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Dynamic Stochastic Volatility Spillover Between Bitcoin and Precious Metals

Bitcoin İle Değerli Metaller Arasında Dinamik Stokastik Volatilite Yayılımı

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ABSTRACT

Since its creation in 2008, Bitcoin has often been compared to precious metals due to their shared characteristics as safe havens, hedges, and risk diversification tools. This study uses the DCC-GARCH model to analyze dynamic conditional correlations and volatility spillovers between Bitcoin and the returns of gold, copper, silver, and platinum. The findings reveal persistent volatility and clustering in the returns of both Bitcoin and these metals. There is a one-way volatility spillover from gold to Bitcoin, and from Bitcoin to copper, silver, and platinum. Significant dynamic conditional correlations are observed between Bitcoin and both gold and copper, while no significant correlations are found with silver and platinum. These results provide valuable insights for portfolio diversification strategies and inform policymaker decisions in financial markets.

MAKALE BİLGİSİ

Makale Türü
Araştırma Makalesi

Anahtar Kelimeler
Kripto Para Belirsizliği
Değerli Metal Oynaklık Tahmini
DCC-GARCH Modeli

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ÖZ

Bitcoin'in 2008'de oluşturulmasından beri güvenli liman, riskten korunma ve risk varlıklarının çeşitlendirilmesi gibi kripto para birimleri ve değerli metallerin paylaştığı çeşitli ortak özellikler geniş çapta tartışma konusu olmuştur. Bitcoin getirileri ile değerli metaller olan altın, bakır, gümüş ve platin getirileri arasındaki dinamik koşullu korelasyonları ve volatilite yayılımlarını analiz eden bu çalışmada DCC- GARCH modeli kullanılmıştır. Bitcoin getirileri ile değerli metaller olan altın, bakır, gümüş ve platin getirilerinin tüm modellerde volatilitelerinin kalıcı olduğu, incelenen tüm getiri serilerinde volatilite kümelenmesinin oluştuğu gözlemlenmiştir. Altın piyasasından Bitcoin piyasasına doğru tek yönlü volatilite aktarımına karşın, Bitcoin piyasasından bakır, gümüş ve platin piyasalarına doğru tek yönlü volatilite aktarımı bulunmuştur. Dinamik koşullu korelasyonlarda Bitcoin ile altın piyasalarında altın piyasası için, Bitcoin ve bakır piyasalarında Bitcoin ve bakır için anlamlı sonuçlar çıkmıştır. Bitcoin ve gümüş ile Bitcoin ve platin piyasaları arasında dinamik koşullu korelasyonlara rastlanmamıştır.

1. Introduction

Satoshi Nakamoto, whose true identity remains unknown, outlined in the 2008 article introducing the first blockchain network the idea of an electronic payment system based on cryptographic proof rather than trust. This system would enable two parties to transact directly without relying on a trusted third party (Nakamoto, 2008). This definition illustrates that Bitcoin is primarily utilized as an alternative currency. A few months later, in January 2009, Bitcoin was launched as a payment alternative. The integration of Bitcoin into our lives has led to numerous technological advancements in the financial sector. Bitcoin and blockchain technology emerged from the combination of various scientific fields including cryptology, mathematics, and engineering. Bitcoin serves the purpose of offering electronic currency. As a digital currency, Bitcoin lacks physical form, with its creation and transactions occurring in virtual realms. Generating

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Bitcoin necessitates advanced mathematical expertise (Kılıç, 2022). Bitcoin serves various roles in the financial system. It functions not just as a means of transaction, but also as a tool for speculative investment (Baur et al., 2018; Wu et al., 2024). Bitcoin is a digital alternative to traditional currency (Baek ve Elbeck, 2015). Bitcoin could potentially replace traditional financial activities in economies experiencing high levels of inflation (Yermack, 2013). Saving time, not needing a physical location for transactions, and cutting costs by avoiding bureaucratic procedures for issuance are some of the benefits of Bitcoin. The limited production of 21 million units also enhances the value of Bitcoin (Kılıç, 2022). Despite its high volatility and large returns, we see that Bitcoin is mainly used as a speculative investment tool. Bitcoin supply is completely predictable and its growth rate will decrease until 2040 and then remain at the 2040 level.

The price formation process of securities traded in financial markets was explained by Fama (1965) through the Efficient Market Hypothesis (EMH). Financial market efficiency refers to the market's ability to quickly adjust security prices in response to new information. In such an efficient market, it is not expected that investors can consistently achieve exceptionally high returns. The hypothesis posits that due to the randomness of price movements, future price trends cannot be predicted by analyzing past price behaviors. Fama (1970) categorized market efficiency into three forms: weak, semi-strong, and strong. According to the Efficient Market Hypothesis, no investor can achieve abnormal returns in financial markets consistently. However, there are instances where price movements deviate from the mean, behaving in a manner inconsistent with the assumptions of market efficiency.

Risk in financial markets is utilized as a measure of uncertainty, indicating the potential distribution of future events. Distribution spillover is assessed through variance, with standard deviation being the square root of variance. As a measure of risk, standard deviation is also commonly used to represent volatility (Tuncay, 2021). Volatility represents the standard deviation of financial asset returns, reflecting sudden price fluctuations in financial asset movements. It is a crucial metric and the most commonly used measure of risk in finance. Access to stable and reliable volatility information is of fundamental interest to both investors and risk managers (Woebbeking, 2021). Volatility can be defined as the rate of change in the price of an asset or index. Analyzing the markets by predicting future prices or responding to past price movements is a crucial factor in increasing profits (Rastogi and Agarwal, 2020). Investor sentiment can be influenced by various positive or negative news, resulting in heightened swings in prices and greater uncertainty in a market known for its speculative nature and frequent extreme volatility (Apostolakis, 2024). Analyzing volatility fluctuations can offer valuable insights for investors. Therefore, accurately forecasting volatility in financial markets is crucial. Identifying the spillover of volatility from one market to another makes it essential for portfolio managers, policymakers, and investors to devise strategies to control contagion during market crashes, financial shocks, and crises.

Studies on gold returns come to the fore regarding volatility spreads between Bitcoin and precious metals. Shahzad et al. (2019) showed that gold and Bitcoin have different safe haven and hedging properties. Li and Lucey (2017) stated that each of the precious metals, namely gold, silver, platinum, and Palladium, functions as a safe haven. According to Baur and Lucey (2010), gold is, on average, a hedging tool against stocks and a safe haven in stock market conditions. Even during the COVID-19 period, gold did not lose its status as a safe haven (Ji et al., 2020). Holding precious metals in a diversified portfolio reduces the impact of geopolitical risk (Baur and Smales, 2020). Gold returns, however, are impacted by geopolitical risk indices (Gozgor et al., 2019). Negative information shocks may be more dominant for precious metals (Çelik et al., 2018). Rehman (2020) demonstrates that Bitcoin exhibits higher Value at Risk (VaR) levels compared to other precious metals, while gold stands out as the most prominent safe-haven asset among them. Yaya et al. (2022) identify bidirectional shock and volatility spillovers between the Bitcoin market and gold or silver markets. Mabrouk (2024) examines asymmetric spillovers between Bitcoin, oil, and four precious metals (silver, gold, platinum, and palladium) using daily returns from August 18, 2011, to October 2, 2019. The study employs a modified version of the Diebold and Yilmaz (2012, 2014) index and a similar approach to Baruník (2017). The results reveal mild volatility spillovers across all systems. Furthermore, the findings indicate that gold, due to its highest volatility rates, is the most influential market in the system. Mensi (2019) provides evidence of volatility spillover effects between precious metals and Bitcoin. Bitcoin offers greater diversification benefits compared to precious metals, as it has a significantly lower impact on volatility forecasting error variance than precious metals.

Sing et al. (2024) and Murty et al. (2022) have conducted an analysis of the return and volatility distributions between Bitcoin and gold using the DCC-GARCH model Sing et al. (2024) demonstrate that Bitcoin exhibits significant hedging potential for investments in Nifty-50, Sensex, GBP-INR, and JPY-INR. Furthermore, it serves as a portfolio diversifier and establishes its robustness as a safe-haven asset for gold. This research suggests that investors seeking protection against market volatility in equities and commodities may consider incorporating Bitcoin into their investment strategies.

Murty et al. (2022) highlight a positive co-movement between Bitcoin and gold during the COVID-19 pandemic, indicating that investors perceived Bitcoin as a relatively safe investment option.

The main purpose of the study is to examine the dynamic conditional correlations and volatility spillovers between Bitcoin returns and the returns of precious metals gold, copper, silver and platinum. Our study makes a significant contribution to the literature. To our knowledge, this is the first study to investigate the dynamic conditional correlations and volatility spillovers between Bitcoin returns and the precious metals gold, copper, silver and platinum returns. The Dynamic Conditional Correlation (DCC) model is useful for examining time-varying correlations between multivariate returns. Unlike other multivariate GARCH models, Engle's (2002) DCC-GARCH model allows for time-varying correlation. It provides researchers with information about the relationship between returns on financial assets. By examining volatility transmission in the Bitcoin market, our study can enrich existing research on volatility spillovers between Bitcoin returns and precious metals returns.

2. Literature Review

The relevant literature on the return and volatility transfer between cryptocurrencies and other assets is extensive and continues to grow, highlighting its significance for investors. Many researchers examine the return and volatility spillover between cryptocurrencies and other assets, and these studies are ongoing. Bitcoin, in particular, is the subject of numerous studies, especially concerning its volatility. Research investigating the impact of investor sentiment on Bitcoin's volatility focus on how news affects investor sentiment and, consequently, Bitcoin's volatility.

López-Cabarcos et al. (2021) assert that investor sentiment significantly impacts Bitcoin's volatility during stable periods, whereas Eom et al. (2019) argue that investor sentiment plays an information effect in forecasting Bitcoin's volatility. Diverse emotional states, such as psychological and financial sentiments, exert medium- to long-term influences on Bitcoin's volatility. The price dynamics of cryptocurrencies are characterized by pronounced volatility, primarily driven by speculative behavior in the market (D'Amato et al., 2022; Sapkota,2022). Bitcoin has evolved from being merely a monetary asset to becoming an investment asset characterized by high volatility and a strong dependence on investor sentiment. Accordingly, in recent years, cryptocurrencies have emerged as a major asset class (Marobhe, 2021; Letho et al., 2022). Negative relationships exist between uncertainty measures and cryptocurrency volatility (Yen and Cheng, 2021). Studies on the relationships between uncertainty measurements and the gold market yield various results. Worsening economic policy uncertainty tends to drive gold prices higher, while gold prices are less likely to decline when economic policy conditions improve (Bilgin et al., 2018; Chiang, 2022).

Symmetric and asymmetric effects are measured in studies examining the volatility occurring between cryptocurrency and gold (Klein et al., 2018; Hassan et al., 2021; Bianchi et al., 2022). From a financial markets perspective, there is evidence that cryptocurrencies and precious metals share several key characteristics, such as serving as safe havens, hedging instruments, and means of risk diversification. These studies reveal that digital assets provide significant diversification benefits to investors and function as safe havens, much like precious metals, during times of economic crises (Corbet et al., 2020). Conrad et al. (2018) state that Bitcoin volatility is closely related to global economic activity. From a portfolio perspective, Bitcoin does not serve as a safe haven, which is a prominent feature of gold (Klein vd. 2018; Elsayed vd. 2022). However, there are also contrary findings regarding gold in the literature (Klein, 2017). Elsayed et al. (2022) shows that gold has the feature of a stable and reliable safe haven against cryptocurrency uncertainty. Woebbeking (2021) constructed a volatility index from cryptocurrency option prices. Comparing through this index with existing volatility benchmarks for traditional asset classes such as stocks or gold confirms that cryptocurrency volatility dynamics are often disconnected from traditional markets but still share common shocks. Kang et al. (2019) examine the relationship between Bitcoin and gold with the DCC-GARCH model and determine that the volatility between Bitcoin and gold is persistent. Ghorbel and Jeribi (2021) examine the relationship between cryptocurrencies and financial indicators utilizing the DCC-GARCH model. Their analysis reveals a bidirectional volatility interaction between gold and cryptocurrencies, highlighting the interplay between these asset classes.

Dyhrberg (2016) conducts an investigation into the interrelationship among Bitcoin, gold, and the dollar employing the GARCH model. His analysis reveals the advantage of including Bitcoin, gold, and the dollar in the portfolio for risk mitigation purposes. Szetela et al. (2016) explore the correlation between Bitcoin and chosen exchange rates. Employing ARMA and GARCH models, they identify a conditional variance between Bitcoin and the dollar, euro, and yuan. However, no significant relationship is found between Bitcoin and the pound or zloty. Shock and volatility spillover are observed within the cryptocurrency realm. Moreover, statistically significant spillover effects from the cryptocurrency market to other financial markets in prominent economies are detected (Liu and Serletis, 2018). Katsiampa (2019) find that both positive and negative shocks exert notable asymmetric effects on the conditional volatility of price returns across all cryptocurrencies. Additionally, the study unveils the existence of time-varying conditional correlations, indicating strong positive correlations among selected cryptocurrencies and highlighting the presence of interdependencies within cryptocurrency markets. Malladi and Dheeriya (2021) indicated that the returns of global stock markets and gold do not exhibit a causal effect on Bitcoin returns. However, it is found that the returns of Ripple have a causal effect on Bitcoin prices.

Zhang and Mani (2021) in their study, examine volatility asymmetry and correlations between gold and three prominent crypto assets, namely Bitcoin, Ethereum, and Dogecoin. The findings real that positive shocks wield a more substantial impact on the volatility of these financial assets compared to negative shocks of equivalent magnitude. Moreover, they employ Dynamic Conditional Correlation (DCC) to analyze correlations between assets, revealing a notably high positive correlation between gold and Bitcoin, as well as a robust positive correlation among cryptocurrencies themselves. Doumenis et al. (2021) research the viability of cryptocurrencies as a currency or asset investment compared to other financial assets. The findings show a positive correlation between Bitcoin's price volatility and other financial assets before and during COVID-19. They confirm that Bitcoin's volatility is higher than other financial assets. In their study employing the GARCH-MIDAS model, which encompasses cryptocurrency policy and price uncertainty alongside other commonly used uncertainty measures, Wei et al. (2023) corroborate the superior predictive capability of cryptocurrency uncertainty concerning volatility prediction in the precious metals market, encompassing gold and silver. Their research indicates that cryptocurrency uncertainty can lead to volatility in the precious metals market vis-à-vis gold markets. Furthermore, they highlight that diverse uncertainties may capture distinct facets of long-term price fluctuations in the precious metals market. Ozturk (2020) examines the relationship among Bitcoin, gold, and crude oil, with a focus on whether Bitcoin exhibits similar hedging properties to gold and can thus be utilized for hedging purposes. Findings from both total connectedness and frequency connectedness methods indicate that volatility connectedness between these assets surpasses return connectivity. The study reveals that although achieving diversification between these three assets is more challenging in the short and medium term, investors can reap diversification benefits in the long term.

In recent years, many studies employ the DCC-GARCH model to analyze the return and volatility spillovers between various return instruments (Engle, 2002; Baumöhl ve Lyocsa, 2014; Klein, 2017; Bala ve Takimoto, 2017; Mishra, 2019; Chen vd., 2020; Gabauer, 2020; Kılıç, 2021; Ustaoğlu, 2022; Akkus ve Gursoy, 2022; İlbasmış, 2024).

In reviewing the existing literature, it's evident that numerous studies utilize analytical techniques exploring behavioral movements, uncertainty measurements, return spillovers, and volatile spillovers concerning cryptocurrencies, notably Bitcoin returns, in comparison to other return instruments. However, to our knowledge, our study represents the first attempt in this field to examine dynamic conditional correlations and volatility spreads between Bitcoin and the returns of precious metals, including gold, copper, silver, and platinum. Consequently, we consider that our research findings will provide valuable insights for both individual and institutional investors, guiding their investment decisions, facilitating portfolio construction, and informing diversification strategies.

3. Econometric Method

3.1. Data Set

The primary objective of this study is to examine the dynamic conditional correlations and volatility spillovers between Bitcoin and the returns of precious metals including gold, copper, silver, and platinum. The study utilizes daily data spanning from January 3, 2012, to December 29, 2023. The data for the study is sourced from tr.investing.com. Analytical analyses are conducted by transforming the variable data into return series.

Returns (Rt) in the financial system are denoted in local currencies. They are computed as the first differences in the natural logarithms of the returns of Bitcoin and the precious metals gold, copper, silver, and platinum under investigation in this study.

$$R_t = [\log (P_t) - \log(P_{t-1})] \qquad (1)$$

where P_t, is the price level of a return instrument (bitcoin, gold, copper, silver and platinum) at time t, calculated in US Dollar (USD) currency (Şeker, 2023a).

In this study, we employ the DCC-GARCH model, a multivariate GARCH framework, to determine the dynamic conditional correlations and volatility spillovers between Bitcoin and the returns of precious metals, specifically gold, copper, silver, and platinum.

3.2. Unit Root Tests

3.2.1. ADF Unit Root Test

Stationarity is crucial for identifying statistically significant relationships between the analyzed variables. Stationarity is when the average and variance of a series are constant, and the covariance depends on the period between two time intervals, not on the time at which it is calculated. The average and variance of a stationary series remain constant regardless of the period in which it is measured (Gujarati, 2003).

Unit root test was first developed by, Dickey and Fuller (DF) (1979, 1981).

The DF test has the three different versions:

The simplest form is given by:

$$\Delta Y_t = \gamma Y_{t-1} + u_t \tag{2}$$

The model with constant term:

$$\Delta Y_t = \alpha_0 + \gamma Y_{t-1} + u \tag{3}$$

The model with constant term and trend:

$$\Delta Y_t = \alpha_0 + \alpha_1 + \gamma Y_{t-1} + u_t \tag{4}$$

As a result of these tests, DF statistics are compared with MacKinnon critical values; the null hypothesis (H_0: $\gamma = 0$), is tested against the alternative hypothesis (H_1: $\gamma \neq 0$). In other words, the null hypothesis accepts that the series is not stationary, indicating the presence of a unit root, while the alternative hypothesis asserts that the series is stationary (Dickey ve Fuller, 1979).

3.2.2. Zivot-Andrews Unit Root Test

Zivot and Andrews (1992) criticizes Perron (1989)'s exogenous break point assumption and develops a new unit root test procedure that allows an estimated break in the trend function under the alternative hypothesis.

Zivot-Andrews (1992) introduces a model that endogenously estimates the break point using a novel approach. The regression equations which are proposed to test for a unit root are as follows:

$$\text{Model A: } Y_t = \mu + \beta t + \delta Y_{t-1} + \theta_1 \, DU(\lambda) + \sum_{i=1}^{k} \delta_i \Delta Y_{t-i} + \varepsilon_t \tag{5}$$

$$\text{Model B: } Y_t = \mu + \beta t + \delta Y_{t-1} + \theta_2 \, DT(\lambda) + \sum_{i=1}^{k} \delta_i \Delta Y_{t-i} + \varepsilon_t \tag{6}$$

$$\text{Model C: } Y_t = \mu + \beta t + \delta Y_{t-1} + \theta_1 DU(\lambda) + \theta_2 \, DT(\lambda) + \sum_{i=1}^{k} \delta_i \Delta Y_{t-i} + \varepsilon_t \tag{7}$$

$$DU(\lambda) = \begin{cases} 1 & t > T_B \\ 0 & t \leq T_B \end{cases} \qquad DT(\lambda) = \begin{cases} t - T\lambda & t > T\lambda \\ 0 & t \leq T_B \end{cases} \tag{8}$$

where t=1,2,...,T refer to time, T_B symbolizes the break date, $\lambda = T_B / T$ is the break point.

After determining the break date, if the calculated t-statistic is greater than the critical value provided by Zivot and Andrews (1992), the null hypothesis of a unit root is rejected. Otherwise, the null hypothesis is accepted, indicating the presence of a unit root.

3.3. ARCH-LM Test

Once stationarity is confirmed for the variables under study, an important step before conducting volatility analysis is to check for the presence of Autoregressive Conditional Heteroscedasticity (ARCH) effects in the regression equations established among them. The presence of this effect is essential for applying autoregressive heteroscedasticity models. To assess whether this effect exists, researchers often employ the ARCH-LM test (Engle, 1979). The ARCH-LM test is constructed using auxiliary regressions as in equation 9.

$$e_t^2 = \beta_0 + \left(\sum_{s=1}^{q} \beta_s \, e_{t-s}^2\right) + v_t \tag{9}$$

e_t^2 indicates the square of the error term in the auxiliary regression. In the ARCH-LM test, the F-statistic derived from the computed LM (Lagrange Multiplier) value is compared against the critical value from a table. If the calculated F-statistic exceeds the table value, the null hypothesis H_0—which suggests the absence of ARCH effects in the return series—is rejected. Consequently, we accept the alternative hypothesis H_1, indicating the presence of heteroskedasticity. In this case, it can be said that the volatilities of the relevant return series are suitable for GARCH type modeling (Şeker, 2023b).

3.4. DCC-GARCH Model

Understanding the volatility of financial asset returns is crucial for hedging, risk management and portfolio optimization. One of the most important features of financial time series is the clustering of volatility that often occurs in financial asset returns. In financial return series, large changes are generally followed by large changes, and small changes are followed by small changes. The fact that using standard deviation to measure volatility and the idea that the variance does not change over time is insufficient to explain financial time series has been understood over time, and ARCH (Autoregressive Conditional Heteroscedasticity) group models have been developed and started to be used. As a result of the frequent occurrence of the ARCH effect in financial time return series, the autoregressive conditional heteroskedasticity (ARCH) model was introduced by Engle (1982). Over time, due to the inability of this model to explain asymmetric effects, the generalized autoregressive conditional heteroskedasticity (GARCH) model, which was expanded by Bollerslev (1986) and included a more flexible lag structure, was constructed.

GARCH model variance equation was created in 10.

$$h_t = \omega + \alpha\varepsilon_{t-1}^2 + \beta h_{t-1}\ , \ \ \omega > 0,\ \ \alpha \geq 0,\ \ \beta \geq 0, \quad \alpha + \beta < 1 \tag{10}$$

GARCH model variance equation is illustrated in equation (10). In the equation, the coefficient ω indicates the constant term in the variance equation, α indicates the shocks to the variable examined, and β indicates the effect of past period volatility on current period volatility.

While the GARCH model analyzes on a single variable, the multivariate GARCH (MGARCH) model was developed by Bollerslev, Engle and Wooldridge (1988).

The GARCH family is extensively employed for both modeling and forecasting volatility in various financial contexts (Bollerslev vd. 1992; Engle, 2004). In particular, multivariate GARCH models are popular for accounting for co-movements of financial volatilities by estimating a conditional correlation matrix. One method of estimating conditional correlation is the constant conditional correlation (CCC) model introduced by Bollerslev (1990). However, this model assumes a constant correlation is constant over time, which is unrealistic in most cases. One of the popular approaches to addressing this problem in the literature is the DCC-GARCH model put forward by Engle (2002).

Engle's (2002) DCC-GARCH model, unlike other multivariate GARCH models, introduces the capability to incorporate time-varying correlation. Additionally, it addresses the dimensionality problem present in other multivariate GARCH models by increasing the number of parameters to be estimated linearly rather than exponentially. The multivariate DCC-GARCH model, as proposed by Engle (2002), operates in two distinct stages. Initially, GARCH parameters are estimated, yielding standardized residuals. Subsequently, in the second stage, dynamic conditional correlations are derived utilizing these standardized residuals obtained from the GARCH model.

The Dynamic Conditional Correlation (DCC-GARCH) model, developed by Tse and Tsui (2002) and Engle (2002), is formulated as follows:

$$r_t = \alpha + \sum_{i=1}^{k} \beta r_{t-i} + y_t \tag{11}$$

$$\gamma_{A,t} = \sqrt{h_{A,t}\varepsilon_{A,t}} \tag{12}$$

$$\gamma_{A,t} = \sqrt{h_{B,t}\varepsilon_{B,t}} \tag{13}$$

$$\rho_t = COV(\beta_{A,t}\beta_{B,t}) = (1-\theta_1-\theta_2)\rho + \theta_1\rho_{t-1} + \theta_2\Psi_{t-1} \tag{14}$$

$$\begin{bmatrix} h_{A,t} \\ h_{B,t} \end{bmatrix} = \begin{bmatrix} y_1 \\ y_2 \end{bmatrix} + \begin{bmatrix} \emptyset_{1,1} & \emptyset_{1,2} \\ \emptyset_{2,1} & \emptyset_{2,2} \end{bmatrix} \begin{bmatrix} y_{A,t-1}^2 \\ y_{B,t-1}^2 \end{bmatrix} + \begin{bmatrix} \delta_{1,1} & \delta_{1,2} \\ \delta_{2,1} & \delta_{2,2} \end{bmatrix} \begin{bmatrix} h_{A,t-1} \\ h_{B,t-1} \end{bmatrix} \tag{15}$$

$$\mathrm{h}_{\mathrm{t}}^{\mathrm{i}} = \omega_i + \alpha_i \, \varepsilon_{t-1}^2 + \beta_i h_{t-1}^i \tag{16}$$

$$Q_t = (1 - \alpha - \beta) \,.\, \bar{\mathrm{Q}} \,. + \alpha \, \epsilon_{t-1} \, e'_{t-1} + \beta \,.\, \bar{\mathrm{Q}}_{t-1} \tag{17}$$

Equation (11) expresses the mean model that follows a kth order vector autoregressive (VAR) process. Equation (12) and equation (13) express the volatility of the first and second financial asset. Equation (14) ρ_t represents the correlation coefficient that varies over time, that is, is not constant. To say that the correlation matrix ρ is statistically significant 0≤θ1, θ2<1 and θ1+θ2≤1 inequalities must be provided. DCC-GARCH model, which is one of the multivariate GARCH models, $\emptyset_{1,1}, \delta_{1,1}$ parameters in equation (15) denote the persistence of volatility belonging to first financial asset. Equation (16) denote the conditional variance, and Equation (17) denote the conditional covariance. These parameters must be significant statistically and their sum must be less than 1 while their coefficients must be positive. The fact that these parameters are statistically significant and close to 1 indicates that volatility clustering is present in the variables in question and is persistent. Accordingly, $\emptyset_{2,2}, \delta_{2,2}$ parameters refer to the volatility of the second financial asset. In addition to the fact that these parameters are statistically significant and have a sum close to 1, the coefficients of the $\emptyset_{2,2}$ and $\delta_{2,2}$ parameters must be positive. The parameters $\emptyset_{1,2}$ and $\delta_{1,2}$ explain the effect of the second financial asset on the volatility of the first financial asset. In order for the second financial asset to affect the volatility of the first financial asset, it is sufficient for the parameters $\emptyset_{1,2}$ and $\delta_{1,2}$ to be statistically significant. Likewise, the parameters $\emptyset_{2,1}$ and $\delta_{2,1}$ provide information about the volatility of the first financial asset and the second financial asset. In order to talk about the existence of volatility spillover from the first financial asset to the second financial asset, the parameters $\emptyset_{2,1}$ and $\delta_{2,1}$ must be statistically significant. In daily data, volatility clustering is commonly observed, where the impact of information leading to price changes persists over time. This phenomenon manifests in high returns following periods of high yield, and conversely, low returns following periods of low yield. Additionally, returns with similar absolute values tend to aggregate within specific periods. Volatility persistence plays a pivotal role in determining the magnitude and duration of shocks on the volatility of the variable being studied. Furthermore, volatility spillover quantifies the augmented influence of a shock in the market, propagating it to other markets (Akçalı et al., 2019).

The rationale behind selecting the DCC-GARCH model for this study lies in its capability to assess volatility interaction and spillover among the considered financial variables. Additionally, it offers insights into the evolving correlations between the return rates of these variables over time. By elucidating volatility spillover between financial assets and tracking changes in correlation coefficients, the DCC-GARCH model furnishes researchers with valuable information regarding the relationships among returns on financial assets. Given these attributes, the DCC-GARCH model, as one of the multivariate GARCH models, is deemed suitable for investigating the dynamic conditional correlations and volatility spreads between Bitcoin and precious metals such as gold, copper, silver, and platinum.

3.5. Results and Assessment

Table 1 presents the descriptive statistics of logarithmically differenced return series. Analysis reveals positive average values for Bitcoin, gold, and copper series, while silver and platinum series display negative values. Bitcoin exhibits the highest standard deviation among the return series, with gold exhibiting the lowest. Furthermore, standard deviation values surpass average values significantly across all return series, indicative of considerable variability and high volatility spillover. Despite Bitcoin boasting the highest average return, it also demonstrates the highest standard deviation, signifying both high returns and volatility. Kurtosis values exceeding the normal distribution threshold of 3 suggest a leptokurtic distribution in all return series. Financial time series typically exhibit higher kurtosis compared to economic time series, reflecting a leptokurtic distribution that implies wider fluctuations. The observed leptokurtic distribution underscores the potential for wider fluctuations experienced by investors. While Bitcoin displays right skewness, all other return series demonstrate left skewness. The Jarque-Bera statistical probability values indicate that not all return series adhere to a normal distribution. The absence of a normal distribution in financial return series underscores the imperative to investigate the presence of the ARCH effect in these series.

Table 1: Descriptive Statistics

Variables	Bitcoin	Gold	Copper	Silver	Platinum
Mean	0.0029	0.0000856	0.0000339	-0.0000663	-0.000112
Median	0.0015	0.0001	0.0000	0.0000	-0.0000528
Maximum	1.4741	0.0577	0.0725	0.0889	0.0993
Minimum	-0.8488	-0.0981	-0.0728	-0.1234	-0.1361
Std. Dev.	0.0602	0.0097	0.0132	0.0180	0.0154
Skewness	3.8096	-0.4610	-0.0214	-0.4221	-0.2824
Kurtosis	140.52	9.8144	4.6762	8.4904	8.5928
Jargue-Bera	2403	5991	356.2	3909	4003
Probability	0.0000	0.0000	0.0000	0.0000	0.0000
Observation	3041	3041	3041	3041	3041

In Figure 1, the graphs depict the level values of the return series, revealing various trends of both increase and decrease over time. Remarkably, all series exhibit behavior indicative of no stationarity, as they do not revert to the mean. This observation suggests the potential presence of a unit root within the series. However, relying solely on visual inspection for detecting unit roots may not offer conclusive evidence. Therefore, it is crucial to conduct unit root tests to validate these observations.

Figure 1: Graphs of Level Values of the Variables

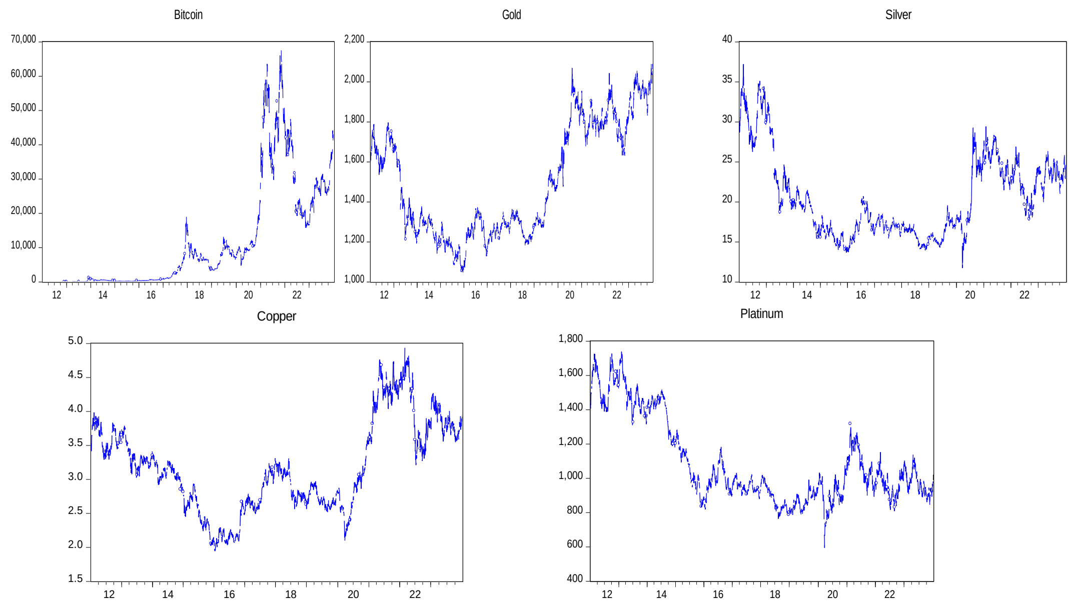
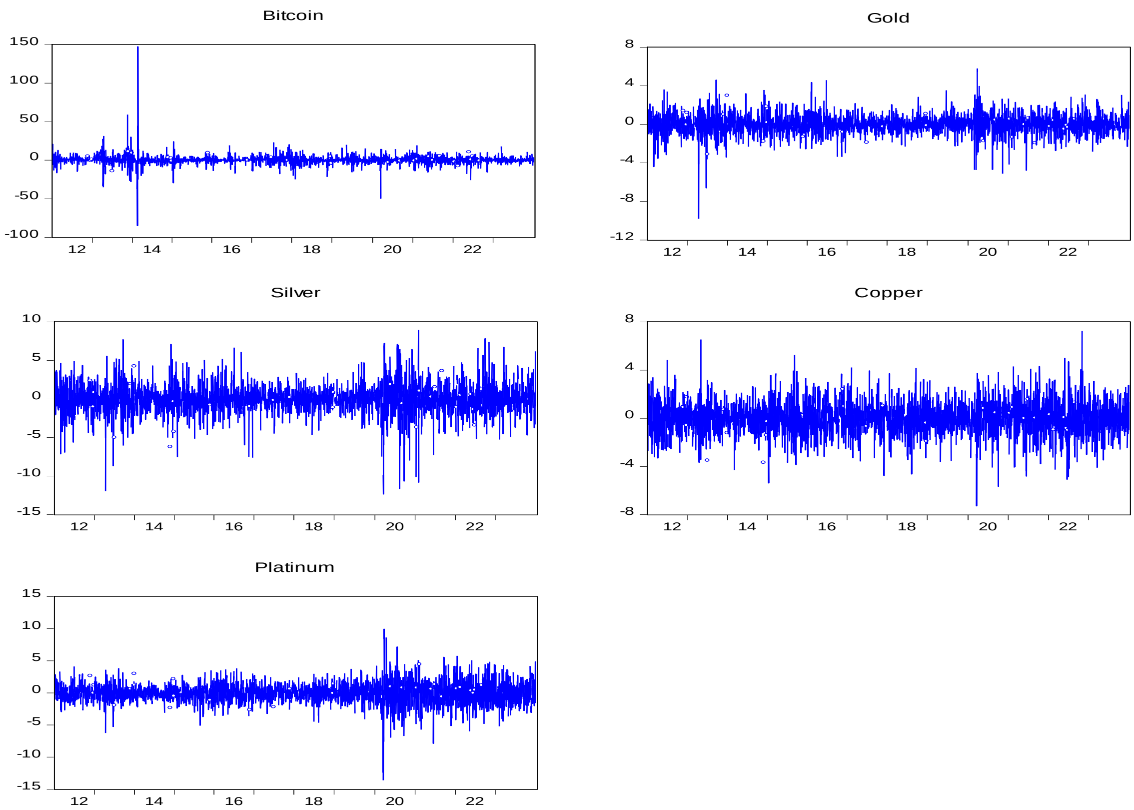


Figure 2 presents graphs generated from the values derived by computing the logarithmic differences of the return series. These graphs distinctly illustrate that while the return series maintain stability on average, they also exhibit pronounced volatility clusters. It gives the impression that there exists heteroscedasticity.

Figure 2: Logarithmically Differenced Graphs of Variables



Whether the variables used in the study met the stationarity condition is examined using ADF and Zivot-Andrews Unit Root Tests. Test results are included in Table 2 and Table 3.

Table 2: ADF Unit Root Test

		Bitcoin	Gold	Copper	Silver	Platinum
Constant	t-stat	-27.2121	-57.4044	-57.3318	-58.1559	-53.2541
	p-value	0.0000***	0.0001***	0.0001***	0.0001***	0.0001***
Constant& Trend	t-stat	-27.2494	-57.4319	-57.3342	-58.1659	-53.2497
	p-value	0.0000***	0.0000***	0.0000***	0.0000***	0.0000***
Trend	t-stat	-27.0725	-57.4095	-57.3406	-58.1648	-53.2603
	p-value	0.0000***	0.0001***	0.0001***	0.0001***	0.0001***

Notes: *** shows significance at 1% significance level.

Table 3: Zivot-Andrews Unit Root Test (Constant &Trend)

Variables	Test Stat	Break Date	p-value
Bitcoin	-25.6998	December 02, 2013	0.0000***
Gold	-57.5163	August 07, 2020	0.0119**
Copper	-57.4615	March 24, 2020	0.0111**
Silver	-25.0072	March 20, 2020	0.0265**
Platinum	-53.3308	March 20, 2020	0.0341**

Notes: *** represents the 1% significance level, **5% represents the significance level.

Table 2 and Table 3 display the outcomes of the unit root tests conducted for the variables. These tests, utilizing both the Augmented Dickey-Fuller (ADF) and Zivot-Andrews methods, assessed the stationarity of the variables. The results indicate that the return series of the variables studied exhibit stationarity at their level values, as affirmed by both unit root tests.

Following the unit root analyses, the null hypotheses proposing unit roots in the examined return series are rejected, affirming the stationarity of these series. Subsequently, the suitability of the return series for GARCH-type modeling is assessed using the ARCH-LM test. The results of this test are shown in Table 4.

Table 4: ARCH-LM Test Results

Tests	Gold	Copper	Silver	Platinum
F-Ist.	1071.28***	175.67***	1231.99***	1355.48***

Notes: *** shows significance at 1% significance level.

The ARCH-LM test assesses the null hypothesis that there is no heteroscedasticity issue in the return series. Significance at the 1% level is observed for all return series, indicating the presence of an ARCH effect, i.e., a heteroscedasticity problem. Consequently, the VAR-DCC-GARCH model, a multivariate GARCH type model, will be employed for the volatility analysis of the return series. Bitcoin returns serve as the dependent variable (the first variable) in all models, while gold, copper, silver, and platinum are individually used as the second variable in each model as independent variables. The outcomes of the applied VAR-DCC-GARCH model are presented below.

Table 5: DCC-GARCH Model Results for Bitcoin and Gold Returns

	Coefficients	Standart Dev.	T-stat	Probability
$\gamma_{Bitcoin}$	1.2041	0.2238	5.3809	0.0000***
γ_{Gold}	0.0223	0.0094	2.3694	0.0178
$\emptyset_{Bitcoin,Bitcoin}$	0.2026	0.0175	11.5676	0.0000***
$\emptyset_{Bitcoin,Gold}$	-0.4041	0.1498	-2.6977	0.0070***
$\emptyset_{Gold,Bitcoin}$	0.0048	0.0031	1.5453	0.1223
$\emptyset_{Gold,Gold}$	0.0341	0.0065	5.2239	0.0000***
$\delta_{Bitcoin,Bitcoin}$	0.7586	0.0170	44.6384	0.0000***
$\delta_{Bitcoin,Gold}$	2.7824	2.7117	1.0261	0.3049
$\delta_{Gold,Bitcoin}$	0.0718	0.0542	1.3241	0.1855
$\delta_{Gold,Gold}$	0.9283	0.0195	47.7170	0.0000***
$\theta_{Bitcoin}$	0.0006	0.0003	1.7349	0.0828
θ_{Gold}	0.9986	0.0028	351.6480	0.0000***

Notes: *** represents the 1% significance level.

Table 5 reports the results of volatility spillover between Bitcoin and gold market returns. ARCH and GARCH parameters of volatility persistence, $\emptyset_{\text{Bitcoin,Bitcoin}}$ ve $\delta_{\text{Bitcoin,Bitcoin}}$,respectively, belonging to Bitcoin market are both statistically significant and their sum is 0.9612. In this case, it can be said that the volatility of Bitcoin return is persistent, that is, volatility clustering. Volatility clustering is an indicator of the persistence of shocks in the market and implicitly indicates that volatility predictions can be made by using current and past realized volatility. The fact that Bitcoin's shock spillovers $\emptyset_{\text{Bitcoin,Bitcoin}}$ and its own volatility spillovers $\delta_{\text{Bitcoin,Bitcoin}}$ have a statistically significant and positive effect indicates that past shocks in Bitcoin are the cause of its current volatility, while it also means that the volatility of past shocks in Bitcoin also increases current volatility. ARCH and GARCH ($\emptyset_{\text{Gold,Gold}}$ and $\delta_{\text{Gold,Gold}}$) accounting for volatility spillovers are statistically significant. Moreover, the ARCH and GARCH parameters are statistically significant with positive coefficients, and their sum is 0.9624, remaining below 1. This implies a persistent volatility in the gold market and indicates the formation of a volatility clustering.

Looking at the inter-market volatility spillover effects, the $\emptyset_{\text{Bitcoin,Gold}}$ ARCH parameter, one of the ARCH and GARCH parameters that explain the interaction of shocks in the Gold market on Bitcoin volatility, is significant at the 1% significance level. A 1% shock in the gold return market reduces Bitcoin return volatility by 0.4041%. In this case, a risk-averse investor is expected to invest in Bitcoin when gold volatility increases. Both ARCH and GARCH parameters ($\emptyset_{\text{Gold,Bitcoin}}$ and $\delta_{\text{Gold,Bitcoin}}$) explaining the impact of Bitcoin on the Gold market are not statistically significant. This means that Bitcoin's past shocks and past volatility have no impact on Gold's current volatility. In this case, it is possible to say that Bitcoin has no effect on the Gold market. It can be said that there is a one-way and negative volatility interaction between Bitcoin and the Gold market. There is a one-way volatility transfer towards Bitcoin in the gold market.

Among the parameters θ_{Bitcoin} and θ_{Gold} , which represent the dynamic conditional correlation, only the θ_{Gold} parameter is statistically significant. It can be concluded that there is a positive and high correlation relationship that changes over time. This situation supports the volatility spillovers explained above.

Table 6: DCC-GARCH Model Results for Bitcoin and Silver Returns

	Coefficients	Standart Dev.	T-stat	Probability
$\gamma_{Bitcoin}$	1.2240	0.0970	12.6123	0.0000***
γ_{Silver}	0.0076	0.0034	2.2048	0.0275**
$\emptyset_{Bitcoin,Bitcoin}$	0.2098	0.0083	25.4120	0.0000***
$\emptyset_{Bitcoin,Silver}$	-0.0429	0.0267	-1.6086	0.1077
$\emptyset_{Silver,Bitcoin}$	0.0077	0.0011	7.3519	0.0000***
$\emptyset_{Silver,Silver}$	0.0233	0.0018	12.7681	0.0000***
$\delta_{Bitcoin,Bitcoin}$	0.7696	0.0086	89.5754	0.0000***
$\delta_{Bitcoin,Silver}$	-0.2394	1.0219	-0.2342	0.8148
$\delta_{Silver,Bitcoin}$	-0.0882	0.0287	-3.0695	0.0021***
$\delta_{Silver,Silver}$	0.9701	0.0023	426.8185	0.0000***
$\theta_{Bitcoin}$	0.0013	0.0040	0.3307	0.7408
θ_{Silver}	0.7820	0.7127	1.0973	0.2725

Notes: *** denotes statistically significance at 1% level, while ** represents significance level at 5%.

Table 6 shows the volatility spillover results between Bitcoin and Silver market returns. The ARCH and GARCH parameters of the volatility persistence of the Bitcoin market ($\emptyset_{\text{Bitcoin,Bitcoin}}$ and $\delta_{\text{Bitcoin,Bitcoin}}$) are both statistically significant at the 1% significance level, their coefficients are positive and their sum is 0.9794. In this context, it can be inferred that the volatility of Bitcoin is persistent. ARCH and GARCH, ($\emptyset_{\text{Silver,Silver}}$ and $\delta_{\text{Silver,Silver,}}$), which explain the volatility persistence of the silver market, are statistically significant at the 1% significance level. The coefficients of the ARCH and GARCH parameters are determined to be positive and their sum is less than 0.9934 and 1. Consequently, this result can be interpreted that the volatility of the silver market is persistent.

Looking at the inter-market volatility spillover effects, it is seen that both the ARCH and GARCH parameters ($\emptyset_{\text{Bitcoin,Silver}}$ and $\delta_{Bitcoin,Silver}$) which explain the impact of shocks in the Silver market on Bitcoin returns, are not statistically significant. This shows that Silver has no effect on Bitcoin. ARCH and GARCH parameters ($\emptyset_{\text{Silver,Bitcoin}}$ and $\delta_{\text{Silver,Bitcoin}}$) explaining the impact of Bitcoin on the silver market are both statistically significant at the 1% significance level. In this case, a 1%

unit shock in the Bitcoin market reduces the returns of the silver market by -0.0805. It is possible to say that there is a one-way and negative volatility interaction between Bitcoin and the Silver market. There is a direct one-way volatility spillover from the Bitcoin market to the Silver market.

The parameters θ_{Bitcoin} and θ_{Silver}), which represent the dynamic conditional correlation, are not statistically significant. Consequently, it can be concluded that no correlation relationship exists between Bitcoin and the silver market.

Table 7 presents the volatility spillover findings between Bitcoin and the copper market returns. The ARCH and GARCH parameters concerning the volatility persistence of the Bitcoin market, $\emptyset_{\text{Bitcoin,Bitcoin}}$ and $\delta_{\text{Bitcoin,Bitcoin}}$, are both statistically significant with positive coefficients, summing up to 0.9852. This suggests a persistent volatility in the Bitcoin variable. Similarly, the ARCH and GARCH parameters, $\emptyset_{\text{Copper,Copper}}$ and $\delta_{\text{Copper,Copper}}$, explaining the volatility persistence of the copper market, are statistically significant at the 1% significance level. Their coefficients are positive, and their sum is less than 0.8802 and 1. Hence, it can be concluded that the volatility of the copper market is also persistent.

Table 7: DCC-GARCH Model Results for Bitcoin and Copper Returns

	Coefficients	Standart Dev.	T-stat	Probability
$\gamma_{Bitcoin}$	1.4563	0.2119	6.8718	0.0000***
γ_{Copper}	0.1032	0.0369	2.7952	0.0052***
$\emptyset_{Bitcoin,Bitcoin}$	0.2098	0.0185	11.3424	0.0000***
$\emptyset_{Bitcoin,Copper}$	-0.0106	0.0699	-0.1518	0.8794
$\emptyset_{Copper,Bitcoin}$	0.0105	0.0040	2.6206	0.0088***
$\emptyset_{Copper,Copper}$	0.0336	0.0084	4.0120	0.0001***
$\delta_{Bitcoin,Bitcoin}$	0.7754	0.0147	52.7096	0.0000***
$\delta_{Bitcoin,Copper}$	-1.0357	0.6488	-1.5964	0.1104
$\delta_{Copper,Bitcoin}$	0.2883	0.0863	3.3412	0.0008***
$\delta_{Copper,Copper}$	0.8466	0.0392	21.6173	0.0000***
$\theta_{Bitcoin}$	0.0013	0.0002	5.6121	0.0000***
θ_{Copper}	0.9955	0.0013	740.1078	0.0000***

Notes: *** represents the 1% significance level.

When analyzing inter-market volatility spillover effects, it is evident that both the ARCH and GARCH parameters, $\emptyset_{\text{Bitcoin,Copper}}$ and $\delta_{\text{Bitcoin,Copper}}$, explaining the impact of shocks originating in the copper market on Bitcoin returns are not statistically significant. Hence, it can be inferred that the copper market does not influence Bitcoin. However, the ARCH and GARCH parameters, $\emptyset_{\text{Bitcoin,Copper}}$ and $\delta_{\text{Bitcoin,Copper}}$, elucidating the impact of Bitcoin on the copper market are both statistically significant at the 1% level. This indicates that a 1% unit shock in the Bitcoin market increases the returns of the copper market by 0.2988. Therefore, it can be concluded that there exists a one-way and positive volatility interaction between Bitcoin and the copper market, with a unilateral volatility spillover from Bitcoin to the copper market.

The statistically significant parameters, θ_{Bitcoin} and θ_{Copper}, representing the dynamic conditional correlation, indicate a positive and notably strong correlation relationship between Bitcoin and copper that fluctuates over time.

Table 8: DCC-GARCH Model Results for Bitcoin and Platinum Returns

	Coefficients	Standart Dev.	T-stat	Probability
$\gamma_{Bitcoin}$	1.1602	0.1025	11.3142	0.0000***
$\gamma_{Platinum}$	0.0108	0.0029	3.7426	0.0002***
$\emptyset_{Bitcoin,Bitcoin}$	0.2092	0.0090	23.1573	0.0000***
$\emptyset_{Bitcoin,Platinum}$	-0.0517	0.0291	-1.7750	0.0759
$\emptyset_{Platinum,Bitcoin}$	0.0036	0.0011	3.3623	0.0008***
$\emptyset_{Platinum,Platinum}$	0.0270	0.0031	8.6872	0.0000***
$\delta_{Bitcoin,Bitcoin}$	0.7712	0.0082	93.8309	0.0000***
$\delta_{Bitcoin,Platin}$	0.2550	0.3468	0.7354	0.4621
$\delta_{Platinum,Bitcoin}$	-0.0079	0.0070	-1.1370	0.2556
$\delta_{Platinum,Platinum}$	0.9695	0.0030	321.1380	0.0000***
$\theta_{Bitcoin}$	0.0000	0.0155	0.0000	1.0000
θ_{Platin}	0.2005	1.1894	0.0000	1.0000

Notes: *** represents the 1% significance level.

Table 8 indicatess the volatility spread results between Bitcoin and platinum market returns.

Both the ARCH and GARCH parameters, $\emptyset_{\text{Bitcoin,Bitcoin}}$ and $\delta_{\text{Bitcoin,Bitcoin}}$, are statistically significant at the 1% level, with positive coefficients summing up to 0.9804. This suggests a permanent volatility in the Bitcoin variable. Similarly, the ARCH and GARCH parameters, $\emptyset_{\text{Platinum,Platinum}}$ and $\delta_{\text{Platinum,Platinum}}$, explaining the volatility persistence of the platinum market, are statistically significant at the 1% level. Furthermore, the coefficients of these parameters are positive, and their sum is less than 0.9968 but still below 1. Hence, it can be concluded that the volatility of the platinum market is also permanent.

When examining inter-market volatility spillover effects, it is observed that both the ARCH and GARCH parameters, $\emptyset_{\text{Bitcoin,Platinum}}$ ve $\delta_{\text{Bitcoin,Platinum}}$, explaining the impact of shocks originating in the platinum market on Bitcoin returns, are not statistically significant. Hence, it can be concluded that platinum has no effect on Bitcoin. However, among the ARCH and GARCH parameters elucidating the impact of shocks in the Bitcoin market on platinum returns, the ARCH parameter, $\emptyset_{\text{Platinum,Bitcoin}}$, is significant at the 1% level. A 1% shock in the Bitcoin market increases platinum returns by 0.0036. Therefore, there exists a one-way and positive volatility interaction between Bitcoin and the platinum market, with a unilateral volatility transfer from the Bitcoin market to the platinum market.

The parameters, θ_{Bitcoin} ve θ_{Platinum} , representing the dynamic conditional correlation, were found to be statistically insignificant. Consequently, it can be concluded that there is no correlation relationship between Bitcoin and the platinum market.

4. Conclusion and Discussion

The emergence of cryptocurrencies due to technological advancements has positioned them as significant subjects of research and investment tools. Understanding the propagation dynamics of Bitcoin volatility is paramount for managing investor risk and informing public policy. The interconnectedness of financial assets influences investor diversification decisions, making it crucial to monitor volatility transfers between markets to mitigate cross-market contagion effects. The findings from such analyses can offer policymakers and investors valuable insights for designing regulatory frameworks and risk management strategies. In this context, this study utilizes the DCC-GARCH model, a multivariate GARCH model, to determine dynamic conditional correlations and volatility spreads between Bitcoin and the returns of precious metals such as gold, copper, silver, and platinum. Daily data spanning from 03.01.2012 to 29.12.2023 is employed. Initially, the stationarity levels of the series are determined. ADF and Zivot-Andrews Unit Root Test results indicate stationarity at the level value for the return series of Bitcoin and the precious metals. Subsequently, the ARCH-LM test reveals the presence of an ARCH effect in the return series. Finally, volatility spread is examined using the VAR-DCC-GARCH model, which belongs to the multivariate GARCH family.

The findings of the volatility spillover analysis between Bitcoin and the Gold market returns reveal several important insights. Firstly, both Bitcoin and Gold exhibit persistent volatility, indicating that past shocks in these markets contribute to current volatility levels. Specifically, a 1% shock in the gold market leads to a decrease in Bitcoin returns by 0.4041%. This suggests that during periods of increased volatility in the gold market, risk-averse investors may find it favorable to allocate more towards Bitcoin as a hedge. Furthermore, it's noteworthy that Bitcoin's past shocks and volatility do not impact Gold's current volatility, implying that the relationship is unidirectional. In other words, there is a one-way volatility spillover from the gold market to Bitcoin. Regarding the dynamic conditional correlation results, a positive and high norm correlation relationship is identified for Gold. This indicates that there is a strong and consistent correlation between Bitcoin and Gold, providing investors with an opportunity to diversify their portfolios. By including Gold in their investment strategies, investors can potentially mitigate the impact of uncertainty arising in the Bitcoin market, thereby enhancing portfolio resilience.

The analysis of volatility spread between Bitcoin and the Silver market returns yields significant findings. Firstly, it indicates that both Bitcoin and Silver exhibit persistent volatility, with their returns influenced by past values. Notably, a 1% shock in the Bitcoin market leads to a reduction in Silver returns by 0.0805%. This suggests that during periods of heightened volatility in the Bitcoin market, risk-averse investors may find it advantageous to allocate more towards Silver. Moreover, Silver's past shocks and volatility do not influence Bitcoin's current volatility, indicating a unidirectional relationship with a one-way volatility transfer from the Bitcoin market to Silver. However, the dynamic conditional correlation result reveals that no correlation relationship exists between Bitcoin and Silver. This implies that there is neither a short-term nor a long-term relationship between their returns that changes over time. Given these findings, investors may consider diversifying their portfolios with Bitcoin to mitigate the impact of uncertainty in the Silver market, as there is no correlation relationship to be leveraged for risk reduction strategies.

The analysis of volatility spread between Bitcoin and the copper market returns reveals significant insights. Firstly, it indicates that both Bitcoin and copper exhibit permanent volatility, with their returns influenced by past values. Notably, a 1% shock in the Bitcoin market leads to an increase in copper returns by 0.2988%. This suggests that during periods of heightened volatility in the Bitcoin market, investors may observe an increase in copper returns. Moreover, copper's past shocks and volatility do not impact Bitcoin's current volatility, implying a unidirectional relationship with a one-way volatility spillover from the Bitcoin market to copper. However, the dynamic conditional correlation result reveals a positive and high norm correlation relationship between Bitcoin and copper. This indicates that there is a strong and consistent correlation between their returns, suggesting that there may be limited portfolio diversification opportunities for investors. Overall, investors may need to consider other assets for diversification, as Bitcoin and copper appear to move in tandem, according to the dynamic conditional correlation result.

The analysis of volatility spread between Bitcoin and the platinum market returns provides valuable insights. Firstly, it indicates that both Bitcoin and platinum exhibit permanent volatility, with their returns influenced by past values. Notably, a 1% shock in the Bitcoin market increases platinum returns by 0.0036%. This suggests that during periods of heightened volatility in the Bitcoin market, risk-averse investors may find it advantageous to allocate more towards platinum. Moreover, platinum's past shocks and volatility do not impact Bitcoin's current volatility, implying a unidirectional relationship with a one-way volatility transfer from the Bitcoin market to platinum. However, the dynamic conditional correlation result reveals no correlation relationship between Bitcoin and platinum. This indicates that there is no significant correlation between their returns, offering a portfolio diversification opportunity for investors. Overall, investors may consider diversifying their portfolios with Bitcoin to mitigate the impact of uncertainty in the platinum market, as there is no correlation relationship to be leveraged for risk reduction strategies.

The findings from D'Amato et al. (2022) and Sapkota (2022) emphasize Bitcoin's high volatility, suggesting that it does not function as a safe haven asset like Gold, as noted by Klein et al. (2018) and Elsayed et al. (2022). Conversely, studies such as Kang et al. (2019) and Zhang and Mani (2021) find persistent volatility between Bitcoin and Gold, indicating a strong positive correlation. Additionally, Klein (2017) asserts Gold's role as a safe haven, a view supported by Shahzad et al. (2019) and Kılıç (2022), who also find a one-way volatility spillover from the gold market to Bitcoin. However, our study results diverge from those of Ghorbel and Jeribi (2021), who suggest a two-way volatility interaction between Gold and cryptocurrencies, as well as Klein (2017), who proposes that silver and platinum serve as safe havens.

Predicting the outcomes of inter-market volatility and transmission mechanisms is crucial for both investors and policymakers when making pricing and investment decisions. High correlation between return instruments in markets poses risks, as while gains can be substantial, so can losses. This is because these markets tend to move together and are similarly impacted by risk factors. Therefore, the findings of the study will provide valuable insights for decision-making and interventions in financial markets, benefiting both local and international investors. Specifically, it will inform portfolio diversification strategies, helping investors manage risk more effectively. Additionally, policymakers can use these findings to implement appropriate measures to stabilize markets and mitigate systemic risks. Overall, the study's contributions will facilitate informed decision-making in financial markets, enhancing both investment outcomes and market stability.

The limitations of this study include the absence of optimal portfolio weights and hedge ratios between the variables. In future studies, a VAR model with more than two variables can be established.

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