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Investigation of dynamic volatility relationships among global indices in the presence of COVID-19 impact: Evidence from TVP-VAR approach

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ABSTRACT

This study aims to examine the dynamic connectedness relationship between global economic and financial indices. In this context, the volatility relationships among Bitcoin, oil, gold, S&P 500 index, US 10-year bond interest, and the US dollar index are examined over the period from April 24, 2015, to March 19, 2024. Studies using such different types and numbers of variables are quite limited in the literature. The TVP-VAR approach with a time-varying covariance structure developed by Antonakakis and Gabauer [1] is used as the analysis method in the study. As a result of the study, it was determined that the relevant variables, the US 10-year bond rate and S&P500 variables, emit net volatility to other variables; oil, gold, US dollar index and Bitcoin variables have also been found to be net volatility receivers. On the other hand, the fact that Bitcoin has less volatility relationship with other variables shows that Bitcoin can provide potential benefits in terms of portfolio diversification with relevant variables. In addition, since the total volatility value among the variables is low, the relevant variables can be used together in international portfolio diversification. This situation is important for decision-makers on issues such as asset pricing, portfolio management, and risk management.

1. Introduction

When an event that increases the volatility of one asset also raises the volatility of other assets, risk is transmitted across the financial system. In such cases, a shock originating in one sector of the economy can extend through interconnected channels, posing a threat to overall stability. A well-diversified portfolio that considers asset spillover effects can help manage systemic risks. Managing a portfolio with minimal interconnections among assets may be easier to regulate. Failure to contain risk spillovers can escalate into regional or even global financial crises. Therefore, economic policymakers should closely monitor volatility-transmitting assets and take necessary precautions to mitigate systemic risks.

Developments in globalization, liberalization, securitization, and information technology have significantly increased the interconnectedness of financial markets worldwide [2]. During financial crises, market volatility intensifies and rapidly spreads across different markets. Consequently, it is crucial to measure and monitor such spillover effects to develop effective “early warning systems”

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for emerging crises and to track the progression of ongoing financial disruptions [3]. The transmission of information across financial markets plays a vital role for investors, policymakers, and portfolio managers, influencing asset pricing, portfolio risk management, asset allocation, and overall market stability [4]. In recent years, particularly following the 2007–2009 global financial crisis, the study of financial crisis spillovers has become a central focus of academia [5].

This study examines the dynamic interconnections among key global economic and financial variables, which are widely recognized as indicators. Among these, gold stands out as a globally strategic commodity, particularly valued during periods of economic and financial instability. Often regarded as a safe-haven asset, gold provides protection against stock market fluctuations and other financial risks. When investors anticipate increased stock market volatility, they tend to reduce their equity holdings in favor of lower-risk assets such as gold [6]. The price of gold generally exhibits an inverse relationship with the U.S. dollar [7]. According to the World Gold Council, the total above-ground gold stock was estimated at 212,582 tons by the end of 2023. Of this, approximately 96,487 tons (45 %) were held in jewelry, 47,454 tons (22 %) in bars and coins (including gold-backed exchange-traded funds), 36,699 tons (17 %) in central bank reserves, and 31,943 tons (15 %) allocated for other uses. Additionally, proven gold reserves are estimated to be around 59,000 tons [8]. In contrast, cryptocurrency has emerged in recent years as a digital asset class, with thousands of different cryptocurrencies available in the market. Among these, Bitcoin (BTC) holds the largest market capitalization, making it the most dominant cryptocurrency. As of October 6, 2024, the total market capitalization of cryptocurrencies stands at $2.53 trillion, with BTC accounting for 54.1 % ($1.37 trillion) of this value [9]. BTC is widely regarded as a hedge against global uncertainties and a safe haven during periods of financial distress. However, due to its rapid expansion and pronounced price volatility, the Bitcoin market may also introduce instability into the broader financial system. Understanding the interconnections between Bitcoin and financial markets is therefore essential for risk management, asset allocation, and financial stability considerations [10]. Oil, another globally strategic commodity, is often viewed as a key indicator of global economic health [6]. Fluctuations in oil prices influence various economic variables, including production costs, inflation, interest rates, investment levels, and economic growth. These changes, in turn, have significant implications for both exchange rate markets and stock markets [11].

The S&P 500 index is widely regarded as one of the most influential indicators for assessing and even determining the performance of the U.S. stock market. It comprises the 500 largest U.S. companies across key sectors and represents approximately 80 % of the total U.S. stock market capitalization. Given that many of these companies operate on a global scale, fluctuations in the index can have far-reaching effects, influencing stock markets worldwide [12]. The U.S. Dollar Index (DXY) measures the value of the U.S. dollar relative to a basket of six major global currencies. As a key indicator of global economic conditions, the DXY significantly impacts financial markets, particularly commodities such as gold and oil, which are typically priced in U.S. dollars. There is an inverse relationship between the U.S. dollar and commodity prices, meaning that as the value of the dollar rises, commodity prices tend to decline, and vice versa. DXY also plays a crucial role in influencing foreign investments and capital flows. Positive economic indicators in the U.S. can lead investors to favor the dollar, prompting capital outflows from other countries, an increase in U.S. 10-year bond yields, and a subsequent rise in the dollar index. Conversely, negative economic indicators may weaken investor confidence, leading to a decline in the dollar index [13]. Additionally, U.S. 10-year bond yields serve as a key indicator for the global economy. Generally, declining yields signal economic concerns, whereas rising yields reflect investor confidence. An increase in U.S. bond yields often attracts capital inflows from other countries into the U.S. market. These yields also influence the stock market by contributing to volatility; higher yields may deter investment in riskier stocks, shifting capital away from equities. Moreover, higher U.S. 10-year bond yields may lead to higher borrowing costs and slow economic growth [7].

This study examines the volatility dynamics among Bitcoin, crude oil, gold, the S&P 500 stock market index, the U.S. 10-year bond yield, and the U.S. Dollar Index, key economic indicators that are widely monitored on a global scale. The inclusion of these six global variables enhances the study's significance by providing a comprehensive perspective on financial market interconnections. While numerous academic studies have explored the relationships between stocks and commodities or between financial assets and cryptocurrencies, research incorporating interest rates, the stock market, gold, the dollar, Bitcoin, and oil simultaneously remains scarce. Furthermore, this study employs the Time-Varying Parameter Vector Autoregression (TVP-VAR) method, a relatively recent econometric approach that dynamically captures the evolving relationships among these variables over time. Additionally, the study analyzes the impact of the COVID-19 crisis on these interdependencies. The findings hold significant implications for risk managers, portfolio managers, and market regulators, offering valuable insights for asset pricing, risk management, and financial stability considerations.

The following parts of this study are structured as follows: Section 2 provides a literature review and Section 3 outlines the methodology of the study. Section 4 details the data set and descriptive statistics, followed by Section 5, which presents the empirical findings and Section 6 presents the discussion part. Finally, Section 7 concludes the study by summarizing the key results.

2. Literature review

Investors select financial instruments based on their risk and return profiles. They may choose interest-bearing securities such as bonds and bills, invest in stocks of companies across various sectors listed on stock exchanges, or purchase commodities with intrinsic economic value, including those in the energy and metals sectors. With commodities being traded on futures markets and the development of derivative financial instruments based on commodities in capital markets, the interconnections between these commodities and other financial assets have deepened. Price fluctuations in one asset class often manifest in the prices of other assets. One common approach to examining these relationships and understanding their responses to shocks is through the measurement of volatility spillovers. A high degree of volatility spillover suggests that markets are moving in tandem and are interconnected. In this context, the following section reviews and summarizes studies in the literature that explore the relationships between various assets and other financial instruments. Oil and stock markets, both of which are strategically significant in the global economy, exhibit a strong interrelationship. Kang, Ratti, and Yoon [14] investigate the impact of oil price shocks on U.S. stock market returns and volatility, findings are statistically significant and substantial. Roubaud and Arouri [11] highlight the crucial role oil plays in transmitting price shocks to both exchange rate and equity markets. Wu et al. [15] assert that crude oil prices serve as the primary source of interdependence between the stock markets of both oil-importing and oil-exporting countries. Additionally, Elsayed et al. [16] identify a high degree of interdependence between oil and stock market volatilities in major global financial markets.

Similar to oil, the volatility spillovers of gold, a significant commodity, have also been investigated in the academic literature. Çelik et al. [17] examined the presence of bubbles in precious metal prices and the volatility spillovers among related variables. Their findings revealed a significant relationship among the returns of gold, silver, and platinum. Cheng et al. [6] analyzed the time-varying linkages among various commodities and Chinese sectoral stocks, identifying asymmetric volatility spillovers among gold, oil, and stocks. Dai et al. [18] discovered dynamic conditional correlations between gold, oil, and stock market indices, with both positive and negative spillovers. They concluded that crude oil and gold act as net recipients of systemic shocks, while stock markets serve as net transmitters. Similarly, Wang, Meng, and Mo [19] examined the dynamic relationships and volatility spillover effects among crude oil, gold, and the stock prices of Chinese electricity companies, finding that volatility in stock market indices spills over into oil and gold markets. Additionally, Younis et al. [20] indicate that the static and dynamic linkages between oil, gold and global equity markets vary over time. According to the findings of their study, in the short run, France, Japan, the UK, and Malaysia stock markets and gold are the main transmitters, while in the long run, France and Singapore stock markets, oil and gold are the main transmitters. Ha et al. [21] find that oil and gold markets are consistently net transmitters of shocks to the energy market. Ping et al. [22] investigated the time-varying volatility relationship between gold markets and the US dollar and concluded that gold and the US dollar index move together and that there is a volatility spillover between these two variables. According to the findings, negative shocks propagate from gold to the US dollar. Gold price and the US dollar index have a strong inverse relationship. Huang et al. [23] investigated the variables that can predict China's financial risk and financial situation with the help of the TVP-VAR model. Accordingly, they identified the five most important variables among 18 variables.

In addition to traditional assets such as the dollar, stocks, gold, and oil, cryptocurrencies have emerged as an important investment instrument in recent years. The relationship between cryptocurrencies and other financial assets has been the focus of several academic studies. For instance, Dyhrberg [24], using GARCH models, found that Bitcoin exhibits characteristics similar to both gold and the dollar. Since Bitcoin is highly sensitive to the federal funds rate, it is suggested that Bitcoin behaves like a currency. However, like gold, Bitcoin also responds symmetrically to both positive and negative news. It is concluded that Bitcoin occupies a unique position between a currency and a commodity, making it a valuable tool for portfolio management. Similarly, Corbet et al. [25] explored the dynamic relationships between various cryptocurrencies and different financial assets, finding that while cryptocurrencies are highly correlated with one another, they are less correlated with other financial and economic assets. This finding suggests that incorporating cryptocurrencies into a diversified portfolio could offer potential benefits for investors. Shahzad et al. [26] explored whether Bitcoin, similar to commodities, exhibits safe-haven characteristics under extreme market conditions, focusing on various stock market indices from both developed and emerging economies (e.g., the U.S. and China). The study's findings reveal that the safe-haven properties of assets fluctuate over time and vary by stock market index. However, Bitcoin, along with gold and commodity indices, can serve as a weak safe haven in certain circumstances. Zhang et al. [10] investigated the risk spillovers among Bitcoin and traditional assets such as currencies, stocks, bonds, and commodities. Their study identified bidirectional downside risk spillovers among Bitcoin and these four asset classes at all times. They concluded that there is a rapid and direct interaction among Bitcoin and these traditional market assets. Cao and Xie [27] examined the volatility spillover effect between Chinese financial markets and cryptocurrencies, finding that the volatility spillover index exhibits asymmetric and time-varying characteristics. While cryptocurrencies exert a stronger impact on financial markets, the reverse effect, financial markets influencing cryptocurrencies, was found to be much weaker. However, negative spillovers have been found to outweigh positive spillovers in magnitude. Specifically, risk spillovers are stronger during bearish periods in the cryptocurrency market and diminish during bullish periods. Within Chinese financial markets, the commodity market and the exchange rate market are the sub-markets most notably influenced by cryptocurrency.

As evidenced by numerous studies in the literature, volatility spillovers have been a focal point of research. One of the key findings of Diebold and Yilmaz [28], who were pioneers in this field, is that between the early 1990s and early 2000s (spanning both non-crisis and crisis periods), global equity markets exhibited no consistent trend in volatility spillovers, instead showing only sporadic bursts. This suggests that while market stress periods occur, market volatility does not follow a continuous trend but rather experiences sudden bursts at specific intervals. Volatility spillovers tend to increase during periods of market uncertainty and in response to significant, unexpected events. In a subsequent study, Diebold and Yilmaz [3] examined daily volatility spillovers across US stock, foreign exchange, bond, and commodity markets, finding that these spillovers intensified as the 2008 financial crisis deepened. Diebold and Yilmaz [29] examined the equity return-volatility connectedness between stocks in the US and Europe, finding that connectedness is bidirectional during non-crisis periods. However, during crises, the direction of connectedness shifts from the region where the crisis originates to the other region. Specifically, during the mortgage crisis of 2007–2008, the connectedness flowed from the US to Europe, while in 2011, when EU financial institutions faced difficulties, the direction of connectedness reversed, moving from Europe to the US. Wen et al. [30] argue that the 2008 financial crisis strengthened the link between financial markets and crude oil prices. Similarly, Elsayed et al. [16] assert that while the energy market's influence on the global financial system is minimal in the long run, its impact intensifies during crisis periods. Liu and Gong [2] studied volatility spillovers across four major crude oil markets, concluding that volatility spillovers increased notably during crisis periods, such as the 2008 crisis, when oil prices experienced significant fluctuations. Dai et al. [18] also find that total volatility spillovers between crude oil, gold, and equity markets increase substantially during major crisis events. Similarly, Cheng et al. [6] observe that spillovers intensify during global emergencies. Younis et al. [20], in their analysis of the static and dynamic connectedness between oil, gold, and global stock markets, also highlight that interconnectedness is particularly high during crisis periods. Ha et al. [21] note that shock spillovers from the oil and gold markets to the energy market became more pronounced during the COVID-19 crisis. Corbet et al. [31] find that the COVID-19 pandemic had a strong and positive impact on the volatility of the Shanghai and Shenzhen stock markets. Collectively, these studies demonstrate that volatility spillovers are amplified during periods of significant events that introduce a shock effect into the markets.

Although the existing literature predominantly focuses on local markets, several studies provide valuable insights into the dynamic behavior of financial indicators during periods of uncertainty. For example, stock market prediction models using neural networks have been applied to the BIST-100 index during financial crises [32,33], while the golden ratio model has been utilized to forecast returns in the context of the COVID-19 pandemic [34]. Furthermore, machine learning-based segmentation methods have been employed to identify the key drivers of volatility in BIST-100 firms [35]. Building upon this line of research, the present study differs by examining time-varying volatility connectedness among major global financial variables, offering broader implications for international portfolio diversification and risk management.

3. Methodology

During financial crises, volatility in financial markets typically rises sharply and extends across various markets. It is crucial to measure and monitor such spillovers to establish “early warning systems” for impending crises and to track the developments of ongoing crises [3].

3.1. TVP-VAR

Diebold and Yilmaz [3,28,36] developed various connectedness approaches to quantify return and volatility spillovers. Among these studies, Diebold and Yilmaz [3,36] introduced significant innovations by addressing several methodological and contextual limitations present in Diebold and Yilmaz [28]. Subsequently, Antonakakis and Gabauer [1] extended and enhanced the existing connectedness measures proposed by Diebold and Yilmaz [3,28,36]. The approach introduced by Antonakakis and Gabauer [1], known as TVP-VAR, was further refined by Antonakakis et al. [5]. Antonakakis et al. [5] improved the connectedness methodology provided by Diebold and Yilmaz (2012, 2014) in the following ways [3,36]:

- Potential changes in parameter values can be identified with greater accuracy.
- The results are not influenced by outliers.
- There is no need to specify an arbitrary rolling-window size.
- Dynamic measurements can be calculated without any loss of observations.

The TVP-VAR model, based on the time-varying variance-covariance structure, is presented in Eq. (1) [5]. The TVP-VAR model was developed to account for the fact that dynamic relationships in economic, financial, and social systems can evolve over time. In contrast to traditional fixed-parameter VAR models, the TVP-VAR model allows for flexible modeling of time-varying relationships. As a result, the TVP-VAR model is particularly valuable in applications such as economic policy analysis, examining the effects of shocks, and detecting structural breaks.

$$y_t = X_t\beta_t + \in_t \quad \in_t \sim N(0,\ \Sigma_t) \tag{1}$$

The dynamics of the parameters in the TVP-VAR model are described by the state-space model in Eq. (2). Traditional VAR models assume that the relationships within the system remain constant over time. However, in economic and financial systems, these relationships can evolve. The TVP-VAR model captures such time-varying relationships by dynamically estimating the β vector. The parameters in the TVP-VAR model are estimated using a Kalman filter, which constructs a state-space model to allow for the time-varying nature of the relationships.

$$\beta_t = \beta_{t-1} + \xi_t \quad \xi_t \sim N(0,\ Q) \tag{2}$$

The TVP-VAR model is solved using the Kalman filter algorithm. At each time step, the parameters and error covariance are updated through the following steps:

1. The estimation of parameters and covariances at the next time step is carried out in a sequence of steps. In the TVP-VAR model, the parameters are updated based on the state from the previous time step. The model learns the change in parameters, which is controlled by the Q matrix. When Q is small, the parameters evolve gradually over time. When Q is large, the parameters change more rapidly, allowing the model to capture sudden structural shifts.
   - The parameter vector predicted at time t, based on the information at time $(t-1)$.
     $\beta_t^- = \beta_{t-1}$
   - Covariance prediction:
     $P_t^- = P_{t-1} + Q$

2. As new observations arrive, the predicted parameters are updated through the following steps. Here, the measurement error covariance R and process noise covariance Q determine the model's flexibility and sensitivity to error. The Kalman filter optimizes these two noise sources by combining the information obtained from the measurement with the model's prediction.
   - Calculate the Kalman gain:

     $$K_t = P_t^- X_t^T \left(X_t P_t^- X_t^T + R\right)^{-1}$$
   - Update the parameters:

     $$\beta_t = \beta_t^- + K_t\left(y_t - X_t\beta_t^-\right)$$
   - Update the covariance:

     $$P_t = (I - K_t X_t)P_t^-$$

After the β_t parameter is obtained using the Kalman filter method, the calculation of $\in_t$ in the model $y_t = X_t\beta_t + \in_t$ is performed. To do this, the error vector is first calculated as follows:

$$e = D - D\beta$$

Following this, the covariance matrix of the error vector e is calculated as shown in Eq. (3). Finally, the white noise error term $\in_t \sim N(0,\ \Sigma_t)$ is computed. This term is randomly sampled from a multivariate normal distribution.

$$\Sigma_{i,j} = Cov\left(e_i, e_j\right) = \frac{1}{n-1}\sum_{k=1}^{n}\left(e_{ki} - \overline{e_i}\right)\left(e_{kj} - \overline{e_j}\right) \tag{3}$$

The symbols and notations used in the method employed in the study are presented in Table 1.

The time-varying coefficients and error covariances are used to estimate the generalized connectedness framework, which is based on the generalized impulse response functions (GIRF) proposed by Diebold and Yilmaz [36], and the generalized forecast error variance decomposition (GFEVD) introduced by Koop et al. [37], as well as Pesaran and Shin [38]. To compute the GIRF and GFEVD, the TVP-VAR model is transformed into the TVP vector moving average (TVP-VMA) model, in accordance with the Wold representation theorem, as outlined by Antonakakis et al. [5].

$$y_t = J'(M_t(z_{t-2} + \eta_{t-1}) + \eta_t), \tag{4}$$

$$= J'(M_t(M_t(z_{t-3} + \eta_{t-2}) + \eta_{t-1}) + \eta_t), \tag{5}$$

$$\vdots \tag{6}$$

$$y_t = J'\left(\mathrm{M}_{\mathrm{t}}^{k-1} z_{t-k-1} + \sum\nolimits_{j=0}^{\mathrm{k}} \mathrm{M}_{\mathrm{t}}^{\mathrm{j}} \eta_{t-j}\right) \tag{7}$$

with

$$M_t = \begin{pmatrix} A_t & \\ I_{m(p-1)} & O_{m(p-1)x\,m} \end{pmatrix} \eta_t = \begin{pmatrix} \in_t \\ 0 \\ \vdots \\ 0 \end{pmatrix} = \mathrm{J}\in_t\mathrm{J} = \begin{pmatrix} I \\ 0 \\ \vdots \\ 0 \end{pmatrix}. \tag{8}$$

In the above equations, M_t; $mp\ x\ mp$ is a matrix of size, η_t; $mp\ x\ 1$ is a vector of size, and J; $mp\ x\ m$ is a matrix of size, J'; the transpose of j matrix. A_t; $m\ x\ mp$ is a dimensional matrix. GIRF, denoted as $\left(\psi_{\mathrm{j,t}}(\mathrm{H})\right)$, represent the responses of all variables (j) following a shock

Table 1
List of the symbols.

Symbol	Description
D	Original data matrix
y_t	Vector of dependent variables at time t
X_t	Delay matrix of observed explanatory variables
β_t	Time-varying parameter vector
$\in_t$	White noise error term
Σ_t	Covariance of white noise error
ξ_t	Process noise modeling the random time-varying changes of parameters
Q	Covariance matrix of state noise
R	Covariance matrix of measurement noise
P_t	Error covariance matrix for parameter uncertainty
K_t	Kalman gain
I	Identity matrix

to variable i. Since this is not a structural model, the differences are computed between a J-step ahead forecast, once with a shock to variable i and once without. The difference can be calculated by applying the shock to variable i, as follows [5].

$$\mathrm{GIRF}_t\left(H, \delta_{j,t}, \Omega_{t-1}\right) = E\left(y_{t+H} \middle| e_j = \delta_{j,t}, \Omega_{t-1}\right) - E\left(y_{t+j} \middle| \Omega_{t-1}\right) \tag{9}$$

$$\psi_{j,t}(H) = \frac{B_{H,t}\Sigma_t e_j}{\sqrt{\Sigma jj,_t}} \; \frac{\delta_{j,t}}{\sqrt{\Sigma jj,_t}} \; \delta_{j,t} = \sqrt{\Sigma_{jj,t}} \tag{10}$$

$$\psi_{j,t}(H) = \Sigma_{jj,t}^{-\frac{1}{2}} B_{H,t}\Sigma_t e_j, \tag{11}$$

e_j; represents the selection vector, which is 1 at the j position and 0 otherwise. Unlike standard impulse-response functions, in the GIRF approach, the ordering of the variables does not affect the results. As a result, the analysis obtained from this approach is more robust [39]. The GFEVD $\left(\tilde{\phi}_{ij,t}(H)\right)$ represents the bidirectional connection from i to j, and it illustrates the effect of variable j on variable i in terms of the forecast error variance share. These variance shares are subsequently normalized, so that the sum of each row equals 1 (one), meaning that all variables together explain 100 % of the forecast error variance of variable i. The GFEVD is computed as follows [5]:

$$\tilde{\phi}_{ij,t}(H) = \frac{\Sigma_{t=1}^{H-1}\psi_{ij,t}^{2}}{\Sigma_{j=1}^{m}\Sigma_{t=1}^{j-1}\psi_{ij,t}^{2,g}} \tag{12}$$

with

$$\sum_{j=1}^{m}\tilde{\phi}_{ij,t}(H) = 1 \quad \text{ve} \quad \sum_{i,j=1}^{m}\tilde{\phi}_{ij,t}(H) = m$$

The denominator represents the cumulative effect of all shocks, while the numerator shows the cumulative effect of the shock to variable i.

3.2. Total dynamic connectedness index

The Total Connectedness Index (TCI) is constructed using GFEVD as follows [5]:

$$C_t(H) = \frac{\Sigma_{i,j=1,i\neq j}^{m}\tilde{\phi}_{ij,t}(H)}{\sum_{i,j=1}^{m}\tilde{\phi}_{ij,t}(H)} * 100 = \frac{\Sigma_{i,j=1,i\neq j}^{m}\tilde{\phi}_{ij,t}(H)}{m} * 100. \tag{13}$$

3.3. Total directional connectedness to others

The Total Spillover Index measures the contribution of volatility shock spillovers to the total forecast error variance [3]. This connectedness approach illustrates how a shock to one variable spreads to others. First, the situation in which a shock to variable i is transmitted to all other variables j, referred to as "total directional connectedness to others" is defined as follows [5]:

$$C_{i\rightarrow j,t}(H) = \frac{\Sigma_{j=1,i\neq j}^{m}\tilde{\phi}_{ij,t}(H)}{\sum_{j=1}^{m}\tilde{\phi}_{ij,t}(H)} * 100. \tag{14}$$

3.4. Total directional connectedness from others

Secondly, the situation in which variable i receives shocks from the other variables j, referred to as "Total Directional Connectedness from Others" is defined as follows [5]:

$$C_{i\leftarrow j,t}(H) = \frac{\Sigma_{j=1,i\neq j}^{m}\tilde{\phi}_{ij,t}(H)}{\sum_{i=1}^{m}\tilde{\phi}_{ij,t}(H)} * 100. \tag{15}$$

3.5. Net total directional connectedness

Finally, "Net Total Directional Connectedness" which can be interpreted as the effect of variable i on the entire network of variables, is obtained by subtracting the Total Directional Connectedness from Others from the Total Directional Connectedness to Others, as follows [5]:

$$C_{i,t} = C_{i\rightarrow j,t}(H) - C_{i\leftarrow j,t}(H) \tag{16}$$

If $C_{i,t}$ is positive, this indicates that variable i is “influencing more than being influenced” by the network. Conversely, if $C_{i,t}$ is negative, it suggests that variable i is “driven by the network” [5].

3.6. Dynamic net bidirectional connectedness

To examine bilateral relationships by calculating Net Bilateral Directional Connectedness (NPDC), we further divide the Net Total Directional Connectedness [5]:

$$\mathrm{NPDC}_{ij}(H) = \left(\widetilde{\phi}_{jit}(H) - \widetilde{\phi}_{ijt}(H)\right) * 100. \tag{17}$$

If $\mathrm{NPDC}_{ij}(H) > 0$, it indicates that variable i dominates variable j, whereas the opposite is true if it is negative.

4. Data set and descriptive statistics

The study examines the relationships among six global variables commonly utilized by both investors and academics. Daily data spanning from April 24, 2015, to March 19, 2024, are employed, thereby capturing the effects of the COVID-19 period. Details of these variables are provided in Table 2 below.

Gold is a key commodity often viewed as a safe haven in financial markets, particularly during periods of economic uncertainty. BTC, a cryptocurrency with the largest market capitalization not only among cryptocurrencies but also across all crypto assets, is often referred to as “digital gold.” Representing over half of the cryptocurrency market, BTC has been traded in futures markets since 2017 and was the first crypto asset to be developed. As a financial asset, it attracts significant attention due to both its underlying technology and the volatility in its prices. Crude oil, one of the most vital energy sources globally, is a major asset in commodity markets, influencing production costs either directly or indirectly across industries. The S&P 500 index is a broad benchmark of the US stock market, reflecting market capitalization across a wide range of sectors. DXY, a benchmark established in 1973, tracks the value of the US dollar relative to six major currencies. Given their substantial roles in the global economy, these variables are of critical importance to world markets.

The variables used in the study were transformed into daily logarithmic return series using the formula $\ln(P_t/P_{t-1})*100$, and then the squared logarithmic returns were taken to obtain the volatility series. Descriptive statistics for the volatility values of the variables are presented in Table 3, and the time series plots for the original values of the variables are shown in Fig. 1.

While it is possible to provide a detailed analysis of the movement of each variable shown in Fig. 1 across different dates or periods, such an analysis is beyond the scope of this study. However, to highlight specific instances, it can be observed that crude oil prices turned negative during the first quarter of 2020, coinciding with the onset of the COVID-19 pandemic. The S&P 500 index, which tracks the US stock market, experienced a sharp depreciation on March 23, 2020. This date aligns with the peak of the coronavirus outbreak and the onset of widespread public quarantines. During similar periods, other variables in the study also saw declines, while gold prices, typically considered a “safe haven” asset during times of crisis, experienced a significant increase. The volatility series for the variables are shown in Fig. 2 below.

Fig. 2 illustrates that gold and the US Dollar index exhibit higher volatility compared to the other variables. Another notable observation is the sharp spikes in volatility across all variables during the COVID-19 period.

In the TVP-VAR method used in the study, the results are not affected by the presence of outliers, as explained in the methodology section. Although BTC prices are known for extreme volatility and outliers, it is possible to see such extreme price changes in other assets within the scope of the study. In addition, all sample information is used in this method.

5. Empirical findings

The total dynamic connectedness (TDC) graph, the net TDC graph, the average dynamic connectedness between variables, and the network plot illustrating the relationships between variables, as derived from the TVP-VAR analysis, are presented sequentially. The estimates were made via the Online Estimation Platform provided by David Gabauer, one of the developers of the TVP-VAR method, at https://sites.google.com/view/davidgabauer/econometric-code?authuser=0 (Access by April 1st, 2024).

Table 2
Variables.

No	Abbreviations	Explanations	Source
1	Gold	Once gold closing price	1
2	BTC	Bitcoin closing price	1
3	S&P500	S&P500 index closing price	1
4	Bond	US 10-year bond yield	1
5	Oil	Crude oil closing price	1
6	DXY	US Dollar index	2

Note: Source 1 data were obtained from www.finance.yahoo.com/ and Source 2 data were obtained from www.investing.com/,.

Table 3
Descriptive statistics of volatility series.

	BTC	Bond	Oil	Gold	S&P500	DXY
Mean	19.31160	10.26819	8.854727	0.838393	1.343760	0.190399
Median	3.091425	1.974242	1.901885	0.214112	0.239164	0.062604
Maximum	2159.741	1638.605	1021.657	33.37964	162.9507	5.754141
Minimum	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
Std. Dev.	64.96950	57.72286	44.12902	2.085504	5.633028	0.374089
Skewness	18.23311	18.76530	15.40754	7.678974	16.89556	5.658313
Kurtosis	541.8733	429.8386	280.8451	85.54521	390.1043	53.08618
Jarque-Bera	27,165,887	17,097,729	7277,482.	656,491.9	14,061,090	245,541.9
	(0.000000)	(0.000000)	(0.000000)	(0.000000)	(0.000000)	(0.000000)
Observations	2235	2235	2235	2235	2235	2235
ADF	−17.4829***	−7.05318***	−5.57382***	−11.2527***	−9.85325***	−12.4060***

Note: *** indicates a 1 % significance level. Values in parentheses are probability values. ADF refers to the Augmented Dickey-Fuller unit root test. In the ADF test, the optimal lag length is determined by the Schwarz Information Criterion (SIC).

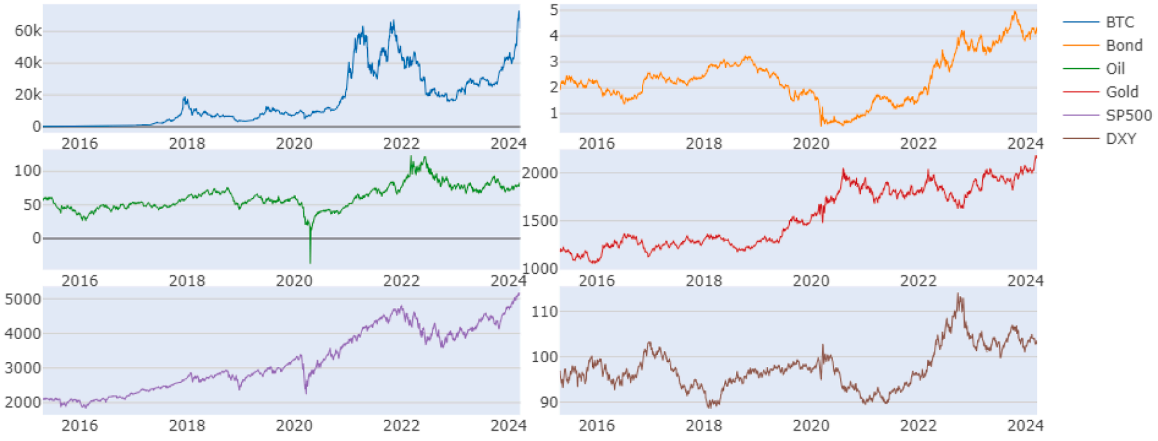

Fig. 1. Price series charts.

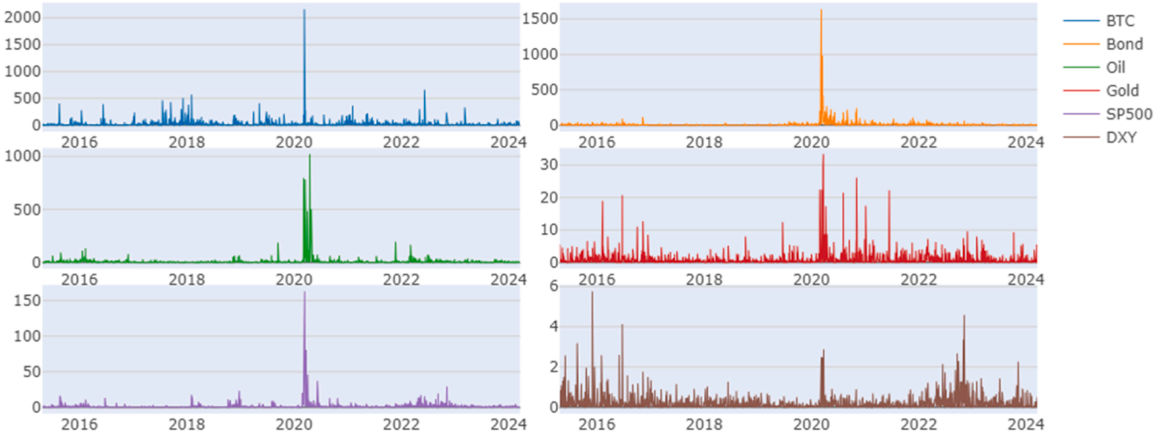

Fig. 2. Volatility series graphs of the variables.

5.1. *Total dynamic connectedness*

Fig. 3 below initially displays the total dynamic interconnectedness of the variables over the specified period.

Total dynamic interconnectedness, which remained relatively low among the relevant variables until the first half of 2016, saw a rapid increase starting in the second half of 2016. It then declined after reaching its peak during the COVID-19 period, before rising again in 2023.

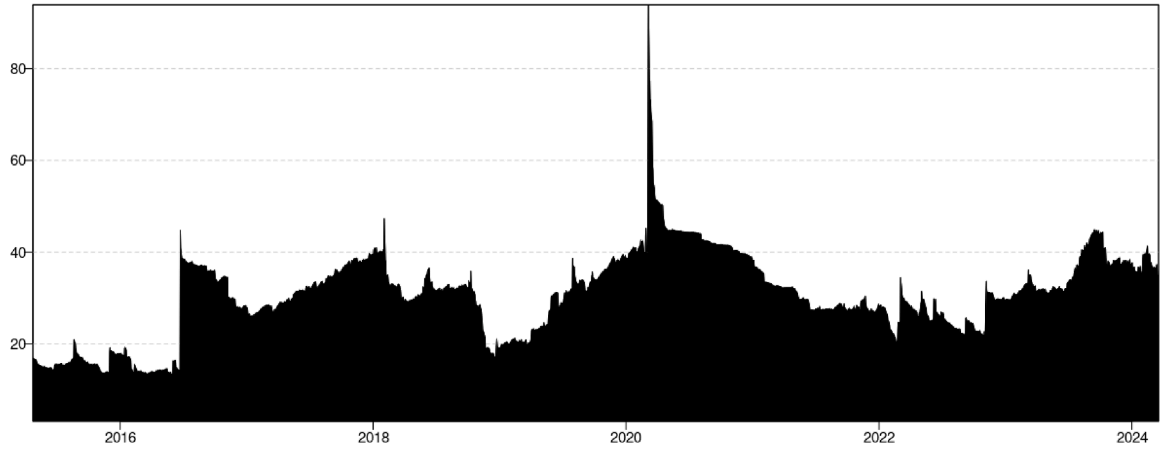

Fig. 3. Total dynamic connectedness graph.

According to Table 4, 82.78 % of the volatility change in BTC is attributable to its own fluctuations, while the remaining 17.22 % is explained by other variables. Specifically, 3.48 %, 1.78 %, 1.93 %, 6.59 %, and 3.44 % of the volatility from the Bond, Oil, Gold, S&P 500, and DXY, respectively, is transmitted to BTC. Conversely, 16.47 % of BTC's volatility is transmitted to other asset classes, with the largest share directed to the S&P 500. As a result, BTC experiences a net volatility transmission of 0.75 %. The interpretation of other variables in Table 4 follows a similar pattern. In general, Bond and S&P 500 are net volatility transmitters, while Oil, Gold, DXY, and BTC are net volatility receivers. Although the S&P 500 is the variable that absorbs the most volatility, it acts as a net volatility emitter due to its high level of volatility transmission. BTC, on the other hand, is the least significant volatility receiver, but due to its relatively lower volatility transmission, it is a net volatility receiver overall. The lower volatility correlation of BTC with other variables suggests that it may offer potential diversification benefits when combined with these related assets in a portfolio. BTC is the smallest asset in terms of market capitalization among the other assets in the study, with a total value of around $2 trillion. However, its recent popularity has been quite high.

The US 10-year bond rate emerges as the dominant volatility emitter. As shown in Table 4, the low total correlation between the variables (25.44 %) suggests that these assets can be utilized for international portfolio diversification. Specifically, 25.44 % of the total variability is attributed to the relationships among the variables in this study, while the remaining 74.56 % is explained by other factors. It is also important to note that volatility correlations between these assets tend to increase during extraordinary periods, such as the COVID-19 crisis.

5.2. Net total directional connectedness

Fig. 4 shows the net TDC between the variables, presented on a cyclical basis.

In Fig. 4, the negative lines indicate that the relevant variable is a "net" volatility receiver during the corresponding period, while the positive lines denote that it is a volatility emitter. Accordingly, the bond variable acts as a net volatility emitter in almost all periods, the S&P 500 variable is a net volatility receiver until the first quarter of 2020 and becomes a net volatility emitter thereafter, while the other variables are generally volatility receivers. Notably, the volatility relationships between BTC and the other variables are minimal. Furthermore, from 2023 onwards, there is a significant increase in the net volatility-emitting role of the bond variable and

Table 4
Table of average dynamic connectedness for the variables.

	BTC	Bond	Oil	Gold	S&P500	DXY	Volatility Received
BTC	**82.78**	3.48	1.78	1.93	6.59	3.44	17.22
Bond	2.00	**77.69**	5.74	4.35	5.94	4.29	22.31
Oil	2.68	12.94	**72.64**	2.50	5.80	3.44	27.36
Gold	2.04	8.07	2.42	**74.16**	5.04	8.27	25.84
S&P500	6.62	9.85	4.06	3.29	**69.90**	6.27	30.10
DXY	3.13	7.91	3.72	6.97	8.10	**70.17**	29.83
Volatility Spilled Over	16.47	42.25	17.73	19.03	31.46	25.72	152.67
NET	−0.75	19.94	−9.63	−6.81	1.36	−4.11	
TCI							25.44

Note: Bold values represent the portion of the volatility changes of the respective variables that is explained by the variables themselves. The values of the variables in the "Net" row show the difference between the volatility spread to "others" and the volatility received from "others". If the difference is negative, the relevant variable is a net volatility receiver, and if it is positive, the relevant variable is a net volatility transmitter. TCI represents the total connectedness index and is calculated with Equation (13). The results are expressed as percentages.

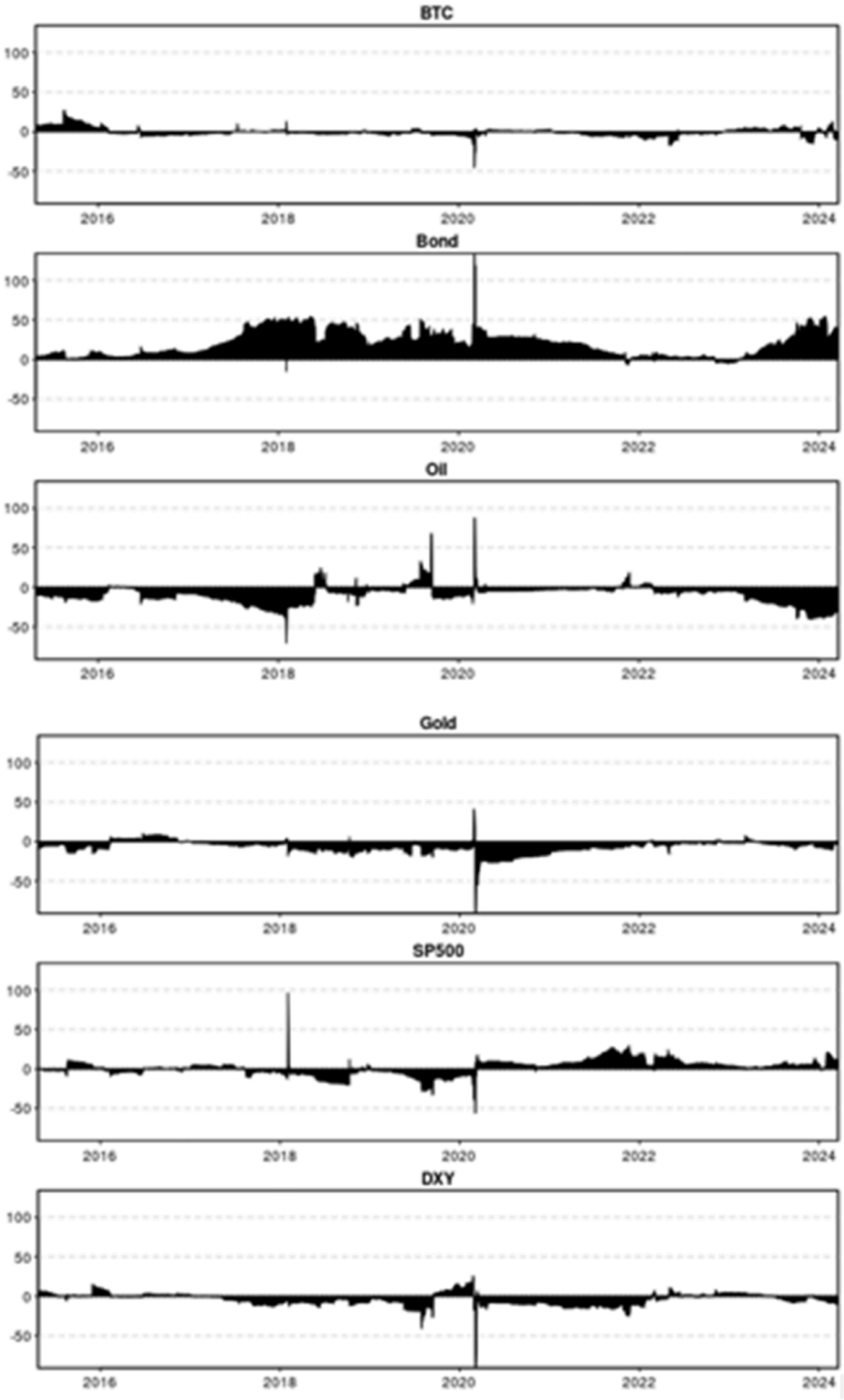

Fig. 4. Net TDC graph.

the net volatility-receiving role of oil.

5.3. *Network plot of volatility spillovers*

Fig. 5 illustrates the volatility spillovers between the volatility series of the relevant assets in the form of network plots. Blue nodes represent volatility emitters, while yellow nodes indicate volatility receivers. Additionally, the size of the nodes reflects the magnitude

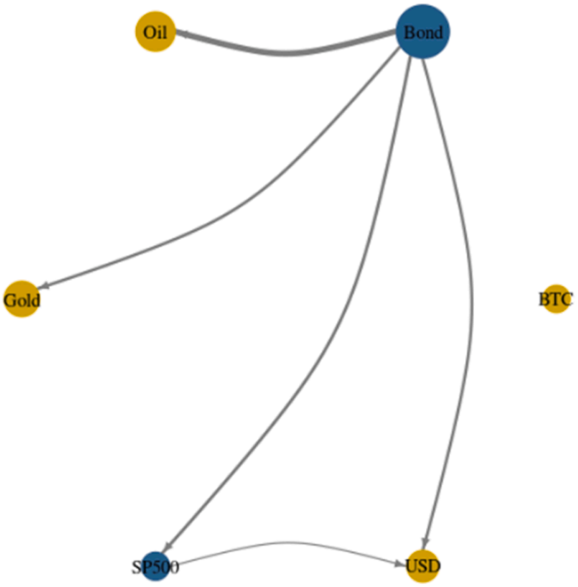

Fig. 5. Network plot of volatility spillover to the variables.

of the spillover effects, and the arrows indicate the direction of the volatility spillovers.

The volatility relationships presented numerically in Table 4 are visually represented in Fig. 5. As observed, the Bond and S&P 500 variables act as volatility emitters, while the other variables are net volatility receivers. The bond variable transmits the largest volatility to the oil variable, suggesting that if these assets are invested together, the potential diversification benefits for the portfolio may not be fully realized. Conversely, a portfolio consisting of BTC and the other variables may offer potential diversification advantages.

BTC is the variable that both emits and receives the least volatility relative to the other assets. It is noteworthy that, despite being relatively new and much smaller compared to other markets, BTC emits as much volatility as it receives. For instance, the S&P 500 index is the second-largest volatility receiver from the BTC market, after the US 10-year bond market. Additionally, BTC receives the largest volatility from the S&P 500.

When looking at the studies in the literature, it is especially stated in many studies that volatility relationships increase during crisis periods. In addition, Dai et al. [18], concluded in their study that crude oil and gold are net receivers of systemic shocks, while Chinese stock markets are net transmitters of systemic shocks. Wang et al. [19] found that volatility in Chinese stock indices spreads to oil and gold. These findings are similar to the findings of our study. Younis et al. [20] reported cases where some stock markets within the scope of the analysis are net transmitters of volatility, while on the other hand, they reported cases where oil and gold are net transmitters of volatility. Corbet et al. [25] reported that the relationship between cryptocurrencies and other assets is low. When the above studies are examined, it is seen that TCI is generally above 50 %. However, in our study, this rate is 25.44 %. Accordingly, a finding that can provide a significant advantage in terms of portfolio diversification has been reached.

6. Discussion

As a result of globalization and the development of information technologies, information flows among international markets are increasing. On the other hand, financial liberalization causes an increase in capital flows as well as goods and services among different countries and markets. Bitcoin, which is especially discussed in this study, completely eliminates borders as a crypto asset that can be stored in a completely decentralized manner and can be transferred directly from peer to peer without any third party. As a result, the increase in the flows among different country economies ensures the integration of the relevant countries and markets.

When considered from a theoretical perspective, first of all, as explained within the scope of the spillover approach by Diebold and Yilmaz [3], it is observed that when a crisis occurs in financial markets, the volatility in these markets increases rapidly and the volatility spills over rapidly to other markets. Secondly, the low volatility spillover relationship between Bitcoin and other traditional assets can be explained within the scope of the modern portfolio theory developed by Markowitz [40]. Accordingly, diversification can be made among low-correlation securities. Thirdly, it is possible to talk about a global financial cycle approach explained by Rey [41]. Accordingly, there is a global financial cycle in capital flows, asset prices and credit growth. One of the determinants of this global financial cycle is the monetary policy practices in the central country (USA). Fourthly, when considering the issue from the perspective of behavioral finance theory, Christie and Huang [42] state that the probability of herding behavior is higher during periods of market stress.

7. Conclusion

Volatility spillovers are a critical consideration for risk management. In this context, identifying volatility-emitting and volatility-receiving variables across different markets or asset classes is of significant interest to risk managers, portfolio managers, and market regulators. This study aims to examine the dynamic interconnectedness among Bitcoin, oil, gold, the S&P 500 index, the US 10-year bond yield, and the US dollar index. The analysis is based on daily data spanning from April 24, 2015, to March 19, 2024, thus encompassing the effects of the COVID-19 period. The study employs the TVP-VAR methodology, as proposed by Antonakakis and Gabauer [1].

The results of the research can be summarized as follows:

1. The total dynamic interconnectedness between the variables has increased rapidly since the second half of 2016, peaked during the COVID-19 period, then began to decline, and has risen again as of 2023.
2. According to the average dynamic interconnectedness results, the US 10-year bond yield and the S&P 500 stock index are net volatility emitters, while oil, gold, the US dollar index, and Bitcoin are net receivers. Notably, the US 10-year bond yield is relatively more dominant in terms of volatility spillovers. These findings are crucial for forecasting the volatility of these variables.
3. The total connectedness between the variables is relatively low, suggesting that these variables can be effectively used together for international portfolio diversification.
4. The findings provide valuable insights for the decision-making processes of risk managers, portfolio managers, and market regulators.

Future research could explore asymmetric volatility relationships for the variables considered in this study. Additionally, a more in-depth analysis of the return and volatility spillover relationships between country-specific stock markets and the variables examined here could provide further insights.

Data availability

Data will be made available on request.

References

[1] N. Antonakakis, D. Gabauer, Refined measures of dynamic connectedness based on TVP-VAR. MPRA Paper No. 78282., 2017.

[2] T. Liu, X. Gong, Analyzing time-varying volatility spillovers between the crude oil markets using a new method, Energy Econ 87 (2020) 104711, https://doi.org/10.1016/j.eneco.2020.104711.

[3] F.X. Diebold, K. Yilmaz, Better to give than to receive: predictive directional measurement of volatility spillovers, Int. J. Forecast. 28 (2012) 57–66, https://doi.org/10.1016/j.ijforecast.2011.02.006.

[4] W. Mensi, I. Yousaf, X.V. Vo, S.H. Kang, Asymmetric spillover and network connectedness between gold, brent oil and EU subsector markets, J. Int. Financ. Mark. Institutions Money 76 (2022) 101487, https://doi.org/10.1016/j.intfin.2021.101487.

[5] N. Antonakakis, I. Chatziantoniou, D. Gabauer, Refined measures of dynamic connectedness based on time-varying parameter vector autoregressions, J. Risk Financ. Manag. 13 (2020), https://doi.org/10.3390/jrfm13040084. MPRA Paper No. 78282.

[6] S. Cheng, M.J. Deng, R. Liang, Y. Cao, Asymmetric volatility spillover among global oil, gold, and Chinese sectors in the presence of major emergencies, Resour. Policy (2023), https://doi.org/10.1016/j.resourpol.2023.103579.

[7] J. Folder, 10-year treasury yield: What it is and why it matters., (2023). https://www.sfgate.com/personal-finance/investing/article/10-year-treasury-yield-18435918.php (05.06.2024).

[8] W.G. Council, Above-ground stock., (2024). https://www.gold.org/goldhub/data/how-much-gold#:~:text=The best estimates currently available, in one form or another (05.06.2024).

[9] https://coinmarketcap.com/charts/, 2024.

[10] Y.-J. Zhang, E. Bouri, R. Gupta, S.-J. Ma, Risk spillover between Bitcoin and conventional financial markets: an expectile-based approach, North Am, J. Econ. Financ. 55 (2021) 101296, https://doi.org/10.1016/j.najef.2020.101296.

[11] D. Roubaud, M. Arouri, Oil prices, exchange rates and stock markets under uncertainty and regime-switching, Financ. Res. Lett. 27 (2018) 28–33, https://doi.org/10.1016/j.frl.2018.02.032.

[12] L. Gasparėnienė, R. Remeikiene, A. Sosidko, V. Vėbraitė, Modelling of S& P 500 index price based on U.S. economic indicators: machine learning approach, Eng. Econ. 32 (2021) 362–375, https://doi.org/10.5755/j01.ee.32.4.27985.

[13] Y. Köse, E. Yılmaz, Dolar endeksi uluslararası bir finansal gösterge olabilir mi? Dünyada önemli borsa endeksleri üzerinde ampirik inceleme, Uluslararası İktisadi ve İdari İncelemeler Derg (2022), https://doi.org/10.18092/ulikidince.930312.

[14] W. Kang, R.A. Ratti, K.H. Yoon, The impact of oil price shocks on the stock market return and volatility relationship, J. Int. Financ. Mark. Instit. Money 34 (2015) 41–54, https://doi.org/10.1016/j.intfin.2014.11.002.

[15] K. Wu, J. Zhu, M. Xu, L. Yang, Can crude oil drive the co-movement in the international stock market? Evidence from partial wavelet coherence analysis, North Am, J. Econ. Financ. 53 (2020) 101194, https://doi.org/10.1016/j.najef.2020.101194.

[16] A.H. Elsayed, S. Nasreen, A.K. Tiwari, Time-varying co-movements between energy market and global financial markets: implication for portfolio diversification and hedging strategies, Energy Econ. 90 (2020) 104847, https://doi.org/10.1016/j.eneco.2020.104847.

[17] İ. Çelik, H.T. Akkuş, N. Gülcan, Investigation of rational bubbles and volatility spillovers in commodity markets: evidences from precious metals, J. Mehmet Akif Ersoy Univ. Econ. Admin. Sci. Faculty 6 (2019) 936–951, https://doi.org/10.30798/makuiibf.586527.

[18] Z. Dai, H. Zhu, X. Zhang, Dynamic spillover effects and portfolio strategies between crude oil, gold and Chinese stock markets related to new energy vehicle, Energy Econ. 109 (2022) 105959, https://doi.org/10.1016/j.eneco.2022.105959.

[19] G. Wang, J. Meng, B. Mo, Dynamic volatility spillover effects and portfolio strategies among crude oil, gold, and Chinese electricity companies, Mathematics 11 (2023) 910, https://doi.org/10.3390/math11040910.

[20] I. Younis, W.U. Shah, I. Yousaf, Static and dynamic linkages between oil, gold and global equity markets in various crisis episodes: evidence from the wavelet TVP-VAR, Resour, Policy 80 (2023) 103199, https://doi.org/10.1016/j.resourpol.2022.103199.

[21] L.T. Ha, T.T. Thanh, V.M. Linh, An exploration of sources of volatility in the energy market: an application of a TVP-VAR extended joint connected approach, Sustain. Energy Technol. Assessments 53 (2022) 102448, https://doi.org/10.1016/j.seta.2022.102448.

[22] P.Y. Ping, M.H.B. Ahmad, N.B. Ismail, Volatility spillover effect study in U.S. dollar and gold market based on bivariate-BEKK model, in: AIP Conf. Proc, 2016 060006, https://doi.org/10.1063/1.4954611.

[23] A. Huang, L. Qiu, Z. Li, Applying deep learning method in TVP-VAR model under systematic financial risk monitoring and early warning, J. Comput. Appl. Math. 382 (2021) 113065, https://doi.org/10.1016/j.cam.2020.113065.

[24] A.H. Dyhrberg, Bitcoin, gold and the dollar – A GARCH volatility analysis, Financ. Res. Lett. 16 (2016) 85–92, https://doi.org/10.1016/j.frl.2015.10.008.

[25] S. Corbet, A. Meegan, C. Larkin, B. Lucey, L. Yarovaya, Exploring the dynamic relationships between cryptocurrencies and other financial assets, Econ. Lett. 165 (2018) 28–34, https://doi.org/10.1016/j.econlet.2018.01.004.

[26] S.J.H. Shahzad, E. Bouri, D. Roubaud, L. Kristoufek, B. Lucey, Is Bitcoin a better safe-haven investment than gold and commodities? Int. Rev. Financ. Anal. 63 (2019) 322–330, https://doi.org/10.1016/j.irfa.2019.01.002.

[27] G. Cao, W. Xie, Asymmetric dynamic spillover effect between cryptocurrency and China's financial market: evidence from TVP-VAR based connectedness approach, Financ. Res. Lett. 49 (2022) 103070, https://doi.org/10.1016/j.frl.2022.103070.

[28] F.X. Diebold, K. Yilmaz, Measuring financial asset return and volatility spillovers, with application to global equity markets, Econ. J. 119 (2009) 158–171, https://doi.org/10.1111/j.1468-0297.2008.02208.x.

[29] F.X. Diebold, K. Yilmaz, Trans-Atlantic equity volatility connectedness: U.S. and European financial ınstitutions, 2004–2014, J. Financ. Econom. (2015) nbv021, https://doi.org/10.1093/jjfinec/nbv021.

[30] F. Wen, M. Zhang, M. Deng, Y. Zhao, J. Ouyang, Exploring the dynamic effects of financial factors on oil prices based on a TVP-VAR model, Phys. A Stat. Mech. Its Appl. 532 (2019) 121881, https://doi.org/10.1016/j.physa.2019.121881.

[31] S. Corbet, C. Larkin, B. Lucey, The contagion effects of the COVID-19 pandemic: evidence from gold and cryptocurrencies, Financ. Res. Lett. 35 (2020) 101554, https://doi.org/10.1016/j.frl.2020.101554.

[32] Ş. Sakarya, M. Yavuz, A.D. Karaoğlan, N. Özdemir, Stock market index prediction with neural network during financial crises: a review on BIST-100, Financ. Risk Manag. Rev. 1 (2015) 53–67, https://doi.org/10.18488/journal.89/2015.1.2/89.2.53.67.

[33] M. Yavuz, N. Özdemir, A feed-forward neural network approach to İstanbul stock exchange, J. Appl. Comput. Sci. Math. 12 (2018) 31–36, https://doi.org/10.4316/JACSM.201802005.

[34] Ö. Kaymak, Y. Kaymak, N. Özdemir, Forecasting of the İstanbul stock exchange (ISE) return with a golden ratio model in the epidemic of COVID-19, Appl. Comput. Math. (2021).

[35] H. Hüseyin Yildirim, A. Akusta, Key drivers of volatility in BIST100 firms using machine learning segmentation, An Int. J. Optim. Control Theor. Appl. 15 (2025) 183–201, https://doi.org/10.36922/ijocta.1707.

[36] F.X. Diebold, K. Yılmaz, On the network topology of variance decompositions: measuring the connectedness of financial firms, J. Econom. 182 (2014) 119–134, https://doi.org/10.1016/j.jeconom.2014.04.012.

[37] G. Koop, M.H. Pesaran, S.M. Potter, Impulse response analysis in nonlinear multivariate models, J. Econom. 74 (1996) 119–147, https://doi.org/10.1016/0304-4076(95)01753-4.

[38] H.H. Pesaran, Y. Shin, Generalized impulse response analysis in linear multivariate models, Econ. Lett. 58 (1998) 17–29, https://doi.org/10.1016/S0165-1765(97)00214-0.

[39] H. Özdemir, Altının riskten korunma etkinliği: farklı dinamik portföy yaklaşımları ile bankacılık sektörü için bir analiz, Ekon. Polit. Finans Araştırmaları Derg. 7 (2022) 889–908, https://doi.org/10.30784/epfad.1217479.

[40] H. Markowitz, Portfolio selection, J. Finan. 7 (1952) 77–91, https://doi.org/10.2307/2975974.

[41] H. Rey, Dilemma not trilemma: the global financial cycle and monetary policy independence, NBER Work. Pap. Ser. (2015).

[42] W.G. Christie, R.D. Huang, Following the pied piper: do individual returns herd around the market? Financ. Anal. J. 51 (1995) 31–37, https://doi.org/10.2469/faj.v51.n4.1918.