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Bitcoin, Gold, and Stock Market Volatility Including COVID-19 Periods: Comparative Analysis Using GARCH and DCC-MGARCH Models

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Abstract

This study investigates the volatility dynamics and time-varying correlations between Bitcoin (BTC) and major financial markets, including gold, oil, NASDAQ, NIKKEI, FTSE, DAX, and the USD Index. Using daily data and GARCH-family models, we quantify persistence, asymmetry, and memory in BTC volatility. The EGARCH model was identified as the most suitable for capturing conditional variance. A DCC-MGARCH framework was then employed to estimate evolving cross-market correlations. Results indicate that BTC volatility is highly persistent with strong reactions to negative shocks. Gold displays the lowest persistence, confirming its role as a stable diversifier. DCC-MGARCH estimates reveal weak positive BTC-Gold correlations and negative BTC-USDINX correlations, implying significant diversification potential. Notably, BTC-NIKKEI and BTC-Gold correlations strengthened during the COVID-19 period. These findings underscore the importance of dynamic portfolio strategies, as optimal weights shift with evolving conditional covariances, rendering static allocations suboptimal. For policymakers, these results can inform leverage and exposure limits, particularly when linkages between BTC and traditional assets intensify..

Keywords: digital currency; non-linear generalized autoregressive conditional heteroskedasticity; hedging features; diversification benefits

JEL Codes: B23, B26, G11

Bitcoin, oro y volatilidad del mercado accionario incluidos los periodos de la COVID-19: análisis comparativo mediante modelos GARCH y DCC-MGARCH

Resumen

Este estudio investiga la dinámica de volatilidad y las correlaciones variables en el tiempo entre Bitcoin (BTC) y los principales mercados financieros, incluyendo oro, petróleo, NASDAQ, NIKKEI, FTSE, DAX y el índice del dólar estadounidense. Mediante datos diarios y modelos de la familia GARCH, se cuantifica la persistencia, asimetría y memoria en la volatilidad de BTC. El modelo EGARCH fue identificado como el más adecuado para capturar la varianza condicional. Posteriormente, se empleó un marco DCC-MGARCH para estimar las correlaciones transversales del mercado. Los resultados indican que la volatilidad de BTC es muy persistente, con fuertes reacciones a choques negativos. El oro muestra la menor persistencia, confirmando su papel como diversificador estable. Las estimaciones del DCC-MGARCH revelan débiles correlaciones positivas entre BTC-oro y negativas entre BTC-índice del dólar, lo que implica un potencial de diversificación. Las correlaciones BTC-NIKKEI y BTC-oro se fortalecieron durante el periodo de la COVID-19. Estos hallazgos subrayan la importancia de estrategias de cartera dinámicas, ya que los pesos óptimos cambian, haciendo que las asignaciones estáticas sean subóptimas. Para los responsables de políticas, estos resultados pueden orientar los límites de apalancamiento y exposición..

Palabras clave: criptomoneda; heterocedasticidad condicional autorregresiva generalizada no lineal; cobertura; beneficios de diversificación

INTRODUCTION

The financial markets are evolving towards the virtual world in the wake of digitalization and technological development. Accordingly, the assets traded on the markets are being diversified through technological developments over time. Digitalization has also revolutionized money and payment systems. In recent years, innovative technologies, especially distributed ledger technology and new market players, have accelerated and intensified the digitalization process in the payment system. New cryptocurrencies emerging in the wake of digitalization are reshaping the nature of the existing monetary system, the architecture of the international monetary system, and the role of public money issued by the government. Cryptocurrencies are a subset of the digital money ecosystem. A cryptocurrency is a digital asset designed as a medium of exchange that uses cryptography to secure transactions and control the creation of additional units of currency (Greenberg, 2011). The daily turnover of cryptocurrencies was $460.27 billion in mid-2023. This can be compared to the global financial markets for foreign exchange, fixed-income securities, and the US stock market, which have daily turnovers of $7.5 trillion, $36 billion, and $478.72 billion, respectively. Current calculations put the market capitalization of cryptocurrency at $2.8 trillion for 2023. Bitcoin (BTC), described as the most important transformation of the global monetary system in the last century, dominates the global cryptocurrency market with a share of almost 49 percent and a market capitalization of $1.39 trillion in the first quarter of 2024; up from $551.7 billion in the first quarter of 2023 (https://www.statista.com). The market size will continue to grow as market participation becomes broader and deeper. Nakamoto (2008), the intellectual creator of digital currency, describes the market and the mechanism of BTC as a decentralized peer-to-peer payment system.

BTC is currently the most successful digital currency, and market participants find BTC extremely attractive due to its lower transaction fees and bid-ask spreads. This is most likely due to its virtual, decentralized, and deregulated nature, as well as some fundamental features, such as its inability to be converted into gold or any other commodity. In particular, BTC, proposed as a cash payment system, is based on a decentralized digital cash system consisting of nodes that record and confirm transactions without the need for a regulatory authority (Akkaya, 2021).

BTC transaction fees have gradually increased after 2016, but the costs of $2.11 in early 2024, $1.37 in early 2023, and $0.56 in 2022 are still considered reasonable. Additionally, the average bid-ask spreads for digital currencies, such as Bitfinex, Kraken, and Coinbase, were 0.0060, 0.0026, and 0.0050, respectively, in 2022–2023. This has increased the demand for BTC and caused the parity of the BTC return with the US dollar to rise to approximately $28,440 in early 2024, compared to $22,840 in the same period in 2023 (https://www.statista.com). BTC has overcome the problem of double-spending, which was its original purpose, using blockchain technology (Scaillet et al., 2017). In addition to the aforementioned advantages, BTC has a unique risk-return profile and follows a distinct volatility pattern, exhibiting low correlation with USDINX values and gold (Baur et al., 2018). Selmi et al. (2018) show significant negative to low positive correlations with the oil price. Cryptocurrencies such as BTC, Ethereum, and Litecoin can be used for portfolio management and risk analysis as they have the characteristics of both stocks and debt instruments (Liu & Serletis, 2019).

The volatility spillover from one market to another can occur in positive or negative, symmetric or asymmetric, linear or non-linear forms. Even though portfolio diversification generally reduces risk, most financial assets, including global equity indices, exhibit a high degree of consensus, making it challenging to maintain the desirable level of risk mitigation. Therefore, the fact that BTC can provide diversification benefits and a hedge against extreme market volatility when combined with other financial instruments makes it an extremely attractive digital currency.

The literature has addressed various issues related to BTC, including its speculative nature (Baur et al., 2018; Dyhrberg, 2016b; Glaser et al., 2014; Yermack, 2015), independence from monetary policy and therefore economic policies (Polasik, 2015) that can result in significant price fluctuations (Kurihara & Fukushima, 2018). Particularly, the BTC price is more volatile during speculative periods, and its volatility persistence prevents it from serving as a unit of account, one of the three basic functions of money (Ammous & D'Andrea, 2022; Lopez-Cabarcos et al., 2021). BTC is prone to speculative bubbles, which ultimately lead to financial instability (Corbet et al., 2018; Diebold & Yilmaz, 2009). With increasing financial globalization, there is concern that volatility in the digital currency market may spread to the FX, fixed income, equity, and commodity markets, causing significant disruption in global markets.

While the literature extensively evaluates the influence of BTC returns on conventional commodities and assets, many aspects remain underexplored. Many studies only look at one asset class at a time. For example, Dyhrberg (2016a) examines the connection between BTC and gold, while Baur et al. (2018) focus solely on the relationship between BTC and gold. They do not look at how BTC affects commodities, currencies, sentiment indices, and the largest stock markets simultaneously. We recognize that conditional correlations—and, henceforth, optimal allocations—change over time; however, portfolio diversification assessments typically assume that weightings remain constant (Guesmi et al., 2019; Okorie & Lin, 2020). This approach may make it harder for us to understand how BTC can truly diversify across all types of financial markets. Methodologically, previous research often considers univariate and multivariate techniques independently. Univariate models elucidate persistence or asymmetry (Ding et al., 1993; Dyhrberg, 2016b), whereas multivariate frameworks (Corbet et al., 2018; Jiang et al., 2022) assess time-varying correlations. However, limited research amalgamates both methodologies into a cohesive sequence that connects volatility to correlation dynamics. It is also worth noting that the behavior of BTC during pandemic conditions is not well understood, as most empirical samples cover time periods before the COVID-19 pandemic began to spread widely around the globe (Al-Yahyaee et al., 2019; Selmi et al., 2018). Finally, even when sophisticated models are applied, such as those of Hou et al. (2022), who map spillovers across regions and regimes, there is a lack of work translating these findings into actionable, regime-aware portfolio strategies. Thus, we aim to fill these gaps in the literature by investigating the current state of volatility spillover between BTC, global, and commodity markets. Specifically, we aim to investigate the interrelationship between BTC price returns and gold in equity markets.

Academic literature has addressed issues related to BTC, including multifractality (Mensi et. al., 2019), its weak form of efficiency (Urquhart, 2016), and long-range memory (Jiang et al., 2018). The presence of long-range persistence indicates a slower decay rate compared to exponential decay, resulting in a heterogeneous degree of information in the BTC return series. These issues can lead to persistent deviations in the financial time series of BTC and other markets. Consequently, several well-fitting and forecasting techniques have been developed to model the dynamics of relationships between different markets. The majority of methods have been developed to account for the unique characteristics of return time series. To rigorously chart the volatility interactions between BTC and gold and equity returns—and thereby assess its diversification potential—we proceed through a sequence of nonlinear volatility models. We begin with the conventional GARCH (1,1) model to determine the baseline persistence in each series. Then, we add GJR-GARCH and EGARCH (1,1) to examine the differences in how BTC and traditional assets behave when leveraged. Next, FIGARCH (1,1) indicates that volatility exhibits long memory, and PARCH (1,1) allows us to observe how different shocks of varying sizes impact the system differently. Finally, we integrate these insights into the dynamic conditional correlation DCC-MGARCH framework to estimate the time-varying correlations across all assets. These phases work together to help us achieve our primary goal: demonstrating how and when BTC can significantly reduce portfolio risk for investors seeking to protect themselves against losses. The DCC-GARCH technique allows for the independence of parameters in the number of series of the correlation process and is well-suited for analyzing financial data that deviates from the normal distribution, displaying fatter tails originating from infinite moments or the Cauchy distribution. Additionally, return time series volatility clustering, which has recently been noted in the finance literature, can be captured by the model (Azimova, 2022; Fousekis, 2020).

We tested the forecasting performance and compared the estimates of the conventional and dynamic techniques using the conditional variance in the nonlinear structures. In the final step, we compared the prediction accuracy of the models and examined the results between traditional static and dynamic nonlinear models across various time horizons. In particular, we looked at the COVID-19 pandemic, which significantly affected financial markets and caused significant fluctuations in BTC returns.

The results of this study will assist investors in making informed decisions regarding asset allocation, hedging, and risk management. We contribute to the literature in three ways. Firstly, unlike most prior DCC-GARCH studies that focus solely on BTC's relationship with equities or gold, we examine a broad set of eight additional proxies—Brent oil, the USDINX, EUR/USD, VIX, NASDAQ 100, NIKKEI 225, FTSE 100, and DAX—allowing for a more comprehensive assessment of BTC's diversification potential across commodity, currency, sentiment, and equity channels. Secondly, we systematically build both univariate analyses (GARCH, GJR-GARCH, EGARCH, FIGARCH, PARCH) that capture persistence, asymmetry, long-memory, and shock-size effects in each market and a multivariate DCC-MGARCH-t (DCC) model. This stepwise approach not only characterizes BTC's standalone risk dynamics more fully than earlier studies but also shows precisely how those dynamics feed into time-varying correlations. Finally, we cover the COVID-19 crisis period, which allows us to capture extreme co-movements under stress. Finally, by applying conditional minimum-variance simulations under the DCC framework to different variable pairs, we provide practical insights into diversification.

The rest of the manuscript is organized as follows. Section 2 provides the theoretical background, Section 3 presents the techniques used, Section 4 presents the results of all models, and Section 5 concludes.

LITERATURE REVIEW

From the classical gold standard to the present day, countries have regarded gold as a strategic commodity, a means of reserve and safe investment. Gold is used by energy traders as a hedge against a sharp decline in currency markets, equity markets, and oil prices (Al-Yahyaee et al., 2019; Gürgün & Ünalmış, 2014; Mohammadi et al., 2023; Selmi et al., 2018; Wen et al., 2022). The literature indicates that BTC can also be used in conjunction with gold in a portfolio to diversify risk. In particular, Klein et al. (2018) demonstrate that BTC and gold have fundamentally different risk-return characteristics, which make them highly compatible with each other.

Baur and Hoang (2021), Klein et al. (2018), and Kwon (2020) document a low correlation between the daily and monthly returns of gold and BTC. In particular, Baur and Hoang (2021) analyzed the persistent bitcoin-gold correlation puzzle, questioning whether BTC behaves like a safe-haven asset similar to gold. The frequency-dependent, time-varying, and quantile-dependent correlations show values close to zero on average over shorter subsample periods. They explain this result with narrative similarity, which is not adopted by investors, or with other factors such as the catch-up effect and a substitution effect. Kwon (2020) compares the tail behavior of the daily BTC return with that of the dollar, gold, and the stock market index. Based on the estimated conditional autoregressive value-at-risk techniques, the author concludes that the correlation between BTC and gold is low and statistically insignificant. These results are in contrast to other studies that find a positive correlation between BTC and gold. In particular, Jareño et al. (2020) and Zwick and Syed (2019) found a positive and statistically significant correlation between BTC and gold price returns, concluding that gold is an important determinant of BTC price formation.

In addition, Telek and Şit (2020) found a long-term co-integrated relationship between the variables BTC and gold, indicating that in the long run, a 1 % increase in the price of gold ounces results in a 15 % increase in BTC prices. Gökgöz et al. (2025) recently examined the safe-haven qualities of BTC compared to "digital gold," physical gold, and major currencies. They emphasized the importance of understanding its risk profile in a multi-asset context. All of these studies demonstrate the importance of examining the evolving relationships between BTC and various asset classes to determine when BTC can effectively mitigate portfolio risk. Loukil et al. (2025) explain the dynamic interconnection between traditional and digital assets, highlighting the influence of fluctuating economic conditions on these relationships. The research indicates that BTC's ability to diversify and hedge is contingent and fluctuates over time, rather than being fixed.

Oil is another strategic commodity, and the relationship between BTC and oil markets is crucial for policymakers and energy traders. Hou et al. (2022) consider the transmission of volatility in both static and time-varying forms between Bitstamp and ItBit, two of the most prominent BTC markets, and WTI and Brent, two of the largest crude oil markets. Higher-order moments are estimated using a two-state regime-switching model, and the time-varying spillovers are specified using Legendre polynomials. They conclude that, in terms of the static and time-varying transmission of three types of risk between markets, crude oil serves as an information transmitter and BTC acts as an information receiver. Additionally, BTC helps to diversify oil risk, and this effect is amplified by the trade war. In addition to a unidirectional volatility spillover from the crude oil market to the BTC cash market, Okorie and Lin (2020) found evidence of a bidirectional volatility spillover between the crude oil market and Bit Capital Vendor. Lastly, there is a significant unidirectional volatility spillover from the Ethereum, XRP, and ReddCoin cryptocurrency markets to the crude oil markets. While the potential of the Ethereum cryptocurrency to hedge crude oil assets may be limited, the potential to hedge crude oil assets from Solve, Elastos, and Bit Capital Vendor is likely to continue for a very long time. Jin et al. (2019) found that there is a significant volatility transmission between oil and BTC, and that these volatility effects are stronger from the oil to the BTC market. The time-varying correlations are negative for the BTC-oil pair. According to Guesmi et al. (2019), hedging the risk of an oil and BTC investment can significantly lower portfolio risk compared to a portfolio consisting only of gold, oil, and equities.

More recently, Jiang et al. (2022) and Salisu et al. (2023) concluded that the cryptocurrency market is a net sender of spillover effects, while the oil market is a net receiver of spillover effects. Investigating the link between BTC and traditional currencies is becoming increasingly important as the appeal of cryptocurrencies in the financial world grows. Kwon (2020) and Oad Rajput et al. (2022) found negative and statistically significant correlations between the USDINX and BTC. Telek and Şit (2020) found, on the other hand, that there is a long-term cointegrated relationship between BTC and dollar variables. In the long run, a one-unit increase in the USD index results in a 0.28 % increase in BTC prices. Furthermore, using the quantile regression approach, Jareño et al. (2020) discovered the VIX index as the most significant risk factor. This index has a negative and statistically significant impact on BTC returns across most quantiles and time periods. Recent empirical results by Chang et al. (2023) suggest that the momentum premium may rise in response to higher VIX premiums over a one-month horizon.

Ghorbel et al. (2022) and Omri (2023) investigated the asymmetric relationship between cryptocurrencies and stock market prices using data comprising 571 observations from 2019 to 2021. They found a positive and low correlation between BTC and the S&P 500, NIKKEI, DAX 30, as well as a negative and low correlation with the FTSE. They found that cryptocurrencies are important drivers of stock markets. Using the sliding window technique, Wang et al. (2020) and Wang et al. (2022) showed that the S&P 500 has a relatively significant influence on BTC, while the influence of the S&P 500 is weak. Erdas et al. (2018) investigated the asymmetric causal relationships between BTC and the S&P 500. The analysis results reveal a causal relationship between the BTC return and the S&P 500 index. Furthermore, studies on the relationship between BTC and NIKKEI have found significantly high positive correlations (Guizani & Nafti, 2019; Gupta et al., 2024) and negative correlations (Akkaya, 2022; Uzonwanne, 2021). Additionally, the academic literature confirms a statistically significant relationship between the FTSE and BTC (Kwon, 2020). Munyas and Atasoy (2021) conclude that there is no statistically significant causal relationship between DAX and BTC. This study complements academic research by examining the diversification benefits between BTC and strategic commodities and markets.

METHODOLOGY

This study examines the relationships between BTC and various daily financial time series using GARCH models, covering the period from December 11, 2017, to October 30, 2023, as well as the COVID-19 subperiod. To better understand the relationships between BTC and financial and commodity markets, it is necessary to examine a subperiod that includes the pandemic. We applied GARCH, EGARCH, GJR, FIGARCH, PARCH, and DCC-GARCH models, which are the GARCH (Non-Linear Generalized Autoregressive Conditional Heteroskedasticity) class. The ARCH model, developed by Engle (1982), has been criticized for yielding the same response to both positive and negative shocks, as well as for exhibiting a delayed response to shocks. The GARCH model was introduced to the literature by Bollerslev (1986). Bollerslev added conditional heteroscedasticity to the moving average items in the ARCH formula. In the generalized autoregressive conditional heteroscedasticity model, existing volatility is related to previous residual observations and volatilities. In this model, the conditional variance's own lag value was added to the model. The GARCH model is given in Equation 1:

$$\sigma_t^2 = \alpha_0 + \alpha 1\ u_{t-1}^2 + \beta\sigma_{t-1}^2 \qquad [1]$$

One of the most significant limitations of GARCH models is that they do not account for the sign effect of negative and positive shocks, as the model uses the squares of errors. In the finance literature, it has been observed that negative shocks cause more volatility in time series than positive shocks of the same size. Therefore, there was a need to develop models that take these situations into account. GJR (Glosten et al., 1993) and Exponential GARCH (EGARCH; Nelson, 1991) are examples of these models. The GJR model of Glosten et al. (1993) is a simple extension of the GARCH model, where a variable that accounts for positive asymmetricity is added to the GARCH model. The GJR-GARCH model is given in Equation 2:

$$\sigma_t^2 = \alpha_0 + \alpha_1\ u_{t-1}^2 + \beta\sigma_{t-1}^2 + \gamma u_{t-1}^2 I_{t-1} \qquad [2]$$

One of the asymmetric models developed based on the logic that positive news and negative news have different effects on the volatility of financial assets, depending on the perception of financial markets, is the EGARCH model developed by Nelson (1991). This model assumes that the error terms follow a generalized error distribution. In addition to the existence of an asymmetric relationship, the EGARCH model also enables the determination of the effect known as the "leverage effect." The leverage effect refers to the situation where negative news entering the market creates more volatility in the prices of financial assets than positive news. One of the most important advantages of the EGARCH model over the GARCH model is that it directly satisfies the non-negativity conditions since it takes the logarithm of the variance. If there is a negative relationship between returns and volatility, γ may be negative, indicating that the model allows for asymmetry (Brooks, 2008). The EGARCH model is given in Equation 3:

$$ln(\sigma_t^2) = \omega + \beta\, ln(\sigma_{t-1}^2) + \gamma \frac{u_{t-1}}{\sqrt{\sigma_{t-1}^2}} + \alpha\left[\frac{u_{t-1}}{\sqrt{\sigma_{t-1}^2}} - \sqrt{\frac{2}{\pi}}\right] \qquad [3]$$

In the FIGARCH model, the continuity of the effects of shocks on conditional variance or the degree of long memory is measured by the fractional integration parameter d. If d = 0, the FIGARCH (p, d, q) process is reduced to a GARCH (p, q) process. If d = 1, the FIGARCH process is an IGARCH process. Baillie et al. (1996) showed that when $0 \leq d < 1$, the effect of a shock on the conditional variance of FIGARCH (p, d, q) processes decreases slowly at a hyperbolic rate in accordance with Equations 4, 5, and 6:

$$r_t = \mu_t + \varepsilon_t \, , \varepsilon_t = z_t \sqrt{h_t} \, , z_t \sim i.i.d \,(0,1) \qquad [4]$$

$$\phi(L)\,(1-L)^d\,(\varepsilon_t^2 - h_t) = w + [1-\beta(L)]v_t \qquad [5]$$

$$h_t = w + [1-\beta(L)]^{-1}\,[1-\phi(L)(1-L)^d]\,\varepsilon_t^2 \qquad [6]$$

Where h_t is the conditional variance, L is the lag operator, w is the constant, $\phi(L)$ and $\beta(L)$ are lag polynomials in order q and p, $0 \leq d \leq 1$ is the fractional integration parameter.

In the PARCH model developed by Ding et al. (1993), γ, the power parameter of the standard deviation, can be estimated. The δ parameter is optionally included in the model to capture asymmetry in the process. The fact that the δ parameter is statistically significant indicates asymmetry in the process, as shown in Equations 7 and 8:

$$r_t = \mu_t + \varepsilon_t \, , \varepsilon_t = z_t \sqrt{h_t} \, , z_t \sim i.i.d \,(0,1) \qquad [7]$$

$$h_t^{\delta/2} = w + \textstyle\sum_{i=1}^{q} \alpha_i \,(|\varepsilon_{t-i}| - \gamma_i \varepsilon_{t-i})^{\delta} + \textstyle\sum_{j=1}^{p} \beta_j \, h_{t-j}^{/2} \qquad [8]$$

Where h_t is the conditional variance, $\delta \geq 0$ power parameter, $w > 0, \alpha_i > 0, \beta_j > 0, \gamma_i$ is the asymmetry (leverage) parameter, if $\gamma_i > 0$, negative shocks increase volatility more than positive shocks of the same magnitude.

The Dynamic Conditional Correlation (DCC) Model is built on the basis of decomposing the conditional covariance matrix into conditional variances and correlations. The Dynamic Conditional Correlation GARCH (DCC-GARCH) model, developed by Engle (2002), is formulated as presented in Equation 9:

$$P_t = (I \otimes Q_t)^{-1/2}\, Q_t \,(I \otimes Q_t) \qquad [9]$$

Q_t matrix under a > 0, b ≥ 0, (a + b) < 1 conditions is specified as Equation 10:

$$Q_t = (1 - a - b)s + aV_{t-1}\,V_{t-1} + bQ_{t-1} \qquad [10]$$

Where Q_t is a positive definite matrix.

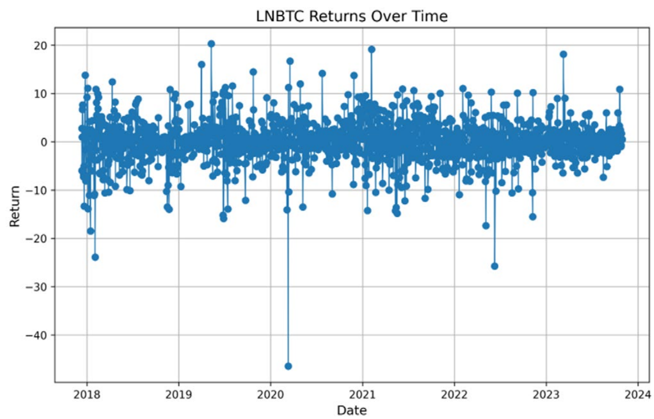
RESULTS

In this research, we aim to investigate whether BTC's price changes can be a reliable method for diversifying a portfolio by examining their impact on different markets. The variables we have studied include assets and indices from traditional investment classes, as well as investors' sentiment. In particular, we included gold as a classic safe-haven asset and store of wealth that investors often turn to when they are worried about the economy. Its price changes and how it moves in relation to BTC provided us with clues about whether BTC acts like a safe-haven asset or delivers diversification benefits on its own. To understand the conditions in the global economy and the risk factors in the commodity market, we used Brent oil prices for the specified time period. Oil price shocks can affect the stock and currency markets, allowing us to see if BTC reacts to changes in the economy in the same way that other commodities do. The USDINX and the euro-dollar parity are two key currency indicators that measure the strength of the US dollar and the fluctuations in the euro-dollar pair over time.

People typically think of BTC as a distinct kind of asset, while currencies are evolving. Many people use the CBOE Volatility Index (VIX) as a measure of market fear and investor sentiment. By incorporating the VIX, we can observe how periods of high market uncertainty or stress impact BTC's conditional volatility and its relationship with other assets. We then added four key stock market indices of the largest countries with the world's largest economies to illustrate the performance of their stock markets: the NASDAQ 100 (USA), the Nikkei 225 (Japan), the FTSE 100 (UK), and the DAX (Germany). These indices give a full picture of how the international stock market works, which is important for looking at how BTC interacts with other hazardous assets and figuring out its place in a globally diversified portfolio. The BTC price series comprises the daily US dollar closing prices and spans a period of 1,537 days, from December 11, 2017, to October 30, 2023. To prepare the series for volatility modeling, we first transformed raw price levels into continuously compounded returns by taking the natural logarithm of the price ratios. We applied the equation n return $=\ln\frac{r_t}{r_{t-1}} * 100$ to all variables except for the VIX. This transformation stabilizes the variance, reduces the impact of scale differences across assets, and produces a return series suitable for time series analysis. The VIX is an indicator of implied volatility that measures the market's expectations for 30-day volatility in the S&P 500. The amount directly correlates with the expected market uncertainty or risk. Employing the level of VIX preserves that intuitive significance. On the other hand, measuring returns on the VIX can generate noise and make it less economically significant, as the VIX does not function like a traditional asset price. Logarithmic return series for all variables and the VIX level series are shown in Figure 1.

Figure 1.

Return Series of Variables



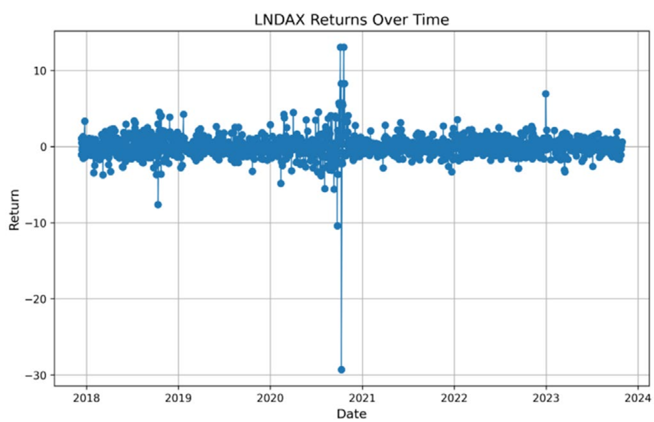
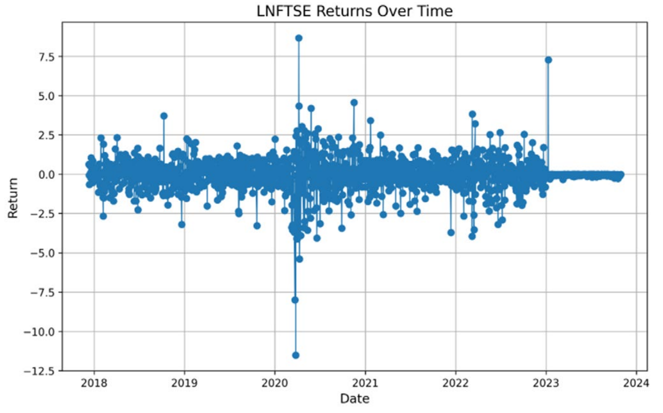
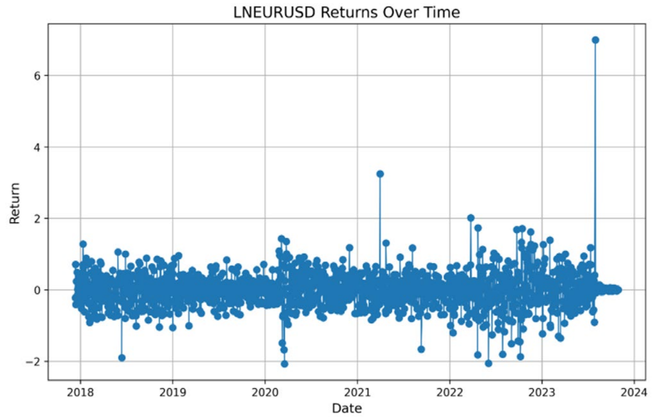
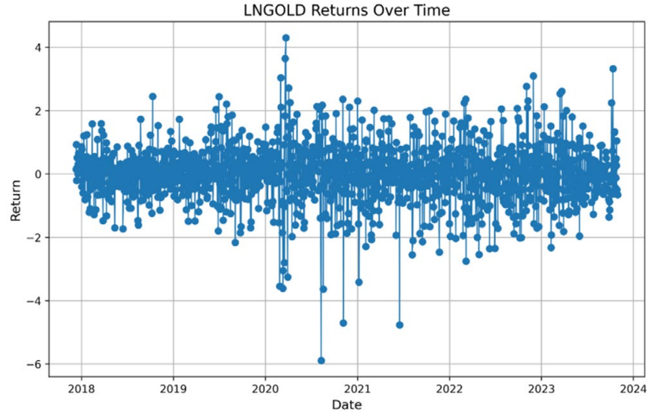


Figure 1 (continued)







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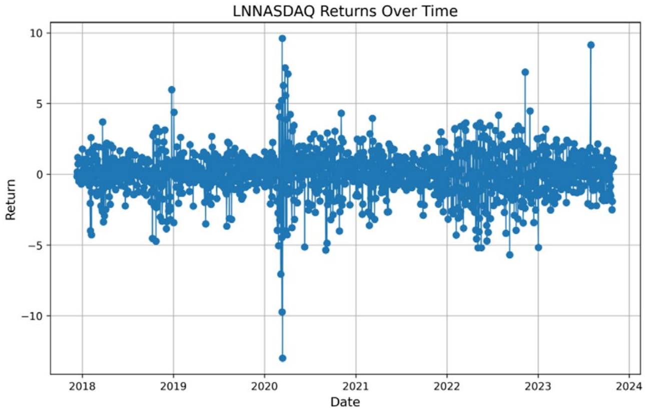

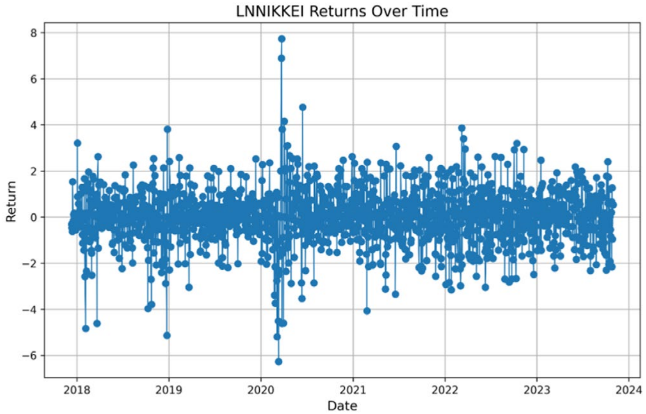

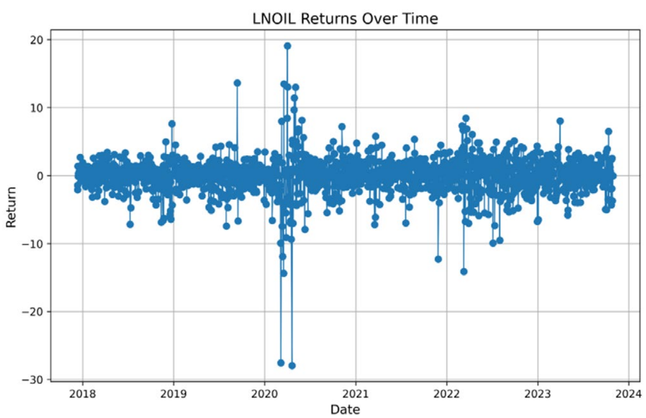

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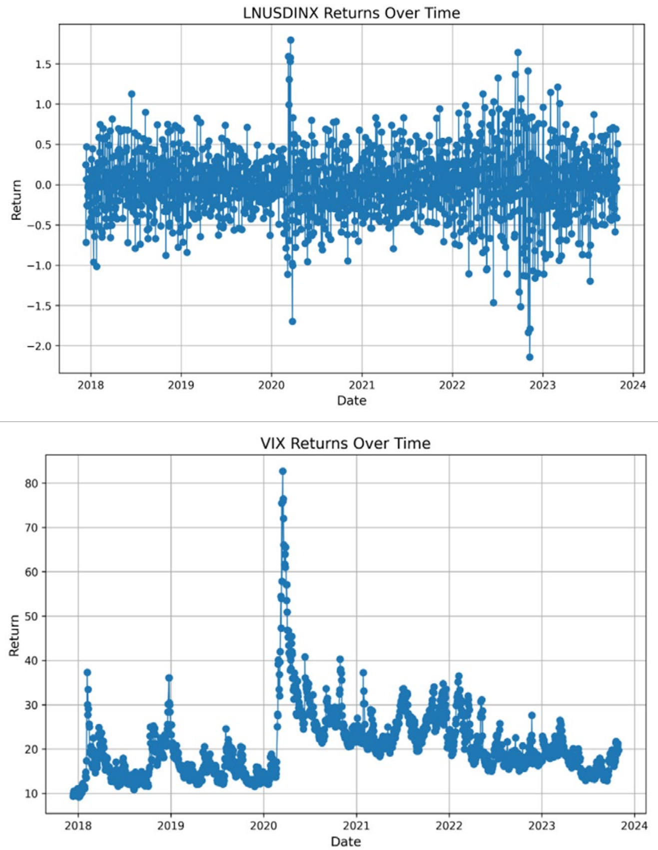


Source: Authors' estimations

Table 1 shows descriptive statistics for BTC and other variables. The skewness coefficient of the BTC series is negative, that is, the BTC series is left-skewed. The negative skewness is largest for BTC and EUR-USD, respectively, demonstrating that negative returns are more prevalent. Apparently, the return data for BTC and other indices are positive and exhibit fat tails. The positive skewness in the NASDAQ, NIKKEI, OIL, USDINX, and VIX return series indicates the presence of asymmetry and a fat tail on the right side of these financial markets. In addition, a leptokurtic distribution with a heavy tail in the stock data suggests that the index is prone to extremely high return outlier values, which increases the risk associated with the investment. The conventional and dynamic models used in this study are suitable for reconciling the statistical characteristics of financial return data that deviate from normality.

Table 2 presents the correlation coefficients between BTC and variables. The highest correlation is between BTC and NASDAQ (0.8582). The NIKKEI also shows a high correlation (0.7684). The DAX shows the lowest and most negative correlation (-0.3805). The USDINX also shows a negative correlation with BTC.

Al-Yahyaee et al. (2019) and Dyhrberg (2016a) use the bivariate and univariate GARCH models to estimate BTC volatility. This study also applies Dyhrberg's (2016a) approach and the model by Al-Yahyaee et al. (2019) to estimate volatility and volatility spillover on BTC returns.

Before estimating GARCH family models, we conducted unit root and stationarity tests to verify that all return series are stationary. Gujarati (2002) demonstrates that spurious relationships can often occur in non-stationary time series. The non-stationary time series can potentially undermine meaningful volatility estimates of GARCH models. We applied the ADF (Augmented Dickey-Fuller) test, developed by Dickey and Fuller (1981), to analyze stationarity. Since the *p*-values calculated

Table 1.

Descriptive Statistics

	BTC	DAX	FTSE	EUR-USD	GOLD	NASDAQ	NIKKEI	OIL	USDINX	VIX
Mean	21,195.70	13,498.40	7,144.97	1,1380	1,649.24	10,775.37	25,334.86	71.48	97.57	20.65
Median	16,610.71	13,217.67	7,277.73	1,1356	1,745.11	11,288.32	25,349.60	71.49	96.90	19.07
Maximum	67,566.83	16,469.75	8,014.31	1.2510	2,063.19	16,573.34	33,753.33	127.98	114.11	82.69
Minimum	3,242.48	8.44	4,993.89	0.9560	1,174.16	5,899.35	16,552.83	19.33	88.59	9.15
Std. Dev.	15,877.10	1,639.72	536.34	0.0585	256.92	3,084.87	3654.49	18.96	5.31	8.00
Skewness	-0.92	-0.09	-1.28	-0.45	-0.44	0.08	0.23	0.05	0.65	2.46
Kurtosis	2.82	2.33	4.26	2.8596	1.71	1.61	2.05	3.31	2.93	14.29
Observations	1537	1537	1537	1537	1537	1537	1537	1537	1537	1537

Source: Authors' estimations

Table 2.

Correlation Matrix

	DAX	EUR-USD	FTSE	GOLD	NASDAQ	NIKKEI	OIL	USDINX	VIX
BTC	-0.3805	0.2332	0.0709	0.6254	0.8582	0.7684	0.3826	-0.0759	0.1737

Source: Authors' estimations

for the variables used in the analysis are smaller than the critical value of 0.01, they are stationary at the level and do not contain unit roots (Table 3). Confirming stationarity at the return level validates that shocks to volatility are properly captured by the subsequent models.

After running several ARMA (p, q) models, we identified the best model, ARMA(1,0), which can accurately fit the conditional values of the parameters and test for an ARCH effect in the time series. The ARMA (1,0) test results are shown in Table 4. To determine the average equation, the analysis was performed up to the 12th lag. Figure 2 shows the BTC's ARCH effect. The results of the ARCH-LM estimates show that the ARCH effect is present in the residuals of the return time series.

Table 3.

ADF Unit Root Tests Results

Variable	Test statistic	MacKinnon approximate *p*-value for Z (t)
BTC	-39.9710***	0.0000
GOLD	-39.1300***	0.0000
OIL	-37.3590***	0.0000
EUR-USD	-38.3230***	0.0000
USDINX	-37.7290***	0.0000
VIX	-5.3530***	0.0000
NASDAQ	-45.9040***	0.0000
NIKKEI	-38.7750***	0.0000
FTSE	-40.7340***	0.0000
DAX	-42.3030***	0.0000

***, **, * represent significance levels of 1 %, 5 %, and 10 %, respectively.

Source: Authors' estimations

Table 4.

ARCH-LM Test Results

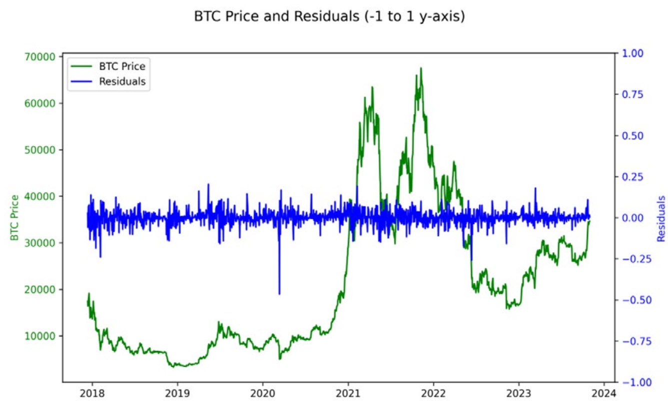
Full period	BTC	GOLD	OIL	EURUSD	USDINX	VIX	NASDAQ	NIKKEI	FTSE	DAX
lag4	16.265***	36.905***	86.005***	0.636	192.347***	218.675***	251.771***	207.567***	223.894***	91.207***
lag8	26.832***	72.643***	138.845***	1.292	258.521***	236.926***	292.098***	271.758***	319.781***	160.441***
lag12	27.384***	75.494***	160.875***	1.402	262.224***	256.379***	297.830***	298.025***	348.722***	179.291***

***, **, * represent significance levels of 1 %, 5 %, and 10 %, respectively.

Source: Authors' estimations

Figure 2.

ARCH-LM Test Graph



Source: Authors' estimations

To investigate the volatility interactions between BTC and other financial proxies such as gold and equity indices, we first estimate a set of univariate GARCH-family models that capture the essential features of each asset's conditional variance. The GARCH model identifies the baseline volatility persistence that underlies the interaction of shocks across markets. EGARCH and GJR-GARCH are used to calculate leverage effects, which show how negative events in a particular market may cause larger volatility responses compared to positive shocks of the same magnitude. FIGARCH contains long-memory movement, used to investigate the transmission and endurance of volatility events across markets caused by a single asset. The PARCH model has a power term used to assess the different impacts of moderate and substantial shocks. The power term indicates whether extreme events in BTC or other proxies have an adverse impact on cross-market volatility. These mathematical frameworks collectively form the basis for understanding how shocks in one asset propagate to others and set the stage for the multivariate DCC-MGARCH investigation of time-varying correlations.

Maximum likelihood calculations were carried out for the entire sample, taking into account volatility spillovers from the submarket to the other sub-markets. The first moment interdependencies for the entire period, as shown in Table 5, indicate that GARCH (1,1) and other GARCH models are significant. The estimates reveal five statistically significant models. All GARCH models identify volatility spillover interactions that extend across multiple markets, including the gold ounce price, the NASDAQ, the USDINX, as well as the BTC return and market volatility. Notably, the GARCH (1,1) specifications have GARCH coefficients that are both higher than 0.8, which may indicate strong persistence over time. This result implies that there is minimal tendency for shocks in the volatility process to return to the volatility mean. This outcome shows that large price moves today will keep markets on edge for an extended period rather than quickly reverting to calmer conditions. Practically, this underlying “stickiness” of volatility clustering necessitates that risk managers anticipate elevated risk levels will decay only slowly over time, thereby requiring hedges or protective strategies to remain in place well beyond the initial disturbance. For investment professionals, it accentuates the necessity of maintaining defensive positions (such as options or stop-loss orders) for extended periods after cyclical days, as the heightened level of uncertainty does not dissipate immediately with a single day of muted returns.

The parameter for the asymmetric effect of the EGARCH (1,1) model (λ or μt-i/ht-1) is negative and statistically significant at the 1 % significance level. Negative shocks of the same size have a greater impact on volatility than positive shocks, a phenomenon known as the “leverage effect.” The apparent “leverage effect” implies that a decrease in the prices of BTC, gold, or equities provokes larger volatility responses than upward moves of the same magnitude. Practically, this suggests that risk managers and investors should expect market turmoil following negative returns to be more intense and persistent, so volatility forecasts should be adjusted upward more aggressively after losses than after gains. Portfolio hedging strategies—such as purchasing out-of-the-money options or widening stop-loss thresholds—should therefore be calibrated to respond more sensitively to price declines. Risk capital allocations must account for the fact that downside shocks will exacerbate uncertainty more severely than upside shocks.

Our estimations show that the PARCH (1,1) model is statistically significant and captures the asymmetric volatility process. In addition, the PARCH (1,1) model shows that the time-dependent volatility of the BTC series is high and resilient in terms of continuity. Our PARCH (1,1) results are significant, indicating that volatility responds differently to small versus large returns and that BTC’s risk level remains elevated and persistent over time. In practical terms, this means that both minor and major price moves contribute to a persistently high-volatility environment, rather than causing brief spikes that quickly subside. As a result, investors and risk managers should design their strategies—such as dynamic rebalancing or volatility-targeting overlays—around a sustained baseline of uncertainty, rather than expecting risk to decline sharply after individual shocks. A fractionally integrated parameter *d* between 0 and 1 in the AR (1)–FIGARCH (1,d,1) model indicates that volatility shocks in BTC decay at a moderate pace—slower than in a standard GARCH but faster than in a pure long memory process. Practically, this means that after a volatility spike, BTC's risk level does not snap back immediately; instead, it remains elevated for a sustained period before gradually reverting toward its long-term average. Therefore, investors and risk managers should extend their forecasting and hedging horizons to account for this medium-term persistence, recognizing that elevated volatility will fade only gradually rather than dissipating after a few days. Together, our sequence of volatility models indicates that the continuity of the impact of shocks on the conditional variance of BTC from other markets remains positive and statistically significant throughout the entire period. Univariate GARCH, GJR-GARCH, and EGARCH models establish baseline persistence and asymmetry in each series, demonstrating how shocks are unevenly translated into risk. FIGARCH and PARCH then illustrate that there is medium-to long-term memory and the varying effect of shock size.

As in the entire period, we applied GARCH models to the COVID-19 subperiod to analyze the volatility of the BTC return and the volatility spillover between the variables. The first human case of COVID-19 was reported on or around November 16, 2019, in Wuhan, China. The period from 11/18/2019 to 05/05/2023 is modeled as a COVID-19 subperiod. Table 6 presents the prediction results of various GARCH models for BTC during the COVID-19 period. All selected GARCH models are significant, as they are throughout the entire period. As in the entire period, the gold ounce price, the NASDAQ, and the USDINX have an impact on the volatility of the BTC return. The parameter for the asymmetric effect of the EGARCH (1,1) (λ or μt-i/ht-1) is negative, and the leverage effect takes place in the COVID-19 period. The presence of an asymmetric effect suggests that negative news amplifies the volatility of stock returns more than positive news. Remarkably, negative innovations (shocks) during the COVID-19 period have a greater effect on the volatility of the following period than positive innovations (good news) of comparable magnitude.

These results suggest that, during calamities such as COVID-19, negative shocks have more weight than positive shocks of the same size, leading to larger and more persistent increases in future volatility. Practically, this means that risk managers and investors cannot rely on speedy recoveries after downturns; instead, they must prepare for extended periods of heightened uncertainty following negative news. In portfolio construction, this entails maintaining defensive hedges—such as put options or volatility-targeting overlays—for longer durations after losses, adjusting margin requirements to reflect the heavier impact of downside moves, and setting risk limits that account for the fact that bad news amplifies future risk more than good news mitigates it.

The AR (1)-FIGARCH (1,d,1) process is a fractionally integrated parameter, which indicates that the volatility of BTC during the COVID-19 period exhibits a moderate tendency to return to its mean. A fractional integration parameter of 0.2499 during the COVID-19 period means that volatility shocks to BTC decay more slowly than in a standard GARCH model but still revert toward the long-run mean at a moderate pace. Practically, this indicates to risk managers and portfolio allocators that, after a turbulence event—in this case, driven by pandemic-related news—elevated volatility in BTC will persist for weeks rather than dissipate immediately. As a result, forecasting and hedging horizons should be extended, and models used to set margin requirements, VaR limits, or dynamic rebalancing rules must account for this medium-term stickiness in order to avoid underestimating risk. A power parameter of 0.8362 in the PARCH model indicates that volatility reacts disproportionately to the size of shocks: large price moves drive volatility up more sharply than small moves, and this response is asymmetric. Investors and risk managers must understand how extreme events, such as sudden BTC crashes, will influence the risk estimates. Therefore, tail risk hedges, such as deep out-of-the-money options or volatility targeting overlays, should be designed with sensitivity, ensuring protective measures are in place when markets experience large swings.

Together, these findings indicate that during crisis episodes, BTC's risk behavior is both "sticky" and highly sensitive to the size of the shock, resulting in prolonged bouts of turbulence following major moves. By quantifying this medium-term persistence and asymmetry, we gain critical insight into when and how BTC's inclusion will meaningfully alter a mixed portfolio's risk profile. Specifically, knowing that risk remains elevated and reacts sharply to extreme events allows investors to time and size BTC allocations—and to calibrate hedging overlays—so as to maximize its potential to dampen aggregate volatility and achieve the study's overarching goal of demonstrating BTC's diversification benefits under stressed market conditions.

Table 5.

Bitcoin GARCH Models Results for All Periods between 12/11/2017 and 10/30/2023

	GARCH (1,1)	Prob.	GJR-GARCH	Prob.	EGARCH (1,1)	Prob.	FIGARCH (1,1)	Prob.	PARCH (1,1)	Prob.
ω	1.5749	0.0011	1.1351	0.0000			4.0817	0.0000	0.2119	0.0025
β	0.8413	0,0000	0.8424	0.0000			-0.1199	0.0157		
φ										
γ			0.0776	0.0000						
μ					0.2203	0.0000	0.3279	0.0000		
λ					-0.0492	0.0000				
θ					0.9192	0.0000				
d							0.2499	0.0000		
y									-0.0568	0.0003
δ									0.6741	0.0000
Log(L)	-4,332.91		-4,327.06		-4,328.77		-1,442.78		-1,422.71	
AIC	5.66		5.65		5.66		5.90		5.82	
Schwarz	5.70		5.71		5.71		6.02		5.95	
Hannan-Quinn	5.68		5.67		5.68		5.94		5.87	

Source: Authors' estimations

Table 6.

Bitcoin GARCH Models Results for the COVID-19 Period between 11/18/2019 and 05/05/2023

	GARCH (1,1)	Prob.	GJR-GARCH	Prob.	EGARCH (1,1)	Prob.	FIGARCH	Prob.	PARCH	Prob.
ω	1.2026	0.0000	1.2105	0.0000			17.7600	0.0000	0.5709	0.0154
β	0.8123	0.0000	0.8125	0.0000			0.6001	0.0000		
φ										
γ										
			0.1293	0.0000						
μ					0,0649	0.0952	0.1500	0.0092		
λ					-0,0884	0.0000				
θ					0,9175	0.0000				
d							0.4000	0.0000		
y									0.3411	0.0000
δ									0.8362	0.0000
Log(L)	-2,555.18		-2,549.26		-2,546.97		-2,549.26		-2,548.19	
AIC	5.68		5.66		5.66		5.66		5.66	
Schwarz	5.74		5.74		5.73		5.74		5.74	
Hannan-Quinn	5.71		5.69		5.69		5.69		5.69	

Source: Authors' estimations

To determine which model best describes the conditional dependence in the volatility process, we utilized the information criteria (LL, SIC, and AIC). Since all models are nested, this is achievable. According to Sin and White (1996), the model that minimizes the SIC and AIC criteria and maximizes the LL function is the best fit for describing the data. The EGARCH (1,1) specification is found to be the best model to capture the dependence in the conditional variance, while other models can also be applied to test the volatility interdependence between the BTC and other variables, based on the LL and AIC criteria. Table 7 presents the results of model comparison.

Building on the insights from these univariate models, we proceeded to the DCC-MGARCH framework to capture the time-varying conditional correlations and assess how volatility shocks in BTC, gold, and equity markets interact dynamically, which is central to evaluating BTC's potential diversification benefits. By employing the DCC–MGARCH (1,1)-t model, we obtain a dynamic, joint view of how BTC co-moves with gold and equity markets under different market conditions, including periods of stress. The "t" specification captures fat tails, ensuring that extreme events—when contagion is most likely—are properly reflected in our correlation estimates. Practically, this allows us to see exactly when and to what extent BTC behaves as a shock absorber versus a shock transmitter. Table 8 presents the results from DCC–MGARCH (1,1)-t model, which captures the impact of conditional correlations and summarizes the key findings for both the entire period and the pandemic crisis periods. We estimated the conditional heteroscedasticity (ARCH) term to characterize the short-run dynamics in each market, and we computed the conditional variance to comprehend the impact of past innovations. $\alpha\ (\varepsilon_{t-j})$ is the pertinent coefficient for the conditional heteroskedasticity and $\beta(h_{t-j})$ is the pertinent coefficient for the conditional variance. From the DCC-MGARCH model, both $\alpha\ (\varepsilon_{t-j})$ and $\beta(h_{t-j})$ are statistically significant for the whole period and the pandemic. The ARCH effect for gold is the least persistent, while the ARCH effect for indexes and BTC is more persistent. In fact, the ARCH effect for FTSE is the most persistent.

Table 7.

Model Comparison

Criteria	GARCH (1,1)	GJR-GARCH	EGARCH (1,1)	FIGARCH	PARCH
AIC criteria	5.68	5.66	5.66	5.66	5.66
SIC criteria	5.74	5.74	5.73	5.74	5.74
Log likelihood criteria	-2,555.18	-2,549.26	-2,546.97	-2,549.26	-2,548.19

Source: Authors' estimations

Table 8 summarizes the main estimates of the DCC–MGARCH (1,1)-t model between the digital currency, major commodity, and index markets. The correlations appear to be very persistent, as indicated by λ1 and λ2, which also demonstrate how heavily the covariance matrix Qt depends on the lagged matrix Qt−1. The process is strictly stationary since λ1 and λ2 are both positive and their sum is less than one.

Although investigating the interrelationship between BTC and other financial instruments is the motivation for this research, we primarily focused on the relationship between the BTC financial and commodity markets. The relationships between BTC and other financial and commodity markets are examined for the COVID-19 period and for all periods and presented in Table 9. The purpose of defining the time interval is to determine whether the COVID-19 period has an impact on the relationship between the variables.

A statistically significant and positive relationship was found between the returns of BTC and gold, as well as the NASDAQ, in all time periods and during the COVID-19 period. In particular, the relatively low conditional correlation coefficient of 0.1341 indicates a low spillover effect between BTC and gold. Correlations have increased from 0.1341 to 0.1674 for the BTC and gold pair during the COVID-19 period, but this increase is unlikely to have a material impact on investors' positions. This result can be compared with the outcomes from Selmi et al. (2018), who demonstrated that combining BTC and gold in a single portfolio offers protection against extreme market fluctuations. Furthermore, the BTC seems to be most influenced by the contagion effects of NASDAQ during pandemic turmoil. This result seems to be in line with common sense, considering that the

Table 8.

Estimation Outputs of the DCC-MGARCH

	Full period			COVID-19 period		
	Constant (ω)	α (ε_{t-j})	β (h_{t-j})	Constant (ω)	α (ε_{t-j})	β (h_{t-j})
BTC	1.6591***	0.1370***	0.7900***	37.5432***	0.0057***	-0.9207***
GOLD	0.0175***	0.0538***	0.9247***	0.1151***	0.0680***	0.8172***
OIL	0.1897***	0.1230***	0.8554***	0.2753***	0.1586***	0.8214***
USDINX	0.0023**	0.0554***	0.9298***	0.0052**	0.0934***	0.8795***
VIX	1.0820***	0.7661***	0.2463***	1.5105***	0.8464***	0.1811***
NASDAQ	0.0754***	0.1645***	0.8141***	0.0672***	0.1304***	0.8494***
NIKKEI	0.0839***	0.0891***	0.8478***	0.1097**	0.1008***	0.8260***
FTSE	0.0839	0.1704***	0.8784***	0.0849***	0.1374***	0.8037***
DAX	0.1004***	0.1614***	0.7862***	0.1112***	0.1765***	0.7772***

***, **, * represent significance levels of 1 %, 5 %, and 10 %, respectively.

Source: Authors' estimations

cryptocurrency market is mainly concentrated in the USA. A statistically and negatively significant relationship was found between the BTC and USDINX variables, as indicated by a correlation of -0.1300. The correlations have remained relatively unchanged during the pandemic crisis; therefore, this influence can be considered negligible. This finding supports the evidence of potential diversification benefits for market participants when combining USDINX with cryptocurrencies. Although there was no statistically significant relationship between BTC and NIKKEI variables across all time periods, a positive and relatively stronger relationship was found during the COVID-19 period at the 10 % significance level, compared to all other time periods. This suggests that idiosyncratic innovations, as opposed to systematic shocks, are primarily responsible for the fluctuations in business cycles in normal times. Moreover, the volatility spillovers can change their pattern and become more influential during times of turmoil. Overall, the DCC–MGARCH-t model's conclusions on BTC connection with other variables were supported by the EGARCH (1,1) specification results, which were selected as the most desirable model, based on information criteria.

The digital currency remains uncorrelated with the oil, VIX, FTSE, and DAX variables. This result has important implications for German investors and indicates pronounced risk-return characteristics of BTC, which follow volatility phases that differ from those of the DAX index. This result aligns with that of Baur et al. (2018), who found distinct volatility patterns between BTC and USDINX stocks. The fact that the direction of the relationship between BTC and FTSE and DAX is negative can be interpreted as individual or institutional investors can benefit by investing in these exchanges together with BTC. When examining the relationships between other variables, a negative and statistically significant relationship is observed between the gold and the USDINX variable, both during the COVID-19 period and in all other time periods. Although there is no statistically significant relationship between the variable gold and the NASDAQ across all time periods, a positive and statistically significant relationship exists during the COVID-19 period. The variable oil remains correlated with the variables NASDAQ and NIKKEI in both COVID-19 and all time periods. While there was a statistically significant and negative relationship between the USDINX variable and the NASDAQ and NIKKEI variables in all time periods, as well as in the COVID-19 period, this relationship was more pronounced in the COVID-19 period. The results are consistent with those of Ng (2000), who shows that the estimated standardized Japanese and American residuals share conditional normality and a univariate normal distribution. According to Ng (2000), adding the asymmetric effect of the conditional variance of the local idiosyncratic return shock to the model increases the contagion effect.

Table 9.

Estimation Outputs of the Dynamic Correlation Coefficients with DCC-MGARCH

		Full period			COVID-19 period		
		Correlation coef.	Z Test	Probability	Correlation coef.	Z test	Probability
BTC	GOLD	0.1341	3.9400***	0.0000	0.1674	4.4200***	0.0000
	OIL	0.0192	0.5600	0.5750	0.0217	0.5500	0.5830
	USDINX	-0.1300	-3.7900	0.0000	-0.1418	-3.6500***	0.000
	VIX	0.0232	0.6600	0.5111	0.0601	1.4700	0.1410
	NASDAQ	0.1321	3.9500***	0.0000	0.1897	5.0300***	0.0000
	NIKKEI	0.0246	0.7100	0.4780	0.0646	1.6500*	0.1000
	FTSE	-0.0341	-1.0200	0.3070	-0.0396	-1.0200	0.3070
	DAX	-0.0050	-0.1400	0.8860	-0.0217	-0.5600	0.5740
GOLD	OIL	-0.0155	-0.4600	0.6460	-0.0082	-0.2100	0.8310
	USDINX	-0.3028	-9.1900***	0.0000	-0.3283	-9.4200***	0.0000
	VIX	-0.0016	-0.0400	0.9650	-0.0475	-1.2000	0.2320
	NASDAQ	0.0157	0.4600	0.6430	0.0898	2.3300**	0.0200
	NIKKEI	-0.0252	-0.7400	0.4590	0.0083	0.2200	0.8290
	FTSE	-0.0114	-0.3400	0.7310	-0.0311	-0.8100	0.4170
	DAX	-0.0117	-0.3400	0.7330	-0.0223	-0.5800	0.5630
OIL	USDINX	-0.0048	-0.1400	0.8880	-0.0244	-0.6300	0.5320
	VIX	-0.0066	-0.1900	0.8490	0.0469	1.2100	0.2250
	NASDAQ	0.1193	3.5100***	0.0000	0.1081	2.8200***	0.0050
	NIKKEI	0.1448	4.3400***	0.0000	0.1366	3.5400***	0.0000
	FTSE	0.0308	0.9300	0.3510	0.0469	1.2100	0.2250
	DAX	-0.0134	-0.3700	0.7110	-0,0188	-0.4800	0.6280
USDINX	VIX	-0.0244	-0.7000	0.4870	0.0045	0.1100	0.9110
	NASDAQ	-0.0667	-1.9300	0.0530	-0.1240	-3.1900***	0.0010
	NIKKEI	-0.0591	-1.7200	0.0860	-0.1260	-3.2700***	0.0010
	FTSE	0.0238	0.7000	0.4870	0.0524	1.3700	0.1720
	DAX	-0.0256	-0.7300	0.4670	0.0182	0.4700	0.6380
VIX	NASDAQ	0.0181	0.5200	0.6030	0.0282	0.6900	0.4890
	NIKKEI	-0.0154	-.3.5600***	0.0010	-0.0858	-2.1500**	0.0320
	FTSE	-.0417	-1.2200	0.2240	-0.0494	-1.2600	0.2070
	DAX	-0.0075	-0.2100	0.8333	-0.0697	-1.7400	0.0810
NASDAQ	NIKKEI	0.1573	-4.6700***	0.0000	0.1351	3.5400***	0.0000
	FTSE	0.0184	0.5500	0.5800	-0.0131	-0.3400	0.7350
	DAX	0.0221	0.6500	0.5180	-0.0068	-0.1800	0.8600
NIKKEI	FTSE	0.0348	1.0300	0.3030	0.0348	0.9000	0.3680
	DAX	0.0812	2.3500**	0.0190	0.0526	1.3500	0.1760

Table 9 (continued)

			Full period			COVID-19 period	
FTSE	DAX	0.00006	0.0000	0.9980	0.0199	0.51	0.6130
			Full Period			COVID-19 period	
	λ_1		0.0074			0.0119	
	λ_2		0.9653			0.9078	

***, **, * represent significance levels of 1 %, 5 %, 10 %, respectively.

Source: Authors' estimations

A statistically significant and negative relationship was found between the VIX variable and the NIKKEI variable, both during the COVID-19 period and in all other time periods. This condition can be interpreted to mean that increasing investor appetite does not affect the NIKKEI stock market. A statistically significant and positive relationship is observed between the NASDAQ and NIKKEI stock market in both COVID-19 and all-time periods. Although there is no statistically significant relationship between the NIKKEI and the DAX during the COVID-19 period, there is a positive and statistically significant connection between NIKKEI and DAX when the entire period is taken into account. The results suggest a link between conditional volatilities for advanced economies with remote geographical locations. The literature suggests that these connections can be even stronger in neighboring countries with strong economic integration and political cooperation (Azimova, 2022). The results of the FTSE variable show that it follows different volatility patterns compared to the DAX variable and remains uncorrelated for the entire period and the pandemic period.

CONCLUSIONS

While commodity and asset markets remain volatile, investors seeking to mitigate the risks in their portfolios have recently shown interest in BTC. As a result, one area of intense research interest is the relationship between BTC and the major financial and commodity markets. This paper contributes to ongoing efforts to model and forecast the conditional correlation and volatility spillover between the BTC-oil and BTC-gold pairs, as well as the BTC-NASDAQ, BTC-NIKKEI, and BTC-FTSE. For an in-depth analysis, we consider six GARCH models with different features, including GARCH, EGARCH, TGARCH, GJR, FIEGARCH, and PARCH. Each of these mathematical frameworks adds a crucial piece to the puzzle. First, a GARCH benchmark quantifies how past shocks persist in BTC, gold, and equities, establishing baseline risk dynamics. We then used the GJR-GARCH model to capture the "panic" effect—how negative returns amplify volatility more than positive ones—followed by the EGARCH model to measure leverage and asymmetry without imposing non-negativity constraints.

To determine whether volatility shocks diminish progressively over weeks or months, we fit a FIGARCH model and interpret the fractional parameter as evidence of medium-term memory in BTC's risk. Next, the PARCH power term distinguishes the impact of small versus large events, highlighting the outsized role of extreme moves in driving conditional variance. We used information criteria (LL, SIC, and AIC) to determine the most suitable model for describing our sample. We observe that the EGARCH technique is the most suitable model for capturing the dependence in the conditional variance. Finally, we synthesized these univariate insights within a DCC-MGARCH framework, estimating time-varying correlations across all assets to pinpoint the predictive dependence and gain a better understanding of the co-movement of BTC and asset/commodity returns, as well as the correlation dynamics of the standardized residuals. Taken together, these analyses not only characterize BTC's unique risk profile but also identify the precise conditions under which it can serve as an effective diversification tool for downside protection.

Using the DCC-MGARCH model, we found evidence of the persistence of the ARCH effect in the BTC and equity markets. Our estimates show that the ARCH effect is the least persistent for gold. We observed a weak positive correlation between BTC and gold; however, the comparatively low conditional correlation coefficient suggests that there is little contagion between the two markets. During the COVID-19 period, correlations for the BTC and gold pair increased, but this increase is unlikely to materially affect investors' positions. We have found negative time-varying conditional correlations between BTC and USDINX. This result shows that there are no contagion effects. Furthermore, we found a positive and relatively stronger relationship between the BTC and the NIKKEI during the COVID-19 period at the 10 % significance level, compared to all other periods. This suggests that idiosyncratic innovations, as opposed to systematic shocks, are primarily responsible for the fluctuations of business cycles in normal times. Furthermore, we did not find a significant conditional correlation between BTC-oil and BTC-DAX pairs, implying isolation and diversification opportunities. Additionally, we observed that negative shocks of the same magnitude have a greater impact on the BTC model's volatility than positive shocks. We also noted that the time-varying volatility of the BTC series is high and resilient in terms of continuity, and that BTC volatility exhibits a moderate tendency to revert to the volatility mean. Moreover, we unveiled the continuity of the impact of shocks on the conditional variance of BTC from other markets.

Our findings—that BTC exhibits significant volatility persistence, pronounced shock sensitivity, and time-varying correlations with traditional assets—carry important implications for investors and policymakers seeking to preserve market stability while recognizing the diversification potential of cryptocurrencies. The strong persistence and asymmetric impact of past innovations in BTC indicate that investors are highly sensitive to past innovations and short-term market dynamics, and are likely to consider BTC as a relatively less liquid market, not yet adhering to a robust investing philosophy. Additionally, the lower persistence in gold suggests that investors perceive gold as a tangible and strategic investment option. However, by incorporating BTC alongside other commodities and equity indices, the high persistence captured by FIGARCH and the pronounced shock sensitivity revealed by PARCH and EGARCH models can be substantially mitigated through diversification. When BTC's return series—characterized by medium-term volatility memory (FIGARCH's fractional parameter) and asymmetric responses to shocks (PARCH's power term and EGARCH's leverage effect)—is combined with assets such as gold, oil, and USDINX whose risk drivers are less correlated or exhibit different volatility dynamics, the idiosyncratic persistence extreme shock effects are "smoothed out" in the aggregate portfolio variance.

In practice, this means that while building their portfolios, investors can utilize digital currency and incorporate BTC-gold, BTC-oil pairs, as well as the BTC-USDINX pair to manage risk more efficiently, achieve greater diversification benefits, and reduce the need for aggressive hedging measures. In addition, the results from DCC-MGARCH covariance matrix show that the optimal portfolio weights to minimize variance will shift as a time series of conditional covariances and correlations evolve. This finding supports the idea that investors should adjust their portfolios, which consist of BTC and traditional assets, and adopt time-varying weightings rather than static allocations. Additionally, this finding suggests that policymakers should establish thresholds based on conditional correlations and volatility persistence metrics. Tightening leverage limits when BTC's linkages to equities or commodities strengthen, and easing them when diversification benefits are demonstrably high. Because cryptocurrencies are traded across borders, regulators in different countries need to collaborate. Organizations like the Bank for International Settlements (BIS) and the International Organization of Securities Commissions (IOSCO) should coordinate this cooperation. A coordinated plan for monitoring cryptocurrencies will enhance early warning systems and mitigate the risk of contagion.

This study has several limitations that call for attention. We execute the GARCH-family and DCC-MGARCH techniques, implementing other nonlinear methods, such as regime-switching GARCH or copula-based dependence structures, may provide additional valuable results. Moreover, our study does not explicitly account for the role of macroeconomic announcements and regulatory intervention variables, which could influence the dynamics of BTC. Future research could address these limitations by examining macroeconomic and regulatory variables in the transmission process of cryptocurrency volatility. Additionally, investigating the impact of emerging central bank digital currencies and regulatory frameworks on BTC's diversification potential would provide valuable insights for both policymakers and investors.

AVAILABILITY OF DATA AND MATERIAL

The data is available upon request.

CONFLICTS OF INTERESTS STATEMENT

The authors declare that they have no competing interests

AUTHORS' CONTRIBUTIONS

All authors contributed equally to the research design, methodology development, data analysis, literature review, and interpretation of results.

ETHICAL USE OF AI

Artificial intelligence (AI) tools were used solely to assist with language polishing, grammar corrections, and formatting during manuscript preparation. All conceptualization, methodology, data analysis, interpretation of results, and drawing of conclusions were performed entirely by the authors. The authors reviewed and approved all content generated with AI assistance to ensure accuracy and integrity.

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