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Evaluation of the association between cryptocurrencies with oil and gold prices using the BEKK multivariate GARCH model

Behrouz Shakeri[a], Artin Beytari[b,*], Mohammadreza Ghorbanian[b], Rouhollah Javadi[c]

[a] *Department of Humanities, Shahr-e-Qods Branch, Islamic Azad University, Tehran, Iran*

[b] *Department of Accounting, Shahr-e-Qods Branch, Islamic Azad University, Tehran, Iran*

[c] *Department of Accounting, Payame Noor University, Tehran, Iran*

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Abstract

Due to the emergence of cryptocurrencies in the world, many people save their capital and assets like cryptocurrencies. Cryptocurrencies are associated with prices of gold and oil, and stock market indices. On this basis, the present study aimed to evaluate the association between cryptocurrencies with oil and gold prices. To this end, the study performed an evaluation using the BEKK multivariate GARCH method. Therefore, two regression models were estimated to evaluate the association between cryptocurrencies and oil and gold prices. Based on the results, the mutual relationship between cryptocurrency volatility and gold and oil prices was confirmed. In general, volatility in oil and gold prices has a positive effect on cryptocurrency volatility. Given that volatility in oil and gold prices has a positive effect on cryptocurrency volatility, and these effects will be more manifested in future periods, cryptocurrency investors are recommended to examine oil and gold prices, especially oil prices in the last 10 years, before purchasing cryptocurrencies.

Keywords: cryptocurrencies, oil price, gold price, multivariate GARCH model
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1 Introduction

Due to the daily progress and change in the world, earning money and trading as the most important issues, which are associated with almost all other issues, have also undergone changes and provided the ways by which people can receive or pay prices of goods. "Cryptocurrency" is the latest emerged concept. Over the past decade, cryptocurrencies have emerged as a new asset class that has attracted the attention of many investors and researchers [6]. Cryptocurrencies make it easier to transfer money between the parties of a transaction. This facilitation is due to the use of public and private keys for security purposes. The fund transfer is performed by paying the minimum processing fee and exempts users from paying various fees to banks and financial institutions in network transfers. Since prices are set based on supply and demand, the exchange rate of cryptocurrencies has great volatility against other currencies [16]. Despite the importance of cryptocurrencies and their great popularity, there is little information about the association between cryptocurrencies and other markets [24].

*Corresponding author
Email addresses: behroz_hs@yahoo.com (Behrouz Shakeri), J.Beytari@Qodsiau.ac.ir (Artin Beytari), m.ghorbanian@qodsiau.ac.ir (Mohammadreza Ghorbanian), javadi1423@gmail.com (Rouhollah Javadi)

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The first electronic payment system, called Bitcoin, was launched in 2009. Bitcoin is now the most popular cryptocurrency market. Since the emergence of Bitcoin, the cryptocurrency literature has grown steadily to explore the advantages and disadvantages of this new exchange tool. Given that Bitcoin was the first cryptocurrency and the largest currency in terms of the capital market, the initial studies focused mainly on examining various features of Bitcoin [28]. Along with Bitcoin, other cryptocurrencies such as Ethereum, Dash, Ether, Litecoin, Stellar, Monero, and Ripple are also popular all over the world. Investment in the cryptocurrency market was equal to 117.6 billion dollars in the first trimester of 2018 and reached 40.5 billion dollars in mid-2017, and 0.04 billion dollars in 2012 (The World Bank, 2021).

Gold has always played an important role in the history of civilization and monetary systems worldwide due to its uniqueness, and an increase in wealth and prosperity. Gold is a precious metal on earth and its value has been used as a standard for many currencies throughout history (called the gold standard). Gold is a sign of purity, worth, and privilege. Its consumption grew rapidly during the liberalization of gold import policy, economic growth, and favorable movements in gold prices in the 1990s. It is now used as an alternative to the dollar as well as international exchanges [27]. Gold is a metal element that is the most valuable metal used as a medium of trade and exchange, but the meaning of gold has changed and the current gold paradigm uses it as a better investment tool that can be the best tool for investing in volatile markets. As the price of gold rises, many changes occur in the overall economy. The impact of rising international gold prices is reflected in rising domestic gold prices. Despite the sharp rise in gold prices in recent years, the demand for gold is still stable and increasing because it is not only considered a savings component but also has great cultural and social importance in third-world countries [19]. Due to the importance of gold for investment, it can have a two-way relationship with the cryptocurrency market.
The importance of the oil sector in the world is a way that the boom or bust of production and the resulting income have always had positive and negative effects on the economic development of countries. Oil prices can be associated with volatility in cryptocurrencies. The dynamics of oil price volatility in the cryptocurrency market can be theoretically explained by the fact that the valuation of these currencies is based on the sum of the discounted value of their expected future cash flows. These cash flows can be affected by macroeconomic variables such as oil shocks [17].

Spillover effects are exogenous factors of economic activities or processes that are not considered direct effects. Risk spillover or volatility spillover between two markets means the transfer of variances and covariances of returns from one market to another [31], and the effect of risk spillover means that a historical record of severe risk in a market can predict it in other markets. The volatility and turbulence between the financial asset market and the way of their spillover among the markets should be carefully monitored and evaluated to avoid and control risk between the financial asset markets. The volatility spillover in cryptocurrencies is also related to important global markets. Therefore, the volatility spillover has mutual relations between the cryptocurrency market and the prices of gold and oil as the most important markets in the world.

Given the importance of this issue and the relationship between cryptocurrencies and gold and oil prices, the present study aimed to evaluate the relationship between cryptocurrencies and oil and gold prices.

2 Research literature and background

2.1 Oil price and cryptocurrencies

Undoubtedly, oil price shocks have played an important role in advancing financial markets and vice versa. Articles such as Ghazani and Khosravi [11] and Okorie and Lin [21] emphasize that crude oil is an important commodity market worldwide and acts as a key asset in the trading of various financial tools in global financial markets and plays a key role. The growing importance of oil-related industries and the increasing impact of cryptocurrencies on oil price shocks have become apparent in most economies over the past few years. According to Yin et al. [30] oil market shocks may be an important source of uncertainty for the cryptocurrency market, as oil price shocks may pose a level of risk similar to macroeconomic news. Furthermore, some previous studies claimed that changes in oil prices were significantly associated with inflation, real production, monetary policy, changes in international interest rates, etc.; hence, changes in oil prices may be a key factor in cryptocurrency uncertainty. Therefore, the study of oil price changes may be very important for investors, companies, and resource policymakers whose analyses focus mainly on the impact of oil price volatility on other financial markets such as cryptocurrency markets or the impact of cryptocurrency markets and oil prices [14].

According to Gronwald [12] about the question of whether cryptocurrencies are commodities or not, the cryptocurrencies, mainly Bitcoin, are commodities with most of their characteristics such as demand shock, and large price movements and are compared to oil and gold market behaviors, except for the uncertainty in the supply of crude oil and gold that are resolved in the Bitcoin market. Since cryptocurrencies can be considered commodities, the oil price can affect their price changes and vice versa. Some researchers have examined the association between cryptocurrency markets and traditional goods and assets. Wang et al. [29] and Shahzad et al. [26] presented empirical evidence for claiming Bitcoin as a safe haven. In this regard, cryptocurrencies are connected to other investment options. For example, active trade and cryptocurrency mining are significantly related to the electricity market [13]. Cryptocurrencies are related to commodity markets [3]. cryptocurrencies are associated with energy commodities [15], and they can also affect crude oil prices [25], stocks [5, 20], and gold prices [21, 22].

2.2 Gold prices and cryptocurrencies

There are a variety of reasons to put cryptocurrencies in convergence and convergence tests. For example, a correlation between prices of gold and cryptocurrencies indicates that prices of gold and cryptocurrencies are interdependent; hence, connecting cryptocurrencies to the price of gold, which has recently been proposed, will be an appropriate step because there is an inherent relationship between them in the long term. The convergence between prices of cryptocurrencies and gold indicates that cryptocurrencies with relatively low prices will probably grow faster in the future. Therefore, investors can make more profit by purchasing cryptocurrencies at a lower price and selling gold at a relatively higher price. In other words, there are arbitrage opportunities. The Bitcoin price rose from less than the US $ 1000 in early 2014 to more than the US $ 17,000 in early 2018. Dash prices rose from less than the US $ 2 in early 2014 to more than the US $ 400 in early 2014. During the same period, the price of 1 ounce of gold was about US $ 1,050 and US $ 1,400. Furthermore, the convergence between prices of cryptocurrencies and gold must be predictable and definite; hence, the relative price may be useful for forecasting goals, economic modeling, and policy formulation [1]. Researchers such as Adebola et al. [1], Catania et al. [4], Phillip et al. [23], and Gil-Alana et al. [11] investigated the relationship between prices of gold and cryptocurrencies.

2.3 Research background

Quamara and Singh [24] conducted a study titled "A systematic survey on security concerns in cryptocurrencies: State-of-the-art and perspectives" and examined the most advanced technologies related to security concerns in cryptocurrencies from a variety of perspectives. In the first step, they examined advanced consensus mechanisms because they were basic concepts of cryptocurrencies, and then they examined various applications of cryptocurrencies. Subsequently, they provided a detailed review of various contributions from the literature on the security aspects of cryptocurrencies. In a study titled "Returns, volatility, and the cryptocurrency bubble of 2017-18", Cross et al. [6] concluded that intervening in random volatility provided more accurate returns and volatility predictions than the random criteria. Jareno et al. [14] conducted a study titled "Cryptocurrencies and oil price shocks: A NARDL analysis in the COVID-19 pandemic". According to the results, demand shocks had the greatest correlation with the returns of cryptocurrencies. Furthermore, short and long-term results indicated a greater interdependence between oil and cryptocurrencies during periods of the economic turmoil such as the coronavirus crisis.

Askari [2] conducted a study titled "Currency and cryptocurrency ratios in the Iranian legislative system" and indicated that the principle of correctness and impropriety governs the transfer of cryptocurrencies in the current status, and does not face a cancellation of the transaction or punishment of the perpetrator. The freedom of cryptocurrency transactions and their accuracy, despite the prohibition and invalidity of some examples of currency exchange transactions, can be damaged despite the unity of the two functions, and perhaps the greater effectiveness of cryptocurrency transactions without regulations in economic turmoil. Therefore, this study suggests the legislator's immediate measure on the rules related to currency and cryptocurrency transfer under an article called the minimum and temporary step, and independent and comprehensive regulation in the field of rules governing the cryptocurrency mining and transfer in the Iranian legislative system as an optimal and ultimate step. Dadgar et al. [7] conducted a study titled "A study of the synchronicity of exchange rate cycles with prices of oil, gold, and stocks in Iran using the Markov switching model with a component structure" and found a positive and cyclical relationship between the exchange rate with prices of gold, oil, and stocks. The relationships between exchange rate and gold prices, and also oil price and exchange rate were statistically significant, but the relationship between stocks prices and exchange rate was insignificant. Fotros and Hoshidari [9] conducted a study titled "Dynamic relationships between oil prices, gold prices, and exchange rates with the Tehran Stock Exchange indices" and indicated that there was a conditional correlation between returns on oil price, gold price, and exchange rates with the Tehran Stock Exchange indices over time. The dynamic conditional correlation between the returns of the Tehran Stock Exchange indices and the return on the exchange rates fluctuated between zero and 0.001 (very low) until mid-2003, and then their correlation fluctuated between zero and 0.005 with a shock and returned to its previous process. The correlation intensified from mid-2008 and fluctuated between zero and 0.006. The dynamic conditional correlation between the return of the Tehran Stock

Exchange indices and the return on the gold price also had a process similar to the return on the exchange rate, indicating a high correlation between the return on the exchange rate and the return on the gold price. The correlation between the return of the Tehran Stock Exchange indices and the return on oil prices had an average of 0.5, but it was highly volatile.

Based on the literature review and background, cryptocurrencies are still controversial in domestic research, especially because most domestic studies have considered only Bitcoin as a cryptocurrency. Therefore, the study of the relationship between cryptocurrencies and the prices of oil and gold, which are important markets in the world, is innovative among previous studies.

3 Research methodology

Model specification and estimation methodology

In order to accurately capture the characteristic heteroskedasticity of may financial data, which refers to the fact that the market volatility varies and tends to cluster in periods of high volatility as well as periods of low volatility, the ARCH model was introduced by Engle.

Even hough this model captures the varying volatility of financial time series in contrast with the constant volatility in previous research, there was still need for a better model to measure risk which is reflected as the volatility. This section mainly concerns a more generalized model of the ARCH model from the univariate case to multivariate cases.

3.1 ARCH models

The mean process of ARCH models can be expressed by

$$r_t = \mu + \varepsilon_t, \qquad t = 1, \cdots, T \tag{3.1}$$

Here, μ is the mean of the time r_t and ε_t denotes its residual. T is the number of observations.

Regarding the residual's variance process of ARCH models, assume $\varepsilon_t = \sigma_t z_t$, where $z_t \sim N(0,1)$ and the series σ_t^2 are modeled by

$$\sigma_t^2 = \alpha_0 + \alpha_1 \delta_{t+1}^2 + \cdots + \alpha_q \varepsilon_{t-q}^2, \tag{3.2}$$

where $\alpha_0 > 0$ and $\alpha_j \geq 0, i > 0$.

It specifies a stochastic process for the residuals and predicts the average size of the residuals.

However, it has its own drawbacks in that the assumption that positive and negative shocks have the same effects on volatility goes contrary to the reality. It is very common that the price of a financial asset responds differently to positive and negative shocks. In addition, it is always the case that ARCH models require the estimation of a large number of parameters as a high order of ARCH terms has to selected for the purpose of catching the dynamic of the conditional variance.

3.2 GARCH models

The following subsections introduce the general formulation of a univariate GARCH model, the most widely used GARCH form-GARCH (1,1) and some extensions.

3.2.1 General form of GARCH models

In view of the ARCH model's limitations, proposed the Generalized ARCH model (GARCH), in which the conditional variance satisfies the following form.

$$\sigma_t^2 = \alpha_0 + \alpha_1 \varepsilon_{t-1}^2 + \cdots + \alpha_q \varepsilon_{t-q}^2 + \beta_1 \sigma_{t-1}^2 + \cdots + \beta_p \sigma_{t-p}^2 \tag{3.3}$$

where $\alpha_t > 0$ and $\beta_t > 0$

In GARCH models, residual's lags can be replaced by a limited number of lags of conditional variances, which simplifies the lag structure and as well the estimation process of coefficients.

3.2.2 GARCH (1,1) models

The most frequently used GARCH model is the GARCH (1,1) model. In GARCH (1,1), the conditional variance matrix is calculated from a long-run average variance rate, V_L, and also from the lag terms σ_{n-1} and ε_{n-1}. The equation of the conditional variance for GARCH (1,1) is

$$\sigma_n^2 = \gamma V_L + \alpha\varepsilon_{n-1}^2 + \beta\sigma_{n-1}^2 \tag{3.4}$$

where γ is the weight assigned to V_L a is the weight assigned to ε_{n-1}^2, and β is the weight assigned to σ_{n-1}^2. In addition, the weights sum to one, that is,

$$\gamma + \alpha + \beta = 1 \tag{3.5}$$

The GARCH (1,1) models specifies that σ_n^2 is based on the most recent observation of ε_n^2 and the most recent variance rate σ_{n-1}^2.

Setting $\omega = \gamma V_L$, the GARCH (1,1) model can be rewritten as

$$\sigma_n^2 = \omega + \alpha\varepsilon_{n-1}^2 + \beta\sigma_{n-1}^2 \tag{3.6}$$

This is the form that is usually used for the estimation of parameters in the univariate case.

3.2.3 Extensions of the GARCH models

There are many extensions of the standard GARCH models. Nonlinear GARCH (NGARCH) was proposed by Engle and Ng in 1993. The conditional covariance equation is in the from $\sigma_t^2 = \omega + \alpha(\varepsilon_{t-1} - \theta\sigma_{t-1})^2 + \beta\sigma_{t-1}^2$, where $\alpha, \beta, \omega > 0$. The integrated GARCH (IGARCH) is a restricted version of the GARCH model, where the sum of all the parameters sum up to one. The exponential GARCH (EGARCH) introduced by Nelson is to model the logarithm of the variance rather than the level. The GARCH -in-mean (GARCH-M) model adds a heteroskedasticity term into the mean equation. The quadratic GARCH (QGARCH) model can handle asymmetric effects of positive and negative shocks. The Glosten-Jagannathan-Runkle GARCH (GJR-GARCH) model (1993) can also model asymmetry in the GARCH process. The threshold GARCH (TGARCH) model is similar to GJR-GARCH with the specification on conditional standard deviation instead of conditional variance. Family GARCH (FGARCH) by Hentschel is an omnibus model that is a mix of other symmetric or asymmetric GARCH models.

3.3 Multivariate GARCH models

The basic idea to extend univariate GARCH models to multivariate GARCH models is that itis significant to predict the dependence in the comovements of asset returns in a portfolio. To recognize this feature through a multivariate model would generate a more reliable model than scparate univariate models.

In the first place, one should consider what specification of an MGARCH model should be imposed. On the one hand, it should be flexible enough to state the dynamics of the conditional variances and covariances. On the other hand, as the number of parameters in an MGARCH model increases rapidly along with the dimension of the model, the specification should be parsimonious to simplify the model estimation and also reach the purpose of easy interpretation of the model parameters. However, parsimony may reduce the number of parameters, in which situation the relevant dynamics in the covariance matrix cannot be captured. So it is important to get a balance between the parsimony and the flexibility when designing the multivariate GARCH model specifications. Another feature that multivariate GARCH models must satisfy is that the covariance matrix should be positive definite.

3.3.1 Formulations of multivariate GARCH models

This section emphasizes on giving a brief introduction to several different multivariate GARCH models.

• VEC/DVEC-GARCH models

The first MGARCH model was introduced by Bollerslev, Engle and Wooldridge in 1988, which is called VEC model. It is must general compared to the subsequent formulations. In the VEC model, every conditional variance and covariance is a function of all lagged conditional variances and covariances, as well as lagged squared retums and cross-products of returns. The model can be expressed below:

$$vech(H_t) = c + \sum_{j=1}^{q} A_j vech(\varepsilon_{t-j}\varepsilon_{t-j}') + \sum_{j=1}^{p} B_j vech(H_{t-j}), \tag{3.7}$$

where vech $(\cdot)$ is an operator that stacks the columns of the lower triangular part of its argument square matrix, H_t is the covariance matrix of the residuals, N presents the number of variables, t is the index of the observation, c is an $N(N+1)/2 \times 1$ vector, A_j and B_j are $N(N+1)/2 \times N(N+1)/2$ parameter matrices and ε is an $N \times 1$ vector.

The condition for H_t to be positive definite for all t is not restrictive. In addition, the number of parameters equals $(p+q) \times (N(N+1)/2)^2 + N(N+1)/2$, which is large. Furthermore, it demands a large quantity of computation.

The DVEC model, the restricted version of VEC, was also proposed by Bollerslev, et al. It assumes the A_j and B_j in equation (3.7) are diagonal matrices, which makes it possible for H_t to be positive definite for all t. Also, the estimation process proceeds much smoothly compared to the complete VEC model. However, the DVEC model with $(p+q+1) \times N \times (N+1)/2$ parameters is too restrictive since it does not take into account the interaction between different conditional variances and covariances.

• BEKK-GARCH models

To ensure positive definiteness, a new parameterizations of the conditional variance matrix H_t was defined by Baba, Engle, Kraft and Kroner and became known as the BEKK model, which is viewed as another restricted version of the VEC model. It achieves the positive definiteness of the conditional covariance by formulating the model in a way that this property is implied by the model structure.

The from of the BEKK model is as follows

$$H_t = CC' + \sum_{j=1}^{q} \sum_{k=1}^{K} A'_{kj} \varepsilon_{t-j} \varepsilon'_{t-j} A_{kj} + \sum_{j=1}^{q} \sum_{k=1}^{K} B'_{kj} H_{t-j} B_{kj} \tag{3.8}$$

where A_{kj}, B_{kj}, and C are $N \times N$ parameter matrices, and C is a lower triangular matrix.

The purpose of decomposing the constant term into a product of two triangular matrices is to guarantee the positive semi-definiteness of H_t. Whenever $K > 1$ an identification problem would be generated for the reason that there are not only a single parameterizations that can obtain the same representation of the model.

The first-order BEKK model is

$$H_t = CC' + A' \varepsilon_{t-j} \varepsilon'_{t-j} A + B' H_{t-j} B. \tag{3.9}$$

The BEKK model also has its diagonal form by assuming A_{kj}, B_{kj} matrices are diagonal. It is a restricted version of the DVEC model. The most restricted version of the diagonal BEKK model is the scalar BEKK one with $A = aI$ and $B = bI$ where a and b are scalars.

Estimation of a BEKK model still bears large computations due to several matrix transpositions. The number of parameters of the complete BEKK model is $(p+q)KN^2 + N(N+1)/2$. Even in the diagonal one, the number of parameters soon reduces to $(p+q)K \times N + N \times (N+1)/2$, but it is still large. The BEKK from is not linear in parameters, which makes the convergence of the model difficult. However, the strong point lies in that the model structure automatically guarantees the positive definiteness of H_t. Under the overall consideration, it is typically assumed that $p = q = k = 1$ in BEKK from's application.

• Constant Conditional Correlations (CCC) models

The Constant Conditional Correlation model was introduced by Bollerslev in 1990 to primarily model the conditional covariance matrix indirectly by estimating the conditional correlation matrix. The conditional correlation is assumed to be constant while the conditional variances are varying. Obviously, this assumption is impractical for real financial time series. Then certain modifications were made grounded on this form Annastiina and Timo.

Dynamic Conditional Correlations (DCC) models

The Dynamic Conditional Correlations model was proposed by Engle in 2002. It is a nonlinear combination of univariate GARCH models and it is also a generalized version of the CCC model. The form of Engle's DCC model is as follows:

$$H_t = D_t R_t D_t \tag{3.10}$$

where

$$D_t = diag(h_{11_t}^{\frac{1}{2}}, \cdots, h_{NN_t}^{\frac{1}{2}}),$$

and each h_{ii_1} is described by a univariate GARCH model. Further,

$$R_t = \mathrm{diag}(q_{11_t}^{\frac{1}{2}}, \cdots, q_{NN_t}^{\frac{1}{2}}) Q_t \,\mathrm{diag}(q_{11_t}^{\frac{1}{2}}, \cdots, q_{NN_t}^{\frac{1}{2}}),$$

where $Q_1 = (q_{ij_t})$ is the $N \times N$ symmetric positive definite matrix which has the form:

$$Q_t = (1 - \alpha - \beta)\bar{Q} + \alpha u_{t-1}u'_{t-1} + \beta Q_{t-1}. \tag{3.11}$$

Here, $u_{it} = \varepsilon_{it}/\sqrt{h_{it}}$, α and β are non-negative scalars that $\alpha + \beta < 1$, $\overline{Q}$ is the $N \times N$ unconditional variance matrix of u_t.

The shortcoming of the model is that all conditional correlations follow the same dynamic structure.

The number of parameters to be estimated is $(N + 1) \times (N + 4)/2$, which is relatively smaller than the complete BEKK from with the same dimension when N is small. When N is large, the estimation of the DCC model can be performed by a two-step procedure which decreases the complexity of the estimation process. In brief, in the first place, the conditional variance is estimated via univariate GARCH model for each variable. The next step is to estimate the parameters for the conditional correlation. The DCC model can make the covariance matrix positive definite at any point in time.

• Other multivariate forms

To overcome the difficulty of large number of parameters, the O-GARCH model was proposed by Alexander in 2000. It tries to express a multivariate GARCH in terms of univariate ones. The advantage of this model is that the fluctuating volatility can be explained by a few principle components. One of the disadvantages is that it is usually uncertain whether the unconditional variances have the coherent scaling. Another multivariate GARCH model GO-GARCH model is proposed by Bauwens et al.

3.3.2 Estimation of MGARCH

The most usual way to estimate the conditional covariance matrix in the MGARCH model is by the quasi maximum likelihood method.

Let $H_t(\theta)$ be a positive definite $N \times N$ conditional covariance matrix of some $N \times 1$ residual vector ε_t, parameterized by the vector θ. Denoting the information at time t by $\mathcal{F}_t$, we have

$$E_{t-1}[\varepsilon_t|\mathcal{F}_{t-1}] = 0; \tag{3.12}$$

$$E_{t-1}[\varepsilon_t\varepsilon_t|\mathcal{F}_{t-1}] = H_t(\theta). \tag{3.13}$$

Generally the conditional covariance matrix $H_t(\theta)$ is well specified based on a certain MGARCH model. Suppose there is an underlying parameter vector θ_0 which one wants to estimate using a given sample of T observations. The quasi maximum likelihood (QML) approach estimates θ_0 by maximizing the Gaussian log likelihood function

$$\log L_r(\theta) = -\frac{N.T}{2}\log(2\pi) - \frac{1}{2}\sum_{t=1}^{r}\log|H_t| - \frac{1}{2}\sum_{t=1}^{r}\varepsilon'_t H_t^{-1}\varepsilon_t. \tag{3.14}$$

One needs to notice its assumption that the time series treated should be stationary and the distribution of its residual is pre-defined as a conditional Gaussian distribution.

The latter assumption can mean while give us hints on how to check the adequacy of the established MGARCH model.

3.3.3 Diagnostics of MGACH models

The check of the adequacy of MGARCH models is essential in identifying whether a well-specified MGARCH model can attain reliable estimates and inferences. Graphical diagnostics for MGARCH models can be fulfilled by examining plots of the sample autocorrelation (ACF) and the sample cross-correlation functions (XCF). To ensure the inference from the estimated parameters in the MGARCH model is enough valid, the residuals should be exhibited as a set of white noise with features like expected zero mean vector, no autocorrelations, constant variance, and normal distribution of the residuals.

The autocorrelation and cross-correlation functions for the squared process are shown to be useful in identifying and checking time-series behaviour in the conditional variance equation of the GARCH form.

In the literature, several tests have been developed to test the autocorrelation no matter in univariate or multivariate form. Box and Picrcc derived a goodness-of-fit test, call the portmanteau test. It may be the most popular one among all the diagnostics for conditional heteroscedasticity models. The test statistic may be expressed as a function of the covariances between the residuals of the fitted model.

A multivariate version is given by

$$HM(M) = T^2 \sum_{j=1}^{M} (T-j)^{-1} tr\{C_{\gamma}^{-1}(0)C_{\gamma}(j)C_{\gamma}^{-1}(0)C'_{\gamma}(j)\}, \tag{3.15}$$

where T is the number of observations, $C_{\gamma}(j)$ is the sample autocovariance matrix of order j and $Y_t = vech(y_t y'_t)$.

The distribution of HM(M) is the asymptotical $\chi^2(K^2M)$ under the null hypothesis that there is no MGARCH effects.

But still, the fact is that very few tests are adaptable to multivariate models even though there are many diagnostic tests dealing with univariate models.

To summarize, once the model is assumed to catch the dynamics of the time series, the standardized residual $\hat{z}_i = \hat{H}_t^{-\frac{1}{2}} \hat{\varepsilon}_t$ should satisfy the following conditions

$$1) \qquad E(\hat{z}_t \hat{z}'_t) = I_N; \tag{3.16}$$

$$2) \qquad Cov(\hat{z}_{it}^2 \hat{z}_{jt}^2) = 0, \ for \ \ all \ \ pairs \ \ of \ \ the \ \ variable \ \ indexi \neq j; \tag{3.17}$$

$$3) \qquad Cov(\hat{z}_{it}^2 \hat{z}_{jt-k}^2) = 0, \ for \ k > 0. \tag{3.18}$$

Testing 1) would find the misspecification in the conditional mean; testing 2) is to verify whether the conditional distribution is Gaussian; the purpose of testing 3) is to check the adequacy of the dynamic specification of H_t even without knowing the validity of the assumption on the distribution of z_1.

Concerning the comparison of the BEKK-GARCH model and the DCC-GARCH model, the mean absolute error (MAE) is used to evaluate the fitting performance of both models.

3.3.4 Forecasting

In the class of multivariate ARCH/GARCH models and their extensions, the covariance matrix is no longer constant over time. After such model has been estimated, it is always meaningful to get to understand the mechanism that how the future series can be generated and whether they fit well with the real series.

• Forecasting by the BEKK-GARCH model

In the conditional covariance equation of the BEKK-GARCH model

$$H_t = CC' + A'\varepsilon_{t-j}\varepsilon'_{t-j}A + B'H_{t-j}B, \tag{3.19}$$

H_t is a function of the past information, i.e., H_{t-1} and ε_{t-1}. For this reason, the parameter estimation of MGARCH models can be used to predict the covariance matrix.

• Forecasting by the DCC-GARCH model

The forecast of the covariance matrix of the DCC model is implemented in a two-step procedure. The prediction of the diagonal matrix of the time-varying standard variation through the univariate GARCH models and the forecast of the conditional correlation matrix of the standardized residuals are dealt with separately.

Under the assumption that the volatility at time t is known, what is its forecast value at time $t + k$? In a three-variable case, the answer when $k = 1$ is given below,

$$h_{i,t+1} = \omega + \alpha\varepsilon_{i,t}^2 + \beta h_{i,t} \tag{3.20}$$

where $i = 1, 2, 3$.

To obtain the forecast $h_{i,t+k}$ at time t+k, one just need to repeat the substitution successively.

Cited from the definition formula of the DCC-GARCH model, the structure of the conditional correlation matrix is the equation (3.11).

Under the assumption that $\bar{R} = \bar{Q}$ and $R_{t+i} = Q_{t+i}$ for $i = 1, \cdots, k$, a successive calculation as before can be performed to derive R_{t+k}.

MGARCH models can be used for forecasting. However, by analyzing the relative forecasting accuracy of the two formulations BEKK and DCC, it can be deduced that the forecasting performance of the MGARCH models is not always satisfactory. Many studies, e.g. reveals that the apparent poor forecasting effect of the MGARCH models is due to using the squared shocks as an approximate value for the true conditional volatility.

The research model design

The present study was applied in terms of purpose and descriptive and quantitative in terms of data collection. The statistical population consisted of oil, gold, and cryptocurrency markets, and stock exchange indices. Therefore, information about the period of 4/3/2015 to 30/12/2020 was selected daily and examined as a sample size. The reason for choosing this period was the sufficient number of observations to estimate the regression and also the completeness of the data in this period. Statistical data were extracted from the following websites: `gold.org,investing.com,` `cryptodatadownload.com,andwww.eia.gov/petroleum`.

In the study, two regression models were extracted from articles by Jareno, et al.[14] and Adebola et al. [1] as follows.

$$\mathrm{OIL}_{\mathrm{i.t}} = \alpha_0+\beta_1\mathrm{Bitcoin}+\beta_2\mathrm{Litecoin}+\beta_3\mathrm{XRP}+\beta_4\mathrm{Dash}+\beta_5\mathrm{Monero}+\beta_6\mathrm{Stellar}+\beta_7\mathrm{Ethereum}+\varepsilon_{\mathrm{i.t}} \tag{3.21}$$

$$\mathrm{GOLD}_{\mathrm{i.t}} = \alpha_0+\beta_1\mathrm{Bitcoin}+\beta_2\mathrm{Litecoin}+\beta_3\mathrm{XRP}+\beta_4\mathrm{Dash}+\beta_5\mathrm{Monero}+\beta_6\mathrm{Stellar}+\beta_7\mathrm{Ethereum}+\varepsilon_{\mathrm{i.t}} \tag{3.22}$$

where the dependent variables were OIL: oil price; GOLD: gold price; and the independent variables included cryptocurrencies: Bitcoin, Litecoin, XRP: Ripple, Dash, Monero, Stellar, and Ethereum.

The reason for choosing the above cryptocurrencies was the availability of their data and also their greater use than other cryptocurrencies among the people of the world. All regression analyses were performed by Eviews11 software. The BEKK diagonal approach was used to analyze models (3.21) and (3.22) and estimate the multivariate GARCH model.

Due to the expansion of information systems and the increasing relationship of financial markets with each other, it has been proven that asset price fluctuations are transmitted to each other and other financial markets. This has led to the interdependence of different assets and financial markets. It has complicated the forecast in financial markets. Therefore, M-GARCH models have been widely developed in recent years to model performance dynamics. The multivariate generalized autoregressive conditional heteroskedasticity (M-GARCH) models should be used to investigate the transfer of momentum, volatility spillovers, and shocks between different markets [8]. The use of multivariate time series models has two important advantages. First, it is very effective in identifying the relationship between series, and second, it increases the precision of prediction. For example, if the past values of one series affect another, it is better to use multivariate models. However, using systemic or multivariate models instead of univariate models has two important limitations. First, the more estimated parameters, the less accurate results, and thus we need more data to make the results reliable. Second, the results do not often have high explanatory power; hence, we usually look for simple structures.

The number of parameters increases sharply as the model dimension increases in multivariate GARCH models, and on the other hand, the variance matrix needs to be positive. Establishing these properties by the estimated parameters is not easy.

The variances and covariances of the series must be estimated simultaneously, and the maximum likelihood method should be mainly used to estimate the turbulence propagation between two or more time series of estimation through multivariate GARCH models. Equations (3.23) to (3.26) present the mean equations and conditional variance of the M-GARCH model (p, q) respectively:

$$Y_t = \mu_t + \sigma_t Z_t \quad Z_t \sim \mathrm{NID}(0.1) \tag{3.23}$$

$$\mu_t = a + \sum_{i=1}^{k} b_i X_{i.t} \tag{3.24}$$

$$\sigma_t^2 = \alpha_0 + \alpha_1 \varepsilon_{t-1}^2 + \cdots + \alpha_q \varepsilon_{t-q}^2 + \beta_1 \sigma_{t-1}^2 + \beta_p \sigma_{t-p}^2 \quad \varepsilon_t \sim \mathrm{NID}(0.H) \tag{3.25}$$

$$= \alpha_0 + \sum_{i=1}^{q} \alpha_i \varepsilon_{t-i}^2 + \sum_{i=1}^{p} \beta_i \sigma_{t-i}^2 \tag{3.26}$$

In 1991, Baba, Engle, Kraft, and Kroner (BEKK) introduced another type of multivariate GARCH model called the "Diagonal BEKK model". This model is presented in the continuation of the MGARCH model. The most important feature of this method is its generality. Another feature is that the conditional covariance and variance of this time series affect each other, and lower parameters are estimated than other methods. This method allows us to examine the effect of shocks and disturbance of one series on disturbance of another series. This effect can be symmetrical or asymmetrical. BEKK is specified in Equation (3.27):

$$H_t = C'C + A'\varepsilon'_{t-1}\varepsilon_{t-1}A + B'H_{t-1}B \tag{3.27}$$

The parameters of the multivariate generalized autoregressive conditional heteroskedasticity (M-GARCH) model can be estimated by the maximum likelihood estimation (MLE). The logarithm of the likelihood function is according to Equation (3.28):

$$L(\theta) = T\log 2\pi - 0.5 \sum_{t-1}^{T} \log |H_t(\theta)| \;\; -0.5 \sum_{t-1}^{T} \varepsilon_t(\theta') \log H_t^{-1} \; \varepsilon_t(\theta) \tag{3.28}$$

where T is the number of observations and θ is the vector of parameters that must be estimated. The algorithm proposed by Brent et al. (1974) is used to estimate the parameters using the maximum likelihood method. As noted earlier, the deficit of the conventional generalized autoregressive conditional heteroskedasticity models is that they assume no failure in the volatility structure, but volatility in financial time series faces sudden changes, and thus structural failures in volatility are a possible phenomenon, and ignoring them may lead to false results about the way of disseminating information and spillovers of volatility among financial markets [8].

BEKK models allow simultaneous estimation in two or more markets, and since it belongs to the GARCH model family and the model has heteroskedasticity, it presents the effects of volatility spillovers on conditional variance results.

4 Results

The central indices (mean) and dispersion (standard deviation) of the variables were first calculated in Table 4 to investigate the descriptive parameters of the variables. Among cryptocurrencies, the average Bitcoin is higher than other currencies, and the value of standard deviation indicates high dispersion in most variables.

Table 1: Descriptive statistics of variables

Variable	**Mean**	**Sd**
Oil price	50.745	14.217
Gold price	1601.451	262.836
Bitcoin	7800.926	4134.975
Litecoin	65.109	55.648
Ripple (XRP)	0.368	0.304
Dash	196.617	208.508
Monero	101.620	74.4
Stellar	0.125	0.118
Ethereum	664.885	803.711

Source: Research findings

The stationarity of the variables was then investigated using the Augmented Dickey-Fuller (ADF) and Phillips-Perron tests. Table 2 shows the results of unit root tests. Based on the results of ADF and PP tests, the oil, Litecoin, XRP, Dash, and Monero variables did not have a unit root at a 5% probability level and were thus stationary. Other variables had unit roots and were non-stationary at a 5% probability level.

Table 2: Unit root test

Variable	**ADF statistic (probability level)**	**PP statistic (probability level)**	**Result**
Oil price	-3.741 (0.00)	-4.131 (0.00)	I(0)
Gold price	-0.639 (0.85)	-0.507 (0.88)	I(1)
Bitcoin	3.330 (0.99)	1.067 (0.99)	I(1)
Litecoin	-2.065 (0.03)	-2.682 (0.03)	I(0)
Ripple (XRP)	-2.812 (0.00)	-3.759 (0.00)	I(0)
Dash	-2.037 (0.03)	-1.830 (0.05)	I(0)
Monero	-0.980 (0.29)	-2.072 (0.25)	I(1)
Stellar	-1.934 (0.05)	-2.620 (0.04)	I(0)
Ethereum	2.376 (0.99)	1.529 (0.99)	I(1)

Source: Research findings

Models (3.21) and (3.22) were then estimated by the BEKK method. The optimal number of lags was equal to 1 according to the lowest Schwartz and Akaike, and Hannan-Quinn Criterion. The existence of heteroskedasticity in all models was confirmed by the ARCH-LM test. Tables 3 and **??** present the results of estimating the models for the variables in pairs. According to the results of the first model, the Bitcoin price affects the oil price by -0.00043. The oil price also affects the Bitcoin price by -23.314; hence, Bitcoin and oil have a negative relationship with each other. The Litecoin price has an effect of 0.00608 on the oil price. The oil price has an effect of 0.412 on the Litecoin price; hence, Litecoin and oil have a positive relationship with each other. The XRP price affects the oil price by -1.755. The oil price also affects the XRP price by 0.000529; hence, oil and XRP have an inverse relationship. Dash prices do not have any significant effect on oil prices. The oil price has an effect of -0.55 on the Dash price. Monero price does not have any significant effect on the oil price. The oil price has an effect of 0.077 on the Monero price. The Stellar price has an effect of 3.247 on the oil price. The oil price has an effect of 0.000403 on the Stellar price; hence, Stellar and oil have a positive relationship. The Ethereum prices affect oil prices by -0.0026. The oil price also affects the Ethereum price by -0.466. Therefore, Ethereum and oil have a negative relationship with each other. Furthermore, Bitcoin volatility does not have any significant effect on oil volatility, as shown by C(6). Oil volatility affects Bitcoin volatility by 0.999, as shown by C(8). Litecoin volatility has an effect of 0.36 on oil volatility, as shown by C (6). Oil volatility affects Litecoin volatility by 1.000312, as shown by C(8). XRP volatility affects oil volatility by 0.00132, as shown by C (6). Oil volatility affects XRP volatility by 0.944, as shown by C(8). Dash volatility has no significant effect on oil volatility, as shown by C (6). Oil volatility affects dash volatility by 1.0062, as shown by C(8). Monero volatility affects oil volatility by -0.499, shown by C (6). Oil volatility affects Monero volatility by 5,055, shown by C(8). Stellar volatility affects oil volatility by 0.000755, as shown by C (6). Oil volatility affects Stellar volatility by 1.0405, shown by C(8). Ethereum volatility has no significant effect on oil volatility, as shown by C (6). Oil volatility affects Ethereum volatility by 0.993, shown by C(8).

According to the results of the second model, the Bitcoin price affects the gold price by 0.009. The gold price also affects the Bitcoin price by 197.8; hence, Bitcoin and gold have a positive relationship with each other. The Litecoin price has an effect of 0.374 on the gold price. The gold price also affects the Litecoin price by -0.0185; hence, Litecoin and gold have an inverse relationship. The XRP price affects the gold price by 38.372. Furthermore, the gold price affects the XRP price by -0.00033; hence, XRP and gold have a negative relationship with each other. The Dash price affects the gold price by 2.142. The gold price affects the Dash price by 0.420; hence, dash and gold have a positive relationship with each other. The Monero price affects the gold price by -0.423. The gold price affects the Monero price by 0.0497; hence, gold and Monero have an inverse relationship. The Stellar price affects the gold price by 694.189. The gold price has an effect of 0.0000424 on the Stellar price; hence, Stellar and Gold have a positive relationship with each other. The Ethereum price has an effect of 0.0394 on the gold price. The gold price also has an effect of 0.0699 on the Ethereum price; hence, Ethereum and gold have a positive relationship with each other. Furthermore, Bitcoin volatility affects gold volatility by 909.316, as shown by C (6). Gold volatility affects Bitcoin volatility by 1.00087, as shown by C(8). Litecoin volatility has an effect of -5.370 on gold volatility, shown by C (6). Gold volatility has an effect of 0.825 on Litecoin volatility, shown by C(8). XRP volatility affects gold volatility by 0.026, as shown by C (6). Gold volatility has an effect of 0.779 on XRP volatility, shown by C(8). Dash volatility has no significant effect on gold volatility, as shown by C (6). Gold volatility affects dash volatility by 0.532, shown by C(8). Monero volatility affects gold volatility by 20,929, as shown by C (6). Gold volatility affects Monero volatility by 0.934, shown by C(8). Stellar volatility affects gold volatility by -0.0319, shown by C (6). Gold volatility affects Stellar volatility by 0.8855, shown by C(8). Ethereum volatility has no significant effect on gold volatility, as shown by C (6). Gold volatility affects Ethereum volatility by 0.991, shown by C(8).

Table 3: BEKK results in Model (3.21)

Oil and Bitcoin (mean equation)			
Coefficient symbol	Coefficient value	Z-statistic	Probability level
C(1)	59.83213	146.6888	0.0000
C(2)	-0.000433	-8.380640	0.0000
C(3)	8836.943	66.28305	0.0000
C(4)	-23.31493	-8.757939	0.0000
Oil and Bitcoin (variance equation)			
C(5)	0.886453	17.47324	0.0000
C(6)	-2.356028	-0.138836	0.8896
C(7)	125950.8	35.41237	0.0000
C(8)	0.999717	10.90394	0.0000
C(9)	0.994146	10.80343	0.0000
C(10)	0.076736	6.015454	0.0000
C(11)	-0.024352	-1.787977	0.0738
Oil and Litecoin (Mean equation)			
Coefficient symbol	Coefficient value	Z-statistic	Probability level
C(1)	57.51142	327.3676	0.0000
C(2)	0.006083	2.399409	0.0164
C(3)	22.08278	18.39188	0.0000
C(4)	0.412095	19.07348	0.0000
Oil and Litecoin (variance equation)			
C(5)	0.950368	21.33023	0.0000
C(6)	0.360042	2.671116	0.0076
C(7)	6.098022	17.50223	0.0000
C(8)	1.000312	10.65122	0.0000
C(9)	0.996703	10.50881	0.0000
C(10)	-0.066991	-6.081392	0.0000
C(11)	0.089091	6.728698	0.0000
Oil and XRP (Mean equation)			
Coefficient symbol	Coefficient value	Z-statistic	Probability level
C(1)	58.54335	290.4157	0.0000
C(2)	-1.755094	-4.160854	0.0000
C(3)	0.238962	39.26646	0.0000
C(4)	0.000529	4.718486	0.0000

Oil and XRP (variance equation)			
C(5)	0.952082	17.74000	0.0000
C(6)	0.001323	3.044179	0.0023
C(7)	0.000106	25.41171	0.0000
C(8)	0.944980	19.99568	0.0000
C(9)	0.917160	19.39159	0.0000
C(10)	0.452390	29.65666	0.0000
C(11)	0.527589	31.41418	0.0000
Oil and Dash (mean equation)			
Coefficient symbol	Coefficient value	Z-statistic	Probability level
C(1)	57.65865	369.9310	0.0000
C(2)	-0.001207	-1.413417	0.1575
C(3)	121.6237	37.34902	0.0000
C(4)	-0.550361	-9.522286	0.0000
Oil and Dash (variance equation)			
C(5)	0.829859	18.59556	0.0000
C(6)	0.240894	0.791449	0.4287
C(7)	20.56931	17.77938	0.0000
C(8)	1.006270	11.59726	0.0000
C(9)	0.991572	11.47840	0.0000
C(10)	-0.085632	-6.304411	0.0000
C(11)	0.120318	7.111317	0.0000
Oil and Monero (mean equation)			
Coefficient symbol	Coefficient value	Z-statistic	Probability level
C(1)	57.23768	222.2994	0.0000
C(2)	-0.003063	-1.079439	0.2804
C(3)	60.84803	32.08796	0.0000
C(4)	0.077578	2.319688	0.0204
Oil and Monero (variance equation)			
C(5)	0.933010	22.27683	0.0000
C(6)	-0.499932	-3.918898	0.0001
C(7)	5.075530	11.92996	0.0000
C(8)	0.941975	18.63700	0.0000
C(9)	0.911145	18.00045	0.0000
C(10)	0.365192	18.15847	0.0000
C(11)	0.459251	21.52124	0.0000
Oil and Stellar (mean equation)			
Coefficient symbol	Coefficient value	Z-statistic	Probability level
C(1)	56.55140	377.5218	0.0000
C(2)	3.247093	2.628265	0.0086
C(3)	0.039455	21.81501	0.0000
C(4)	0.000403	12.37933	0.0000
Oil and Stellar (variance equation)			
C(5)	0.824936	17.08864	0.0000
C(6)	0.000755	3.564189	0.0004
C(7)	1.36E-05	19.84056	0.0000
C(8)	1.010564	11.47284	0.0000
C(9)	0.995252	11.33423	0.0000
C(10)	-0.078137	-6.556780	0.0000
C(11)	0.086309	6.304248	0.0000
Oil and Ethereum (mean equation)			
Coefficient symbol	Coefficient value	Z-statistic	Probability level
C(1)	58.73555	346.4113	0.0000
C(2)	-0.002612	-7.937146	0.0000

C(3)	217.8206	26.48894	0.0000
C(4)	-0.466007	-3.194208	0.0014
Oil and Ethereum (variance equation)			
C(5)	0.867293	21.10976	0.0000
C(6)	-1.034561	-1.563047	0.1180
C(7)	106.8463	31.53111	0.0000
C(8)	0.993677	10.15409	0.0000
C(9)	1.001233	10.24836	0.0000
C(10)	-0.152403	-8.232093	0.0000
C(11)	-0.001360	-0.132290	0.8948

Source: Research Findings

Table 4: BEKK results in Model 3.22

Oil and Bitcoin (mean equation)			
Coefficient symbol	Coefficient value	Z-statistic	Probability level
C(1)	1764.312	243.3212	0.0000
C(2)	0.009016	11.31878	0.0000
C(3)	-6055.753	-12.36630	0.0000
C(4)	8.197452	31.01120	0.0000
Oil and Bitcoin (variance equation)			
C(5)	194.1851	21.34700	0.0000
C(6)	909.3165	7.066108	0.0000
C(7)	51438.42	17.50258	0.0000
C(8)	1.000877	12.42870	0.0000
C(9)	1.007452	12.55523	0.0000
C(10)	-0.066186	-3.071017	0.0021
C(11)	0.009707	0.469653	0.6386
Oil and Litecoin (Mean equation)			
Coefficient symbol	Coefficient value	Z-statistic	Probability level
C(1)	1286.175	377.5235	0.0000
C(2)	0.374275	6.117480	0.0000
C(3)	68.07532	46.39711	0.0000
C(4)	-0.018571	-17.24016	0.0000
Oil and Litecoin (variance equation)			
C(5)	119.7335	13.63247	0.0000
C(6)	-5.370380	-12.65376	0.0000
C(7)	0.241968	11.05646	0.0000
C(8)	0.825628	37.36599	0.0000
C(9)	0.824243	37.39380	0.0000
C(10)	0.723527	109.8766	0.0000
C(11)	0.723147	110.0674	0.0000
Oil and XRP (Mean equation)			
Coefficient symbol	Coefficient value	Z-statistic	Probability level
C(1)	1893.636	631.4383	0.0000
C(2)	-382.3798	-67.04537	0.0000
C(3)	0.832457	21.91364	0.0000
C(4)	-0.000335	-15.96940	0.0000
Oil and XRP (variance equation)			
C(5)	98.71799	8.002580	0.0000
C(6)	0.026242	4.384574	0.0000
C(7)	6.60E-05	15.63298	0.0000
C(8)	0.779186	38.74161	0.0000
C(9)	0.770605	38.91417	0.0000

C(10)	0.709958	189.7288	0.0000
C(11)	0.713932	195.1423	0.0000
Oil and Dash (mean equation)			
Coefficient symbol	Coefficient value	Z-statistic	Probability level
C(1)	1141.130	577.2720	0.0000
C(2)	2.142033	169.8813	0.0000
C(3)	-471.3407	-97.84371	0.0000
C(4)	0.420532	118.7596	0.0000
Oil and Dash (variance equation)			
C(5)	22.47850	2.628085	0.0086
C(6)	-2.845969	-1.044628	0.2962
C(7)	2.547195	2.003732	0.0451
C(8)	0.532393	26.04612	0.0000
C(9)	0.532750	26.32635	0.0000
C(10)	0.870002	129.5273	0.0000
C(11)	0.869787	130.0098	0.0000
Oil and Monero (mean equation)			
Coefficient symbol	Coefficient value	Z-statistic	Probability level
C(1)	1832.830	471.6130	0.0000
C(2)	-0.423993	-8.139160	0.0000
C(3)	-32.63981	-4.955377	0.0000
C(4)	0.049708	13.56361	0.0000
Oil and Monero (variance equation)			
C(5)	214.6942	13.13766	0.0000
C(6)	20.92959	10.72975	0.0000
C(7)	7.619005	20.75907	0.0000
C(8)	0.934580	11.13023	0.0000
C(9)	0.960892	11.56623	0.0000
C(10)	0.330495	11.25847	0.0000
C(11)	0.265509	9.743263	0.0000
Oil and Stellar (mean equation)			
Coefficient symbol	Coefficient value	Z-statistic	Probability level
C(1)	1247.785	470.1491	0.0000
C(2)	694.1893	60.25192	0.0000
C(3)	0.009672	1.476787	0.1397
C(4)	4.24E-05	8.505513	0.0000
Oil and Stellar (variance equation)			
C(5)	163.8524	13.76220	0.0000
C(6)	-0.031926	-17.05656	0.0000
C(7)	8.34E-06	13.56213	0.0000
C(8)	0.885584	20.65113	0.0000
C(9)	0.887562	20.72083	0.0000
C(10)	0.577906	45.01266	0.0000
C(11)	0.576990	45.00549	0.0000
Oil and Ethereum (mean equation)			
Coefficient symbol	Coefficient value	Z-statistic	Probability level
C(1)	1710.345	760.1651	0.0000
C(2)	0.039474	15.64848	0.0000
C(3)	67.41220	2.876418	0.0040
C(4)	0.069980	5.125169	0.0000
Oil and Ethereum (variance equation)			
C(5)	130.3250	14.10862	0.0000
C(6)	-10.02310	-1.662033	0.0965

C(7)	80.24789	48.20726	0.0000
C(8)	0.991775	8.810961	0.0000
C(9)	1.002990	8.959325	0.0000
C(10)	0.119043	4.797554	0.0000
C(11)	0.042082	2.018146	0.0436

Source: Research Findings

5 Conclusions and suggestions

Cryptocurrencies such as Bitcoin, Ethereum, and Litecoin have surprised everyone; meanwhile, Bitcoin has attracted more attention than its rivals. Undoubtedly, this new network will be a good platform for governments and nations to invest in. Insufficient information can have an adverse effect on the economy and the lives of its users. Cryptocurrencies are associated with gold and oil prices. Accordingly, the present study aimed to evaluate the relationship between cryptocurrencies with oil and gold prices.

The present study examined the interrelationships between cryptocurrencies and oil and gold prices using the BEKK model. The results of model estimation indicated that the prices of Bitcoin, XRP, and Ethereum had a negative effect on oil prices, and prices of Litecoin and Stellar had a positive effect on oil prices. Monero volatility also had a negative effect on oil price volatility, and Litecoin, XRP, and Stellar volatility had a positive effect on oil price volatility. Therefore, oil prices were affected by cryptocurrencies. However, only an increase in the prices of Litecoin and Stellar could lead to an increase in the oil price. Cryptocurrencies are also affected by the oil price, as the oil price has a negative effect on the prices of Bitcoin, Dash, and Ethereum and a positive effect on the prices of Litecoin, XRP, Monero, and Stellar. Oil price volatility also had a positive effect on Bitcoin, Litecoin, XRP, Dash, Monero, Stellar, and Ethereum volatility. Therefore, oil price volatility had a positive effect on all cryptocurrencies. This result indicated that cryptocurrency volatility had different effects on oil price volatility, but oil price volatility mainly led to increased cryptocurrency volatility. Furthermore, the prices of Bitcoin, Litecoin, Dash, Stellar, and Ethereum had a positive effect on the gold price, and the prices of XRP and Monero had a negative effect on the oil price. Bitcoin, XRP, and Monero volatility had a positive effect on the gold price volatility, and Litecoin and Stellar volatility had a negative effect on the gold price volatility. Furthermore, the gold price had a positive effect on the prices of Bitcoin, Dash, Monero, Stellar, and Ethereum, and a negative effect on the prices of Litecoin and XRP. Gold price volatility had a positive effect on Bitcoin, Litecoin, XRP, Dash, Monero, Stellar, and Ethereum volatility. Therefore, cryptocurrencies had a greater positive effect on oil prices, but gold price volatility generally had a positive effect on cryptocurrency volatility.

The results of the present study were consistent with the results of a study by Jareno et al. [14] in terms of the relationship between volatility of oil and cryptocurrencies and were consistent with a study by Adebolaet al. [1] in terms of the relationship between prices of gold and cryptocurrencies.

Given that volatility in oil and gold prices had a positive effect on volatility in cryptocurrencies and the effects will be more manifested in future periods, investors in cryptocurrencies are recommended to study the process of oil and gold prices in the last 10 years, especially oil price, before purchasing cryptocurrencies. According to the research results, it is suggested that the attractions of investing in cryptocurrencies should be fully introduced to investors, especially government investment in the field of cryptocurrencies due to its affectability by the above-mentioned factors. Since Bitcoin volatility has a very positive effect on gold price volatility, it is suggested to examine the Bitcoin volatility and price changes in recent years to buy gold.

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