlation coefficient between the i-th and j-th standardized residuals, $\overline{\rho}_{\mathrm{ij}}$ is the non-conditional correlation coefficient between the i-th and j-th standardized residuals, which is the sample covariance matrix, and q_a denotes as the influence of the previous standardized residuals, while q_b represents the degree of influence of the previous conditional correlation coefficient on the current conditional correlation coefficient between the Bitcoin return and other asset returns' standardized residuals. Finally, the maximum likelihood estimation (MLE) method is used to estimate the parameters in the model. The logarithmic likelihood function for the multivariate distribution is as follows:

$$L_T(\theta) = \sum_{t=1}^{T} \log f(y_t | \theta, I_{t-1}) \tag{9}$$

Whereby, $f(y_t | \theta, I_{t-1}) = |H_t|^{-1/2} g(z_t(\theta) | \eta)$ are various distributional assumptions for the conditional error term in the multivariate GARCH model. It is common to use the Student's T distribution (Fiorentini et al., 2003; Harvey et al., 1992) to capture the heavy-tailed distribution of assets as equation below [24,25]:

$$g(z_t | \theta, \nu) = \frac{\Gamma\left(\frac{\nu+N}{2}\right)}{\Gamma\left(\frac{\nu}{2}\right)[\pi(\nu-2)]^{\frac{N}{2}}} \left[1 + \frac{z_i' z_t}{\nu - 2}\right]^{-\frac{N+\nu}{2}} \tag{10}$$

Whereby, θ represents the parameter that needs to be estimated, ν signifies the degrees of freedom. It is common to assume that $\nu > 2$. However, when $\nu \to \infty$ approaches infinity, the Student's T-distribution converges towards the normal distribution. Lastly, Γ denotes the Gamma function.

3.3. Hedging Effectiveness

To evaluate the effectiveness of hedging, we need to calculate the optimal hedge ratio and demonstrate the performance of the Bitcoin investment portfolio in relation to other financial assets through index equations. The effectiveness of the hedge ratio is measured by the risk reduction ratio, as shown below:

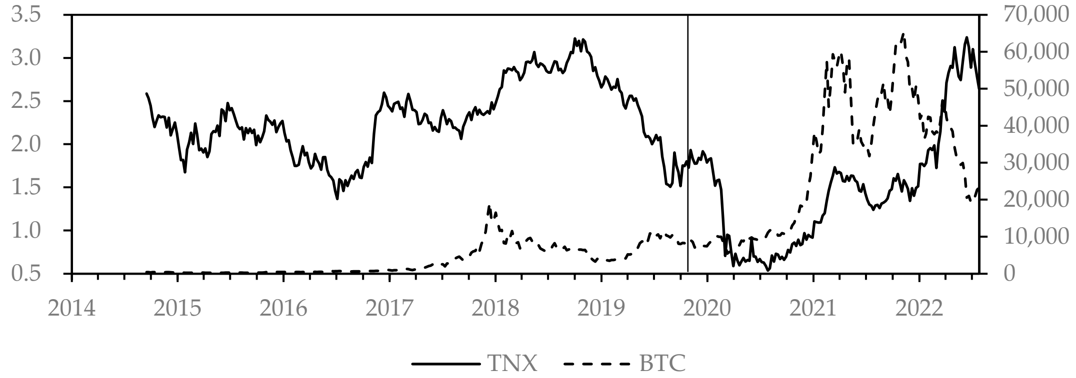
$$HE = 1 - \frac{VAR_{hedge}}{VAR_{unhedge}} \tag{11}$$

HE represents the effectiveness of hedging ratio, which is the ratio of the variance of the hedged portfolio (VAR_{hedge}) to the variance of the unhedged portfolio ($VAR_{unhedge}$). A larger HE ratio indicates a smaller variance of the hedged portfolio, indicating a better hedging effect.

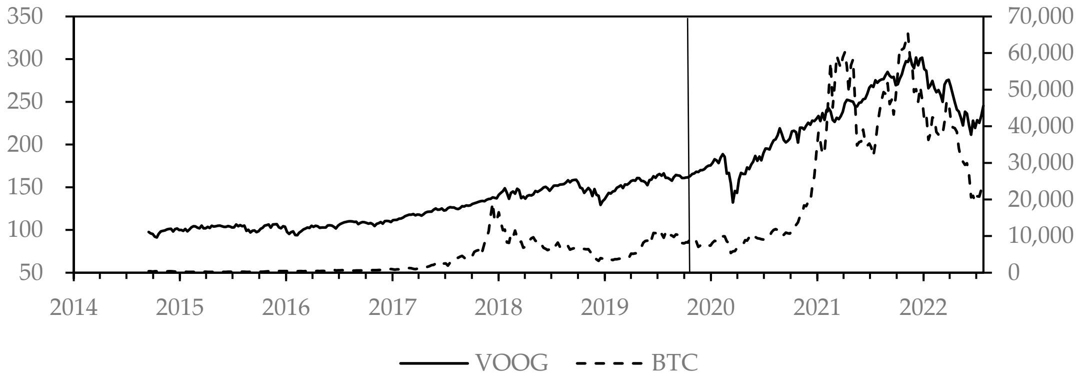
4. Empirical Results

The weekly data, sourced from Yahoo! Finance, for the duration of 29 October 2019 to 31 July 2022, form the foundation for all tables presented in this study, meticulously analyzed via the DCC-GARCH model. Concurrently, the graphs displayed within the Experimental Results segment are the products of our dedicated data processing and computation, with the same model at the helm. These visuals are designed to convey the evolution of relationships and fluctuations amongst our selected variables throughout the studied period. As we navigate through the COVID-19 timeline, these graphical interpretations offer an intuitive insight into the dynamic shifts between the variables, as captured by our model. Each graph is distinctly labeled, denoting that they are the outcomes of our specific data processing and analysis based on the DCC-GARCH model. Despite the raw data being derived from Yahoo! Finance, the graphical representations are the culmination of our in-depth analysis and processing efforts.

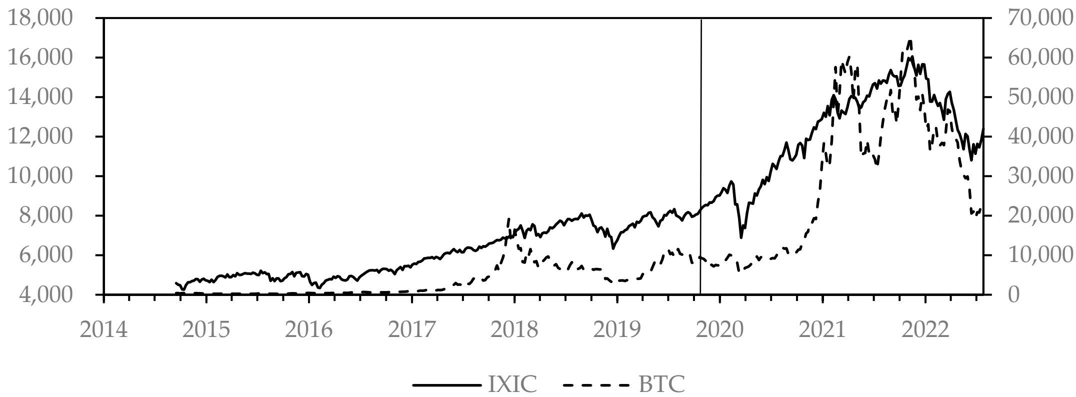
Figure 3a–g illustrate the weekly trends of Bitcoin (BTC, represented by a dotted line) juxtaposed against the weekly returns of seven other financial assets (solid lines) in chronological order. The right axis indicates the BTC price range, while the left axis corresponds to the price range of the other respective assets. BTC shows marked volatility, differing from other assets in the speed and magnitude of its price fluctuations. This characteristic underscores the overall greater risk inherent in the cryptocurrency market.



(**a**)

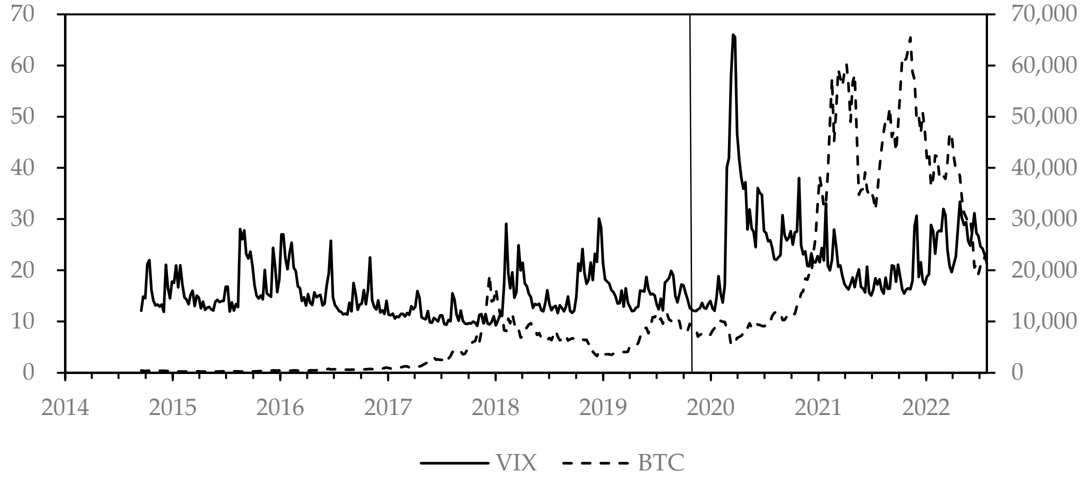


(**b**)

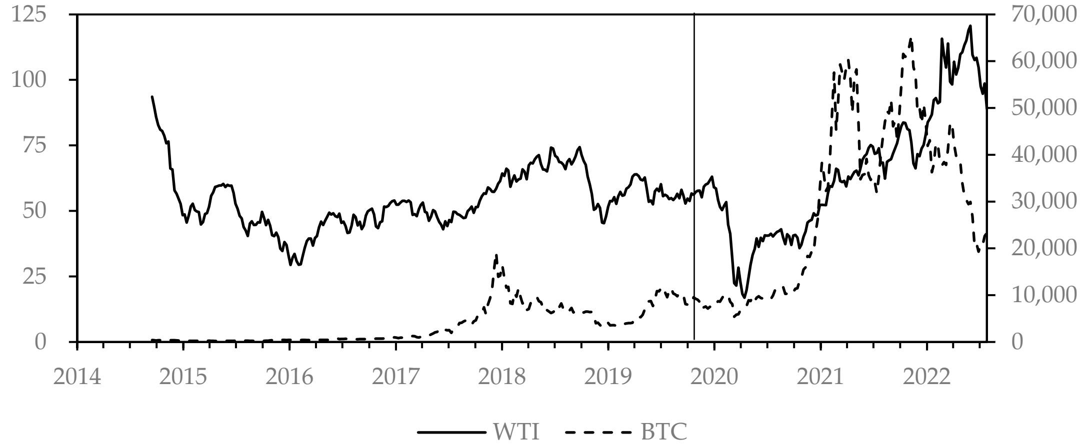


(**c**)

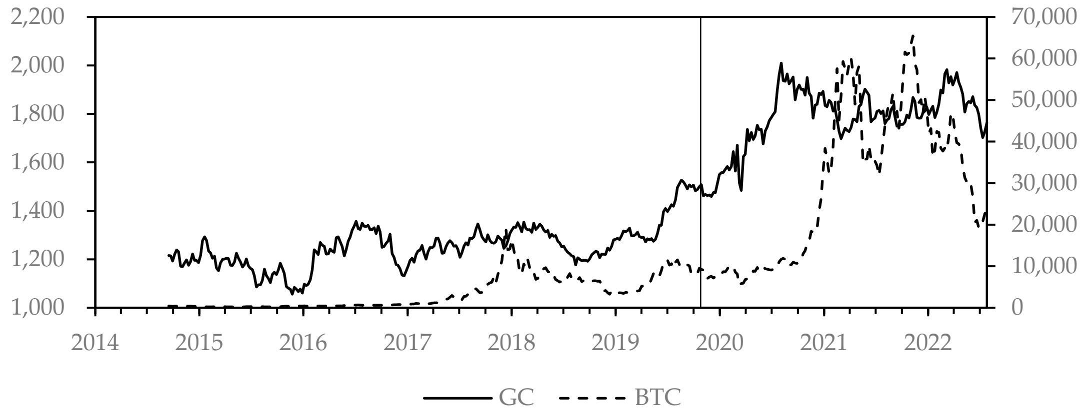
Figure 3. *Cont.*



(**d**)

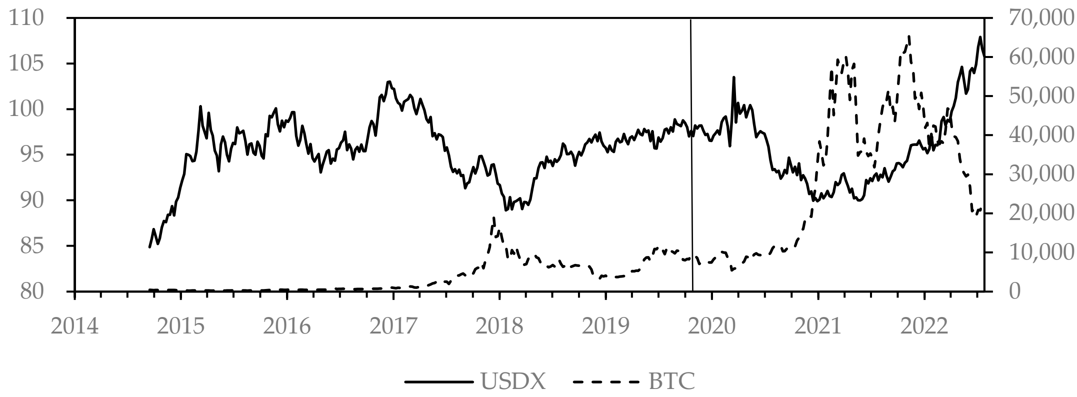


(**e**)



(**f**)

Figure 3. *Cont.*



(**g**)

Figure 3. The Trend Chart of BTC (right axis) and the Relative Underlying Assets (left axis). (**a**) BTC-TNX trend of closed prices, (**b**) BTC-VOOG trend of closed prices, (**c**) BTC-IXIC trend of closed prices, (**d**) BTC-VIX trend of closed prices, (**e**) BTC-WTI trend of closed prices, (**f**) BTC-GC trend of closed prices, (**g**) BTC-USDX trend of closed prices. Data source: Yahoo! Finance.

From an observation of Figure 3a, the TNX price trend underwent a reversal in 2018 and experienced a significant decline from the onset of the COVID-19 pandemic until 2020. It rebounded in 2022 to a peak comparable to that of 2018. Interestingly, TNX displayed a slightly negative correlation with BTC before the pandemic, which altered from a positive to a negative correlation during the pandemic. Figure 3b,c portray trends in the US stock market, which demonstrated a more distinct positive correlation with BTC during the pandemic.

Figure 3d showcases the sentiment of the US stock market, as reflected by the VIX index, indicating that the panic instigated by the pandemic was substantial and inversely correlated with BTC. Figure 3e reveals that oil prices, significantly influenced by multiple factors, including the pandemic, presented an inconsistent correlation with BTC. In contrast, gold, as illustrated in Figure 3e, displayed relative stability compared to BTC during the tumultuous period, functioning as a traditional hedging tool. The relationship between gold and BTC varied, shifting from negative to positive correlation during the pandemic.

Lastly, Figure 3g exhibits a consistent negative correlation between the US dollar index and BTC throughout the entire sample period.

4.1. Hedge Ratio

Table 3 presents static hedge ratios, estimated using the OLS model. A marked distinction is observed between the pre-COVID-19 and during-COVID-19 periods. Prior to the pandemic, no significant correlation was found between BTC and the examined financial assets, rendering the hedge ratios insignificant. However, during the pandemic, a considerable correlation between BTC and the other assets, excluding the TNX interest rate, was noted.

VIX and USDX exhibited a negative correlated with BTC, while VOOG, ICIX, WTI, and GC showed a positive correlation. This suggests that during the pandemic's tumultuous phase, investors holding BTC could circumvent non-systematic risks by purchasing VIX or US dollars, or by divesting from stock market-linked assets, oil, or gold. Nevertheless, Table 3 offers static estimation results. Given the volatility of market, dynamic hedging results, encapsulated in Table 4, provide a more accurate representation.

Table 3. The Static Hedge Ratios.

	Before COVID-19		During COVID-19	
	β	Standard Deviation	β	Standard Deviation
BTC-TNX	0.0614	0.1388	0.0235	0.0862
BTC-VOOG	0.3956	0.3403	0.9952 ***	0.2248
BTC-IXIC	0.2785	0.2989	1.1022 ***	0.2196
BTC-VIX	−0.0398	0.0381	−0.2256 ***	0.0451
BTC-WTI	0.1689	0.1404	0.1902 *	0.1040
BTC-GC	0.0055	0.3645	0.8064 **	0.3416
BTC-USDX	−0.4441	0.6673	−1.5991 ***	0.7760

Note: The period of before COVID-19 sub-sample is weekly data from 15 September 2014 to 28 October 2019, and the COVID-19 period for weekly data is from 4 November 2019 to 31 July 2022. The variable codes are Bitcoin (BTC), US 10-year Treasury yield (TNX), Vanguard S&P 500 Growth ETF (VOOG), Nasdaq Composite Index (IXIC), CBOE Volatility Index (VIX), West Texas Intermediate crude oil futures (WTI), Chicago Mercantile Exchange gold futures (GC), and US Dollar Index (USDX). The tables displayed in this research emanate from meticulous data manipulation and the employment of the DCC-GARCH model, underlining the substantial contribution within the realms of data analysis and interpretation.Numbers in parentheses are t-statistics. *, **, *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

Table 4. Estimation Results for Dynamic DCC-GARCH Variances, Covariances, and Hedge Ratios.

	Conditional Variance BTC		Corresponding Assets		Covariance		Hedge Ratio	
	Mean	Std. Error	Mean	Std. Error	Mean	Std. Error	Mean	Std. Error
Panel A. Before COVID-19								
BTC-TNX	123.8872	100.3006	23.4573	15.5683	−0.4226	1.6780	−0.0035	0.1034
BTC-VOOG	126.9114	103.9345	4.0542	3.4588	1.5179	4.0969	0.4530	0.5646
BTC-IXIC	126.1419	103.2730	5.1985	3.5918	1.4135	5.2471	0.3052	0.6273
BTC-VIX	137.9893	114.9658	316.9120	165.1123	−13.3560	23.7422	−0.0420	0.0443
BTC-WTI	122.9944	98.9849	22.4134	6.0741	3.4647	4.5306	0.1683	0.1957
BTC-GC	122.6402	95.8453	3.2986	0.3317	−0.0268	1.8737	−0.0084	0.6449
BTC-USDX	115.3775	81.6648	0.9570	0.3666	−0.3851	0.6086	−0.4478	0.7464
Panel B. During COVID-19								
BTC-TNX	102.2688	44.8506	91.4148	92.3858	4.4234	34.6408	0.0305	0.0753
BTC-VOOG	99.4953	53.3414	14.3064	20.8211	11.7219	12.2022	1.2211	0.5231
BTC-IXIC	99.7926	59.3302	13.6758	15.3720	13.2568	10.7214	1.2085	0.4058
BTC-VIX	136.2132	103.1311	307.6077	135.4326	−34.9016	37.2990	−0.2572	0.0585
BTC-WTI	113.0279	44.8389	60.5633	85.3326	0.4272	4.4378	−0.0027	0.1043
BTC-GC	113.4736	81.2380	3.9691	1.8081	0.4803	1.8533	0.3047	0.2992
BTC-USDX	96.9793	47.6420	1.0119	1.2762	−1.5476	1.5972	−1.8734	0.6492

Note: The data utilized in this study is segregated into two periods: pre-COVID-19, encompassing weekly data from 15 September 2014 to 28 October 2019, and during-COVID-19, comprising weekly data from 4 November 2019 to 31 July 2022. The variable codes are Bitcoin (BTC), US 10-year Treasury yield (TNX), Vanguard S&P 500 Growth ETF (VOOG), Nasdaq Composite Index (IXIC), CBOE Volatility Index (VIX), West Texas Intermediate crude oil futures (WTI), Chicago Mercantile Exchange gold futures (GC), and US Dollar Index (USDX).The tables displayed in this research are based on meticulous data analysis and the application of the DCC-GARCH model, thus signifying a substantial contribution in the spheres of data interpretation and analytic.

As evidenced in Table 4, apart from VIX, the average conditional variance of BTC significantly outperforms that of other assets, underscoring Bitcoin's characteristic of high volatility. With the onset of the pandemic, the conditional variance of traditional financial instruments notably escalated, yet generally failed to reach the volatility levels of BTC. The pronounced volatility of the VIX index mirrors the dramatic oscillations in investor sentiment.

Aligning with Table 3, Table 4 reveals a distinct discrepancy in results pre- and post-COVID-19 outbreak. During the pandemic, the average conditional covariance between BTC and related assets notably increased, with the connection between BTC and the stock market being particularly close. The higher average hedging ratio during the pandemic period indicates a strengthening of the linkages between commodities amidst the unique market conditions induced by COVID-19. For instance, stock market assets such as VOOG and IXIC had relatively low hedging ratios pre-pandemic, with covariance values between them and BTC at a mere 1.5179 and 1.4135, respectively. Post-outbreak, the average covariance escalated to 11.7219 and 13.2568, respectively, accompanied by an increase in hedging ratios, thus indicating a dynamic shift in the linkage between the stock market and BTC.

As for the interest rate index TNX, its dynamic relationship with BTC inverted from negative to positive, mirrored by gold futures GC. In this study, we further create a hedging investment portfolio based on the estimated hedging ratios in Tables 3 and 4 and juxtapose the hedging performance under varying estimation methods, hedging assets, and market environments. The results are consolidated in Table 5.

Table 5. Hedging Effectiveness.

	OLS Model			DCC-GARCH Model		
	Return	**Variance**	**Hedging Effectiveness**	**Return**	**Variance**	**Hedging Effectiveness**
Panel A. Before COVID-19						
BTC-TNX	1.1862	114.0371	0.00074	1.1937	113.2687	0.00747
BTC-VOOG	1.0986	113.5423	0.00507	1.0864	114.0993	0.00019
BTC-IXIC	1.1138	113.7488	0.00326	1.1044	115.3217	−0.01052
BTC-VIX	1.1771	113.6555	0.00408	1.2333	113.0757	0.00916
BTC-WTI	1.2080	113.5015	0.00543	1.1519	113.3907	0.00640
BTC-GC	1.1764	114.1211	0.00000	1.0930	113.4546	0.00584
BTC-USDX	1.1992	113.9308	0.00167	1.1506	113.5494	0.00501
Panel B. During COVID-19						
BTC-TNX	0.6141	98.0041	0.00052	0.5999	96.1354	0.01958
BTC-VOOG	0.3374	86.1674	0.12124	0.1861	85.0002	0.13314
BTC-IXIC	0.3084	83.2899	0.15058	0.4083	88.2048	0.10046
BTC-VIX	0.7022	83.3965	0.14950	0.6597	85.5493	0.12754
BTC-WTI	0.5596	95.8014	0.02299	0.7478	95.2264	0.02885
BTC-GC	0.5297	94.3536	0.03775	0.5917	93.8870	0.04251
BTC-USDX	0.7097	95.2084	0.02904	0.5953	94.2313	0.03900

Note: The data utilized in this study is segregated into two periods: pre-COVID-19, encompassing weekly data from 15 September 2014 to 28 October 2019, and during-COVID-19, comprising weekly data from 4 November 2019 to 31 July 2022. The variable codes are Bitcoin (BTC), US 10-year Treasury yield (TNX), Vanguard S&P 500 Growth ETF (VOOG), Nasdaq Composite Index (IXIC), CBOE Volatility Index (VIX), West Texas Intermediate crude oil futures (WTI), Chicago Mercantile Exchange gold futures (GC), and US Dollar Index (USDX).The tables displayed in this research are based on meticulous data analysis and the application of the DCC-GARCH model, thus signifying a substantial contribution in the spheres of data interpretation and analytics.

4.2. Hedging Effectiveness

Table 5 presents the average return and standard deviation of the hedging portfolio constructed using OLS and DCC-GARCH models to compute the hedging ratio. This portfolio's hedging efficacy is contrasted with a non-hedging scenario to evaluate whether it can minimize the volatility of the investment portfolio. Based on prior estimations, it is observed that the correlation between BTC and related assets was relatively weak before the COVID-19 outbreak. Consequently, the impact of utilizing financial assets to hedge against BTC risks was limited due to the low hedging ratio, resulting in mediocre hedging performance. However, a closer examination of the figures reveals that the hedging portfolio, when constructed using the DCC-GARCH model, shows enhanced hedging efficacy.

During the pandemic, the hedging performance indicators exhibited marked improvement across the board. Out of seven financial assets, five—namely TNX, VOOG, WTI, GC, and USDX—demonstrated superior hedging performance with the DCC-GARCH model. Within this group, TNX yielded the lowest hedging performance, while VOOG was the most successful in mitigating BTC's volatility risk. This highlights the benefits of employing dynamic models to reduce asset volatility in practical applications. Conversely, the hedging efficiency of IXIC and VIX was more pronounced according to the OLS model. This suggests that the correlation between BTC, IXIC, and VIX remained relatively stable during the pandemic period, with minimal difference between dynamic and static hedge ratios. As such, utilizing the static OLS model for estimating results did not compromise the hedging performance.

In light of Bitcoin's (BTC) considerable volatility, it becomes crucial for investors to select strategic hedging tools. This study primarily focuses on the period after the COVID-19 outbreak, which saw a rise in BTC trading volume. Our findings indicate that stock market instruments serve as the primary hedge against BTC volatility.

As evidenced by Tables 4 and 5, the fluctuations between BTC and the stock market exhibit a correlation coefficient near 1. This suggests that investors holding BTC can reduce portfolio risk by concurrently short-selling stock market assets. However, if using the VIX (a market volatility index) as a hedging instrument, both BTC and VIX should be traded in the same direction, i.e., a long position in BTC should be accompanied by a long position in VIX. The relative hedge ratio here is around 0.25, significantly lower than that of stock market assets. Regarding commodities such as oil and gold, their hedging performance is somewhat weaker, although gold presents a relatively better performance. Previous research has proposed the idea of BTC replacing gold as a hedging tool. While our study acknowledges a positive correlation between BTC and gold, their interconnectedness does not surpass that between BTC and the stock market.

Furthermore, the trend of the US dollar shows a negative correlation with BTC. Shaped by the Federal Reserve's policies during the pandemic, the dynamic hedge ratio reached 1.87. Nevertheless, its hedging performance is not exceptional, even lagging behind gold. Lastly, the TNX (10-year Treasury note yield), which serves as an interest rate target, presented the weakest hedging performance. This does not denote an absence of correlation between interest rates and Bitcoin. Primarily, it can be attributed to TNX representing long-term interest rates, which inherently provide fewer benefits for short-term-focused BTC. Generally, the effects of monetary policy on short-term interest rates are directly mirrored in assets like the stock market, VIX, or exchange rates, which have recently demonstrated significant correlations with BTC. Thus, it is advisable for investors to maintain vigilance regarding these relationships.

5. Conclusions

Our study elucidates the complex dynamics and potential investment opportunities within the tumultuous Bitcoin market. Despite its inherent risks, the prospects for substantial returns in this high-volatility environment are enticing for investors, especially those with a higher risk appetite. Amid the potential pitfalls, the rapid shifts in capital can present both challenges and opportunities. Our study underscores the pivotal role of strategic hedging with other financial assets as a tactic to mitigate risks linked to Bitcoin's price volatility.

Recognizing the practical implications of our research, the hedging strategies we have delineated could prove invaluable for institutional investors and financial managers aiming to optimize their portfolios amidst market volatility. Moreover, our findings could guide policymakers in crafting regulations that curb market manipulation and deter speculative bubble formation. Through the employment of the DCC-GARCH model, we have managed to effectively handle the volatility of financial assets, including Bitcoin. Yet, its practical application poses certain challenges. For instance, transaction costs related to daily adjustments of hedging ratios could impact the model's efficacy in real-world investment scenarios. These results are transparently conveyed in our research, and our conclusions are solidly anchored in these findings. Nonetheless, we acknowledge the need for ongoing refinement of our models and strategies to adapt to the continuously evolving financial market landscape.

6. Discussion and Limitations

In light of recent episodes of market manipulation culminating in speculative bubbles, the necessity for comprehensive risk management strategies is evident. Our study proposes that certain financial assets might act as effective buffers against Bitcoin's volatility. However, these findings warrant careful interpretation due to the current market's susceptibility to manipulation and the unpredictability of Bitcoin's future value. The post-pandemic economic landscape could further perturb the cryptocurrency market. Given the trend of monetary expansion employed by numerous countries to feign low inflation, it is conceivable that funds may gravitate back to tangible assets over the long term. Occurrences such as the 2022 LUNA storm and FTX's bankruptcy filing, the world's second-largest cryptocurrency exchange, in November 2022, underscore the cryptocurrency market's bubble-like character. These events have induced significant investment shocks and added layers of volatility.

Addressing these challenges may involve the conception of sophisticated hedging strategies and the implementation of robust regulatory measures to deter market manipulation. Investors could employ machine learning techniques for swift identification and response to potential market manipulations. Meanwhile, regulatory entities could enhance monitoring systems to ensure transparent and fair trading activities. Our data analysis emphasizes the need to contemplate broader economic variables and their potential influence on Bitcoin and the cryptocurrency market. Moving ahead, we envision our research to inspire further exploration into Bitcoin's practicality as an investment tool, the formulation of effective risk management strategies, and the mitigation of market manipulation in the cryptocurrency sphere.

Author Contributions: L.W. contribution is reflected in the choice of specialized literature, the definition of research hypotheses, investigation and writing—original draft preparation, visualization and editing. M.-C.L. and W.-H.C. contribution are reflected in the definition of the sample, testing of hypotheses, statistical data processing, and interpretation of results, resources and discussion. C.-H.T. and J.-W.Y. contribution is reflected in the interpretation of results, data collection, literature review, formal analysis and conclusions. All authors have read and agreed to the published version of the manuscript.

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