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RESEARCH ARTICLE

Volatility spillovers of global economic policy uncertainty and fear index among cryptocurrencies: A wavelet-based DCC-GARCH approach

Aslan Aydoğdu

Lec. Dr., Sivas Science and Technology University, Projects Office General Coordinator, Türkiye, email: aaydogdu@sivas.edu.tr

Abstract

This research analyzes the dynamic relationships between the economic and political uncertainty index and the fear index in global markets and cryptocurrencies using the wavelet-based DCC-GARCH method, considering different time scales. Monthly data sets for the periods 2012–April 2024 for GEPU,VIX, and Bitcoin and April 2016–April 2024 for Ethereum are used in the study. Findings are obtained in terms of the volatility interaction between cryptocurrencies (Bitcoin and Ethereum) and GEPU and VIX, as well as four different time scales representing the short, medium, and long term. As a result of the analysis based on raw data, it was found that there is no volatility interaction between cryptocurrencies and GEPU and VIX returns. However, there is a volatility interaction between past volatility shocks and current period volatility shocks in the 4-8 and 16-32 month investment cycle periods of VIX, Bitcoin, GEPU, and Ethereum and time scales. These results, which show that volatility shocks persist in both 4-month and 16-month investment cycles, have significant implications for investors and policymakers. They highlight the need for comprehensive information about changes in the global economy and politics, and they are expected to provide insights for both investors and policymakers.

Keywords: Wavelet Analysis, DCC-GARCH, Volatility Spillovers, Cryptocurrencies, Bitcoin

JEL codes: C10, G11, C53

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Corresponding Author:
Aslan Aydoğdu
E-mail: aaydogdu@sivas.edu.tr

1. INTRODUCTION

The concept of investment is generally divided into capital investments and financial investments, and both methods aim to transform savings into capital accumulation. In this context, today's investors prefer many alternative investment instruments to obtain more capital accumulation. However, recently, there has been an orientation towards a different investment instrument. One of these alternative investment instruments is cryptocurrencies. The reasons for the orientation towards cryptocurrencies are technological developments in the payments system, which is a necessity of the digital age that awaits us in the future, and the changing risk perception (Tuncel and Gürsoy, 2020:2000).

The perception that the dollar, which was seen as the safest currency in global markets until the 2008 mortgage crisis, would be dethroned with the crisis, and Nakamoto, who took advantage of this gap, proposed Bitcoin in 2008 and in the following years, different cryptocurrencies such as Ethereum and Ripple emerged. In addition to these cryptocurrencies, the number of cryptocurrencies in actual circulation in the cryptocurrency market is more than 22,000 as of March 2023, with a market capitalization exceeding 1 trillion dollars, showing a significant growth potential (CoinMarketCap, 2023; Aydoğdu, 2024: p.1). Cryptocurrencies, whose functions as money were initially discussed, have recently started to be evaluated as an investment instrument and have been accepted as an alternative investment instrument by a significant mass of investors. With the impact of recent developments, such as; the pandemic and, the Russia-Ukraine crisis, the relationship between the crypto asset market and conventional financial assets has become curious. Especially after the Russia-Ukraine crisis, many people worldwide have questioned financial markets, and decentralized currencies have become a more popular alternative.

Volatility of financial instruments is one of the most important indicators that investors pay attention to when making investment decisions. In addition to the volatility in the national market, investors also follow the volatility in the international market. With the acceleration of globalisation, financial markets are interrelated with each other and a volatility occurring in one of them affects the others. Therefore, investors also take into account the volatility in international markets when making decisions. In this context, the VIX fear index is a volatility index considered by investors (Akdağ, 2019: 236).This index is a risk indicator calculated by the Chicago Options Exchange in the United States based on the differences between the option bid and option ask prices of stocks.

The Volatility Index is an indicator that measures anxiety and fear in the markets and is also known as the VIX Fear Index. Various forecasting methods have been developed to assess the uncertainties in the global economy, and new indexing methods have been emphasised in academic studies. In particular, index that analyse economic and political uncertainties stand out as methods that examine political situations as well as financial risks. The Global Economic Political Uncertainty Index (GEPU), which is the basis of this study, is an index developed by Baker et al. in 2013, representing the economies of 16 countries. This index includes national EPU index based on the frequency of newspaper reports on the economy, uncertainty and politics, and currently includes indices for 21 countries. These 21 countries represent approximately 71 per cent of global output adjusted for purchasing power parity and 80 per cent at market exchange rates (Keser, 2022: p. 121).

Investors portfolio diversification strategies to manage financial risk may vary depending on their investment horizons (short, medium, and long-term). Accordingly, active investors, such as risk-seeker institutional and retail investors, are interested in the interactions between high-frequency (low time-scale) cryptocurrencies and the returns of economic and political uncertainty and fear indices, i.e., short-term fluctuations. On the other hand, passive investors, such as risk-averse and risk-neutral institutional and retail investors, are interested in the interactions between cryptocurrencies at low frequencies (high time-scale) and the returns of the economic political uncertainty index and the fear index, i.e., long-term fluctuations. As a result, investors from different groups face different risks. Studying the relationships between cryptocurrencies and the returns on the economic, political uncertainty, and fear indexes at different time scales is crucial for risk management. As a matter of fact, for investors seeking alternative investment instruments, determining the time scale in which the correlation between the financial assets in the portfolio is low will ensure that the investor will benefit from portfolio diversification (Benhmad, 2013) because a high correlation between assets in a portfolio may cause the investor to make meager gains in terms of risk management. The heterogeneity caused by investors with different investment horizons in the market may cause the spillover effects between markets to change over time and at different frequencies. However, studies examining the relationship between cryptocurrencies and the economic political uncertainty index and the fear index mainly focus on a single time scale and ignore the risks that investors may face according to different time scales and the spillovers between these risks (Uyar and Kangalı Uyar, 2021: p. 310)

With wavelet decomposition analysis, it is possible to examine the change in the relationship between two-time series according to time and different frequencies. Thus, the wavelet approach can help to reveal potential spillover effects by allowing the existence of spillover effects between cryptocurrencies and the economic political uncertainty index, and the fear index returns to be examined according to different time scales. There are many studies on cryptocurrencies in the literature. However, studies on the volatility spillovers between cryptocurrencies and the global economic uncertainty and fear indexes are limited. In addition, no study has been found in the literature that analyses the interaction between cryptocurrencies and GEPU and VIX returns according to different time scales. In short, such a study on cryptocurrencies, whose popularity is increasing day by day and which are at the centre of various debates, will be beneficial to the literature. In addition, analyses based on the combination of both methods can provide inferences on determining the appropriate time periods to benefit from the advantages of portfolio diversification.

Therefore, the purpose of this study is to examine the impact of price movements in the Global Economic Political Uncertainty Index (GEPU) and the Fear Index (VIX) on crypto currencies. For this purpose, in the first section, information on cryptocurrencies, the economic policy uncertainty index (EPI), and the fear index (VIX) are given. A literature review is included in the second part of the study, and studies on volatility spillovers are included. The third section explains information about the data used in the analysis, wavelet decomposition analysis, and the DCC-GARCH model theory. In the fourth section, the findings obtained are interpreted. In the last section, some evaluations are made as a result of these findings.

2. LITERATURE REVIEW

Studies have carried out a comprehensive examination of the relationship between cryptocurrencies and other economic indicators in different time periods and using various analysis methods. These studies aimed to analyse the effects of economic indicators on cryptocurrency markets in detail with the variety of data sets used. However, all of these methods are based on a single time scale. However, recently, studies using methods that take into account different time scales and/or different investment horizons have also taken their place in the literature. The literature on the subject is presented in Table 1.

Table 1. Literature Review

Imprint	Aim	Sampling Period	Method/ Model	Result
Corbet vd. (2018)	It aims to investigate the relationships and frequency fields between crypto currencies and different financial assets.	Daily data set for the periods 29.04.201307. 02.2014 10.02.201430. 04.2017.	Diebold and Yilmaz analysis method/Barunik and Krehlik method of analysis	It is concluded that cryptocurrencies can provide diversification benefits for investors with short investment horizons. Moreover, time variation in linkages is found to reflect external economic and financial shocks.
İltaş (2020)	This research aims to examine the relationship between BIST 100 Index and economic, political, financial and geopolitical risks.	Monthly data set for the period January 1999-December 2014.	Toda-Yamamoto causality test/ Hacker Hatemi-J bootstrap causality test	It has been concluded that economic, political and geopolitical risks have a symmetric and asymmetric causal relationship with stock prices in Turkey.

Bakır (2021)	This research aims to examine the relationship between cryptocurrencies and economic indicators.	Daily data set for the period 03.12.2019-03.20.2020.	Pedroni cointegration test Granger causality test	As a result of the analysis, it is concluded that Bitcoin and Ethereum do not have a long-run relationship with some commodities and economic indicators. However, bidirectional and unidirectional causality relationships were found between Bitcoin and Ethereum and G20 stock market indices, some commodities and volatility indices. Moreover, these cryptocurrencies are found to have significant regression relationships with market volumes, some commodities and economic indicators.
Khan vd. (2021)	It aims to examine the relationship between global economic policy uncertainty and bitcoin prices.	Monthly data set between April 2011 and March 2020.	Rolling window method Granger causality	According to the results of the analyses, it is determined that there is no causality relationship between GEPU and BCP. However, considering the structural changes, it is concluded that the full sample causality relationship between the variables may be different. Moreover, the finding of the rolling window test shows that there is causality in different sub-samples; both positive and negative bidirectional causality between GEPU and BCP were found in these sub-samples.
Gürsoy ve Kılıç (2021)	This research aims to analyse the impact of global economic and political uncertainties on financial markets in Turkey.	Monthly data set for the period March 2010-October 2020.	DCC-GARCH	The analyses reveal that there is a strong volatility relationship between GEPU index, CDS premium and BIST banking index.
Sajeev and Afjal (2021)	It is aimed to examine the contagion effect of Bitcoin on the National Stock Exchange, Shanghai Stock Exchange, London Stock Exchange and Dow Jones Industrial Average by analysing the volatility spread and correlation between these markets.	Daily data set for the period March 2017-May 2021.	BEKK-GARCH / DCC-GARCH	The overall time-varying correlation between Bitcoin and stock markets is low, indicating that Bitcoin can be taken as an asset to hedge against the risk of these stock markets. It was also concluded that these stock markets reacted more to negative shocks than to positive shocks in the Bitcoin market in 2018 and 2021.
İmre (2021)	It is aimed to examine the volatility interaction between Bitcoin and Euro returns.	Daily data set for the period 02 February 2014-28 February 2021	BEKK-GARCH / DCC-GARCH	The analyses revealed a bidirectional volatility interaction between the Euro and Bitcoin. In addition, an asymmetry relationship and a positive, strong dynamic correlation between the two returns were found.
Ghorbel and Jeribi (2021)	It aims to analyse the relationships between five cryptocurrencies and the volatilities of S&P500, Nasdaq and VIX indices, oil and gold.	Daily data set for the period 01 January 2016 - 01 April 2020	BEKK-GARCH / DCC-GARCH	The results of both analyses show evidence of a higher volatility spread between cryptocurrencies and a lower volatility spread between cryptocurrencies and financial assets, and the introduction of Bitcoin futures is found to have a significant impact.

Gökalp (2022)	This research aims to investigate the impact of cryptocurrency market developments on Borsa Istanbul (BIST) indices.	Daily data set for the period 01/01/2014-31/12/2021.	BEKK-GARHCH/DCC-GARCH	According to the analysis results, a positive spillover effect from the cryptocurrency markets to indices has been identified. Oil prices, as one of the control variables, have shown a significant impact on volatility across all models. Furthermore, varying results were observed concerning the influence of the fear index.
Keser (2023)	This research aims to investigate the causality relationship between global economic political uncertainty and geopolitical risk and Bitcoin energy consumption.	Monthly data set from May 2011 to February 2022.	Lee-Strazich unit root test Hatemi-J (2012) causality test	According to the analysis results, it has been determined that global economic political uncertainty and geopolitical risk have an impact on bitcoin energy consumption. It has also been concluded that the negative effects of global uncertainty and geopolitical risks are more dominant.

3. METHODOLOGY

3.1. Purpose of the Research and Data Set

The main objective of this research is to examine the impact of global economic and political uncertainties and changes in the fear index on cryptocurrencies. In this context, the global economic and political uncertainty index (GEPU) developed by Baker et al. (2016) and Davis (2016), the fear index (VIX) created by CBOE, and the cryptocurrencies Bitcoin and Ethereum are determined as the main variables used in this study. Data for the variables were obtained by using the "policyuncertainty.com" database for the global economic uncertainty index. Fear index, Bitcoin and Ethereum data were obtained using the "investing.com" database. In the study, the period between GEPU, VIX and Bitcoin is April 2012-April 2024; For Ethereum, the wavelet-based DCC-GARCH model was run using monthly data between April 2016 and April 2024. While creating the data set of the study, these dates were determined due to data constraints for the variables. In the study, the Wavelet-based DCC-GARCH model determines the volatility interaction and transfer according to different time scales and also indicates the relationship between variables. For this reason, the DCC-GARCH model based on Wavelet was preferred in the study. The returns of the variables were calculated according to the formula in equation (1):

$$r_{i,t} = \log\left(\frac{P_{i,t}}{P_{i,t-1}}\right) * 100 \tag{1}$$

Here $r_{i,t}$, represents the return series of the i'th financial asset at time t; $P_{i,t}$ and $P_{i,t-1}$ show the closing prices of financial assets at time t and t-1, respectively.

3.2. Wavelet Decomposition Analysis

Wavelets can be explained as short fluctuations in time with a specific start and end point (Lehkonen and Heimonen, 2014: p.92).Although the Wavelet approach is more comprehensive than the Fourier approach, it is an approach that allows the behavior of a time series to be separated and examined according to different frequencies over time. This flexibility provided by the wavelet approach allows revealing time series behavior or features that cannot be revealed with only time-dependent approaches. This is because it can be examined how the relationships between variables change over time according to different frequencies. Thus, instead of examining financial asset returns for different periods in finance applications, various return layers that make up the total return can be examined. Similarly, instead of examining volatility for different periods, various volatility layers that make up volatility can be obtained through wavelet decomposition and how the behavior of risk evolves over time can be observed. The wavelet approach allows time series to be analyzed without applying any transformation to non-stationary time series and therefore without loss of observation (Schleicher, 2002:p.27).

Moreover, the non-parametric nature of the wavelet approach allows non-linear relationships between variables to be taken into account without any loss of information. These advantages of the wavelet approach, which is based on time and frequency, are the most important reasons why it is a more effective technique than time-only approaches. The wavelet approach was first applied in the field of economics by Ramsey and Lampart (1998a,b) in order to analyze the relationships with money supply (M1 and M2). In recent years, Rua and Nunes (2009), Jammazi and Aloui (2010), Masih etal., (2010), Ismail et al., (2016), Omane-Adjepong and Alagidede (2019), Uyar and Kangallı Uyar (2021), Hairudin and Mohamad (2023), Aydoğdu (2024) etc. It has been introduced to the literature in economics and finance by researchers such as using this approach.

In wavelet analysis, a time series can be decomposed into different time scales by applying wavelet transformation. Father wavelet in wavelet analysis Two basic functions are defined: mother wavelet and mother wavelet. The father wavelet contains the low-frequency components of the original series and shows the trend of the series; The mother wavelet contains the high-frequency components of the series and shows deviations from the trend, in other words, it reflects the details in the data (Crowley, 2007). The father wavelet and mother wavelet can be defined as in equation (2) and equation (3), respectively (Ramsey and Lampart, 1998):

$$Ø_{j,k}(t) = 2^{-\frac{1}{2}} Ø\left(2^{-j} * t - k\right), j = 1,2, \dots, J; k = 0,1, \dots, 2^{j} - 1 \tag{2}$$

$$\psi_{j,k}(t) = 2^{-\frac{j}{2}} \psi\left(2^{-j} * t - k\right), j = 1,2, \dots., J; k = 1, \dots., 2^{j} - 1 \tag{3}$$

Wavelet functions depend on the scale or frequency parameter j and the location parameter k. Although 2^{j}, is called the scale, it can be treated as a measure of the width of the $Ø_{j,k}$(t) function. Accordingly, as the values of j increase, the function becomes shorter and spreads further. The scale parameter determines the size of the wavelet, while the position parameter sets the location of the wavelet. A scale parameter ranging from 1 to J means that the time series is decomposed at J different levels according to the highest time scale J. $Ø(.)$ ve $\psi(.)$, (-∞,∞) are real-valued functions defined on the real axis, and it is assumed that these functions meet the normalization conditions defined in equations (4) and (5):

$$\int_{-\infty}^{+\infty} Ø(t) dt = 1 \tag{4}$$

$$\int_{-\infty}^{+\infty} \psi(t) dt = 1 \tag{5}$$

A time series such as x(t) defined at $L^{2}(R)^{3}$ can be expressed in terms of wavelet functions as in equation (6):

$$x(t) = \sum_{k=0}^{2^{j}-1} S_{J,k} Ø_{J,k}(t) + \sum_{j=1}^{J} \sum_{k=0}^{k^{j}-1} d_{j,k}\ \psi_{j,k}(t) \tag{6}$$

Here it is defined as$S_{J,k} = \int_{-\infty}^{+\infty} t(t) Ø_{J,k}(t) dt = 1$ ve $d_{j,k} = \int_{-\infty}^{+\infty} x(t) \psi_{j,k}(t) dt = 1$. $S_{J,k}$, are called smooth coefficients, while $d_{j,k}$ are called detail functions. The sizes of these coefficients show the share of wavelet functions in the total data. In the expression in Equation (7);

$$S_{t}(t) = \sum_{k=0}^{2^{j}-1} S_{J,k} Ø_{J,k}(t) \tag{7}$$

ve

$$D_{j}(t) = \sum_{k=0}^{2^{j}-1} d_{j,k}\, \psi_{j,k}(t), j = 1,2, \dots\dots, J \tag{8}$$

When defined as x(t) time series can be re-expressed as in equation (9):

$$x(t) = S_{J}(t) + \sum_{j=1}^{J} D_{j}(t) \tag{9}$$

Here, $S_J(t)$, reflects the trend of the data; because it is the component of the highest level time scale. $D_j(t) = (D_1(t), D_2(t), \dots\dots\dots\dots\dots\dots, D_J(t))$ are the details containing the fluctuations in the data on 2-4, 4-8,…..,$2^J - 2^{J+1}$ time scales, respectively.

Small values of j correspond to the low time scale, thus representing the high-frequency components of $x(t)$, while large values of j correspond to the high time scale, and thus represent the low-frequency components of $x(t)$. Since D_j, includes cyclical movements between coefficients $2^J - 2^{J+1}$,in period D_1, 2-4; In period D_2, 4-8, etc. Includes cyclic movements.

Discrete wavelet transformation can be applied to obtain wavelet coefficients (smooth and detailed coefficients). In discrete wavelet transform (DWT), the researcher determines how many different time scales the time series will be decomposed according to the number of observations. Moreover, in DWT, it is stated that the number of observations must have a dyadic feature, in other words, it must be an integer that is a multiple of two. Since this feature of DWT is restrictive in determining time scales in applications, *"maximum overlap discrete wavelet transform (MODWT)",* a type of discrete wavelet transform, is generally applied instead of DWT. On the other hand, any sample size can be used for MODWT, it does not have to be dyadic. In this study, MODWT will be used to obtain wavelet coefficients due to the restrictive assumptions of DWT.

Wavelet filters with different features (D(4), D(8), LA(8) and Haar wavelet) can be used to obtain wavelet coefficients with MODWT (Gençay et al., 2002: 113-116). Gençay et al. (2002, 2010) and Cornish et al. (2006) and others and frequently used in the literature is LA(8) (least asymmetric wavelet filter of length eight). This is because the LA(8) filter produces smoother and uncorrelated wavelet coefficients than other filters.

In the study, after the wavelet coefficients based on MODWT were calculated for the returns of each variable, the return series were calculated according to four different time scales (D_1-2-4 months, D_2-4-8 months, D_3-8-16 months, Dg=16-32 months, Sg) was isolated. Cycle times for different time scales are defined in Table 2:

Table 2. Wavelet Analysis Time Horizons According to the Multiple Scale Method

Scales	(2^j)	Annual Frequency	Monthly Frequency	Daily Frequency
1	2^1	2-4	2-4	2-4
2	2^2	4-8	4-8	4-8
3	2^3	8-16	8-16 (8 months-1 year 4 months)	8-16
4	2^4	16-32	16-32 (1 years 4 months-2 years 8 months)	16-32 (3 weeks 1 day-6 weeks 2 day)
5	2^5	32-64	32-64 (2 years 8 months-5 years 4 months)	32-64 (6 weeks 2 day-12 weeks 4 day)
6	2^6	64-128	64-128 (5 years 4 months-10 years 8 months)	64-128 (12 weeks 4 day-25 weeks 3 day)
7	2^7	128-256	128-256 (10 years 8 months-21 years 4 months)	128-256 (25 weeks 3 day- 51 weeks 1 day)
8	2^8	256-512	…..	….

Source: Crowly (2007:214). Theoretically, the maximum number of scales is expressed as 9. In the case where the scale number is indicated by j (j = 9), the frequencies are calculated using 2j notation.

Considering the scale frequencies given in Table 2; After a wavelet analysis is performed, predictions will be made for the specified number of scales and coefficients will be estimated for various investment horizons. The time scales in Table 2 are grouped as follows: $(D_1 - D_2 - D_3)$: short term; $(D_4 - D_5 - D_6)$: medium term; $(D_7 - D_8 - S_8)$: long term. This type of grouping was made to examine how the movements of investors with short, medium and long-term investment horizons develop according to different time scales. Short-term investment horizons $(D_1 - D_2 - D_3)$; It refers to short-term changes due to shocks occurring on time scales of 2-16 months and includes daily-weekly spreads. Medium-term investment horizons $(D_4 - D_5 - D_6)$; It shows medium-term changes on time scales of 32-128 months and covers monthly to quarterly spreads. Long-term investment horizons are $(D_7 - D_8 - S_8)$; It indicates long-term changes on time scales of 256 months and longer and is a period covering annual spreads (Uyar and Kangalı Uyar, 2021: p. 319; Aydoğdu, 2024: p. 217-218).

3.3. DCC-GARCH Approach

The dynamic conditional correlation (DCC) approach was developed by Engle (2002) to examine time-varying correlations between asset returns. To examine in more detail how this approach was developed and what assumptions it is based on, let the vector containing the logarithmic returns of k financial assets be denoted by r_t. Financial asset returns have the following distribution under the assumptions that there is no autocorrelation between average returns and that quadratic moments vary over time:

$$r_t \mid I_{t-1} \sim D(\mu, H_t) \tag{10}$$

Here, r_t, is the payoff vector of size I_{t-1},; $t-1$ represents the information set at time t-1; μ is the unconditional mean, which is usually very close to or equal to zero; H_t denotes the dynamic conditional covariance matrix of the k-return series of size kxk, and $D(u, H_t)$, denotes the multivariate density function that depends on the mean vector and the dynamic conditional covariance matrix.

Engle (2002; p. 341) decomposed the covariance matrix as the product of dynamic conditional standard deviations and dynamic conditional correlations:

$$H_t = D_t R_t D_t \tag{11}$$

Here, D_t, is a diagonal matrix of size kxk and its elements consist of time-varying standard deviations obtained from univariate GARCH models. In the D_t matrix, the i'th element of the diagonal can be represented as $\sqrt{h_{it}}$ hit:

$$D_t = \begin{bmatrix} \sqrt{h_{1t}} & 0 & \cdots & 0 \\ 0 & \sqrt{h_{2t}} & \ddots & \vdots \\ 0 & \dots & \cdots & \sqrt{h_{kt}} \end{bmatrix} \tag{12}$$

R_t, is the time-varying correlation matrix of $\eta_t = {D_t}^{-1} * r_t, R_t \sim N(0, R_t)$, standardized residues of size kxk:

$$R_t = \begin{bmatrix} 1 & \rho_{12,t} & \dots & \cdots & \rho_{1k,t} \\ \rho_{12,t} & 1 & \vdots & \ddots & \vdots \\ \rho_{1k,t} & \dots & \rho_{k-1,k,t} & \cdots & 1 \end{bmatrix} \tag{13}$$

Since H_t, is a covariance matrix, it must be a positive definite matrix. Since D_t, is a positive definite matrix due to its positive diagonal elements R_t must also be a positive definite matrix. Finally, the elements in the must be less than or equal to 1 because they include conditional correlation coefficients.

Using the representations in Equations (10)-(11), it can be deduced that the marginal density function of each element of the r_t vector, in other words, the return of each financial asset, *"depends on the time-varying conditional variance"* and the time-varying conditional variance, which is the representative of volatility. can be modeled as a univariate GARCH process. Accordingly the D_t matrix can be created using the univariate GARCH(p, q) model defined in equation (11):

$$h_{it} = \theta_i + \sum_{p=1}^{p_i} \alpha_{ip}\, \varepsilon_{it-p}{}^2 + \sum_{q=1}^{Q_i} \beta_{iq} h_{it-q} \quad i = 1,2,\ldots\ldots,k \tag{14}$$

Here, θ_i is the constant term. non-negativity of parameters and stationarity in variance in the GARCH(p, q) model:

$$\sum_{p=1}^{p_i} \alpha_{ip}\, \varepsilon_{it-p}{}^2 + \sum_{q=1}^{Q_i} \beta_{iq} h_{it-q} < 1 \tag{15}$$

It is assumed that the constraints in equality (15) are satisfied. Satisfying these constraints ensures that the matrix is a positive definite H_t matrix for all time points.

The standardized return vector is obtained by dividing the return of each financial asset by its conditional standard deviation, $\sqrt{h_{it}}$,:

$$\eta_t = D_t{}^{-1} * r_t, \qquad \eta_t \sim N(0, R_t) \tag{16}$$

This vector can be used to define the dynamic conditional correlation structure defined by Engle (2002) for the return series:

$$Q_t = \left(1 - \sum_{m=1}^{M} \alpha_m - \sum_{n=1}^{N} \beta_n\right) * \bar{Q} + \sum_{m=1}^{M} \alpha_m (\eta_{t-m} \acute{\eta}_{t-m}) + \sum_{n=1}^{N} \beta_n Q_{t-n} \tag{17}$$

Here α_m and β_n are non-negative scalars. Due to the stability condition, it is assumed that $\alpha_m + \beta_n < 1$. Providing these assumptions is important for the H_t matrix to be a positive definite matrix. Since $Q_t = \bar{Q}$ if the constraint $\alpha_m = \beta_n = 0$ is met, it can be said that the use of a time-invariant conditional correlation model will be sufficient to examine the relationships (Lebo and Box Steffensmeier, 2008: 694). $\bar{Q}$, is the unconditional covariance matrix of the standardized residuals from the first-stage estimation:

$$\bar{Q} = Cov[\eta_t \acute{\eta}_t] = E[\eta_t \acute{\eta}_t] \text{ ve } \bar{Q} = \tfrac{1}{T}\textstyle\sum_{t=1}^{T} \eta_t \acute{\eta}_t \tag{18}$$

It can be predicted by. Finally, the model defined in equation (17) can be represented as DCC(m, n).

However, since Q_t, does not meet the definition of a dynamic conditional correlation matrix, Engle (2002) suggested the following standardization:

$$R_t = Q_t{}^{*-1} * Q_t * Q_t{}^{*-1} \tag{19}$$

Here $Q_t{}^*$, is a diagonal matrix containing the square roots of the diagonal elements of the matrix $\bar{Q}_t$:

$$Q_t{}^* = \begin{bmatrix} \sqrt{q_{11,t}} & 0 & \cdots & 0 \\ 0 & \sqrt{q_{22,t}} & \ddots & \vdots \\ 0 & \cdots & \cdots & \sqrt{q_{nn,t}} \end{bmatrix} \tag{20}$$

$Q_t{}^*$, rescales the elements of the Q_t matrix to be $|\rho_{ijt}| = \left|\frac{q_{ijt}}{\sqrt{q_{iit} q_{jjt}}}\right| \leq 1$. Q_t must be a positive definite matrix.

The elements of the R_t matrix are in the form $\rho_{ijt} = \frac{q_{ijt}}{\sqrt{q_{iit} q_{jjt}}}$. The fact that the R_t matrix is a positive definite matrix depends on the Q_t matrix being a positive definite matrix.

Engle (2002) defined the logarithmic likelihood function for the maximum likelihood estimation of the DCC model defined in equation (12) as follows:

$$L = \frac{1}{2}\sum_{t=1}^{T} k * \log(2\pi) + \log(|H_t|) + r_t{}' H_t{}^{-1} r_t \quad (21)$$

If the expression where H_t is equal in equation (10) is substituted in equation (15), the logarithmic likelihood function in equation (16) is obtained by using $\eta_t = D_t{}^{-1} * r_t$ equation:

$$L = \frac{1}{2}\sum_{t=1}^{T} k * \log(2\pi) + 2 * \log(|D_t|) + n_t{}' R_t{}^{-1} n_t \quad (22)$$

The definition of the logarithmic likelihood function in equation (22) facilitates the estimation of the DCC model, because the function has two components, namely the volatility component and the correlation component, and the estimation can be carried out by splitting the estimation process into two. The first component is the volatility component and contains only terms in D_t, and the second component is the correlation component and contains only terms in R_t, The reason why the DCC model is estimated in two stages can be explained by this structure. In the first stage, only the part containing the volatility component is maximized, and in the second stage, the correlation component conditional on D_t is maximized, and thus estimates of the parameters of the DCC model, α_m and β_n are obtained. The parameters α_m and are the determinants of the correlation between two series. The parameter shows the short-term effects of volatility, and the β_n parameter shows the long-term permanent effects (Uyar and Kangalı Uyar, 2021: p. 322) .

4. ANALYSIS FINDINGS

In this study using monthly data, descriptive statistics and unit root analysis of the raw returns of the variables were performed. Then, the study analyzes were carried out in two stages. In the first stage, variable returns were decomposed into different time scales using wavelet decomposition analysis. In the second stage, the dynamic correlation relationship between the return series of variables separated according to different time scales was examined according to the DCC-GARCH approach. The DCC-GARCH (1,1) model to be estimated was created as follows:

$$r_t = \mu + \varepsilon_t, t = 1,2,\ldots,T, \varepsilon_t \mid I_{t-1} \sim N(0, H_t) \quad (23)$$

$$H_t = D_t R_t D_t, D_t = diag\left(\sqrt{h_{1t}}, \sqrt{h_{2t}}\right) \quad (24)$$

$$h_{it} = \theta_i + \alpha_i \varepsilon_{it-1}{}^2 + \beta_i h_{it-1}, i = \text{VIX, Bitcoin} \quad (25)$$

$$R_t = Q_t{}^{*-1} * Q_t * Q_t{}^{*-1}, Q_t{}^* = diag\left(\sqrt{q_{11,t}}, \sqrt{q_{22,t}}\right) \quad (26)$$

$$Q_t = (1 - \alpha - \beta) * \bar{Q} + \alpha(\eta_{t-1}\acute{\eta}_{t-1}) + \beta Q_{t-1} \quad (27)$$

Here, the DCC-GARCH (1,1) model is defined to study the dynamic correlation between VIX and Bitcoin. Similarly, the DCC-GARCH (1,1) model is created for other variable returns. DCC-GARCH (1,1) model is defined within the return series of the variables separated into different time scales. These models are defined as wavelet-based DCC-GARCH(1,1) models. In the models, VIX return on time scale D_1 and Bitcoin on time scale D_1, VIX return on time scale D_4, and Bitcoin on time scale , etc. The dynamic correlations between them were examined. Similar matchings were made for return series of variables on other time scales. As a result, 4 DCC-GARCH (1,1) models based on raw data; 16 DCC-GARCH (1,1) models based on four different time scales (4x4) were estimated.

Table 3. Descriptive Statistics of Return Series of Variables

	Bitcoin	Ethereum	GEPU	VIX
Mean	0.0651	0.0604	0.0026	0.0004
Median	0.0277	0.0316	-0.0020	-0.0040
Maksimum	1.7249	1.1426	0.6279	0.8525
Minimum	-0.4665	-0.7719	-0.4987	-0.6142
Standard Deviation	0.2656	0.3135	0.1791	0.2421
Skewness	1.8256	0.4579	0.4104	0.3971
Kurtosis	12.9327	4.0861	4.5647	3.8066
Jarque-Bera	681.2857***	8.1582**	4.6547***	7.7959**
P. Value	[0.0000]	[0.0169]	[0.0000]	[0.0202]
Observations	146	97	146	146

Note: ***, ** and * indicate statistical significance at 1%, 5% and 10% confidence intervals, respectively.

Table 3. includes descriptive statistics of the return series of Bitcoin, Ethereum, Global Economic Political Uncertainty Index (GEPU) and Fear Index (VIX). It can be seen that the mean values of all variables are close to zero and positive. While the highest average return belongs to Bitcoin and Ethereum; When evaluated in terms of volatility, it can be seen that Bitcoin has the highest standard deviation in the examined data range and is the GEPU with the lowest standard deviation. It can be seen that the coefficients of all return series are positive and right-skewed. It is seen that the kurtosis values are positive and greater than three and the series have an extremely flat (leptokortic) structure. Positive skewness coefficients indicate that positive returns occur more frequently than negative extreme returns. When the Jarque-Bera test statistics, which test the normality assumption of all variables, were evaluated, it was confirmed that the return series did not comply with the normal distribution. This result provides an important reason for using the wavelet-based DCC-GARCH approach, which does not make any distributional assumptions, to examine the relationships between markets. Before performing the wavelet-based DCC-GARCH analysis, unit root tests were carried out to determine whether the return series were stationary.

Table 4. Unit Root Tests of Price and Return Series of Variables

		Price			Return		
	Model	ADF	PP	KPSS	ADF	PP	KPSS
Bitcoin	Constant	-0.7065	-0.1610	1.1851	-9.5077***	-9.4382***	0.1863
	Constant and Trend	-2.5251	-1.9965	0.1686	-8.9934***	-9.6142***	0.0469
Ethereum	Constant	0.7220	-1.1838	0.8735	-8.2236***	-8.5232***	0.0766
	Constant and Trend	-2.1279	-2.2658	0.0869	-8.2061***	-8.4822***	0.0568
GEPU	Constant	-2.9564	-2.6875	0.9488	-15.1740***	-15.9600***	0.2318
	Constant and Trend	-3.1453	-2.8006	0.1558	-15.2393***	-16.0917***	0.1117
VIX	Constant	-5.3098	-5.1646	0.4754	-11.59680***	-27.2617***	0.1622
	Constant and Trend	-5.5897	-5.5029	0.1156	-11.5509***	-27.2626***	0.1593

Note: In the ADF test, the maximum number of delays was taken as 13 and the optimum number of delays was determined according to the Schwarz Information Criterion. Long-term variance in PP and KPSS tests was obtained with the Bartlett kernel estimator and bandwidth was determined with the Newey-West method. In ADF and PP tests, critical values are -3.433122 (1%), -2.862651 (5%) and -2.567407 (10%) for the constant model; for the constant and trend model it is -3.962212 (1%), -3.411849 (5%) and - 3.127817 (10%). In the KPSS test, the critical values for the constant model are 0.739000 (1%), 0.463000 (5%) and 0.347000 (10%); For the constant and trending model, it is 0.216000 (1%), 0.146000 (5%) and 0.119000 (10%). The symbols ***, **, and * indicate statistical significance at 1%, 5% and 10% significance levels.

The long-term characteristics of a time series are revealed by determining how the variable value in the previous period affects the current period. In order to understand the evolution of the time series, it is necessary to perform regression analysis of the values in each period compared to previous periods. The unit root analysis method used to determine the stationarity of the series is an effective tool for evaluating this process (Tarı, 2014: 387; Aydoğdu, 2024: 243). In this context, Table 4 includes Augmented Dickey Fuller (ADF), Phillips-Perron (PP) and

Kwiatkowski, Phillips, Schmidt and Shin (KPSS) unit root test results to determine the stationarity of the series examined within the scope of the research. While ADF and PP tests indicate the case of unit root, non-stationarity or I[1] with "H_0*(null hypothesis)";* KPSS test indicates the I[0] process, in other words, stasis (Şahin Dağlı and Çelik, 2022; 2198). According to the ADF and PP tests applied to Bitcoin, Ethereum, GEPU and VIX returns, it is seen that the unit root H_0 hypothesis is rejected, and for the KPSS test statistic result, the I[0] process is reached and H_0 cannot be rejected. As a result, it was concluded that the series do not contain unit roots and have a stationary structure.

Tables 5, 6, 7 and 8 show the predictions of DCC-GARCH (1,1) models for return series disaggregated according to raw data and four different time scales. The coefficient α shows the effect of standardized shocks $(\eta_{t-1}\acute{\eta}_{t-1})$ and the coefficient β shows the effect of lagged dynamic conditional correlations Q_{t-1} on the dynamic conditional correlations in the current period. Statistically significant values of the α coefficient indicate short-term permanence, while large and statistically significant values of the β coefficient indicate long-term permanence.

Table 5. Analysis Results for VIX-Bitcoin Raw Data and Return Scales

Panel A:					
Raw Data	α	p	β	p	$\alpha+\beta$
Bitcoin	-0.0000	0.9999	0.5972	0.2570	0.5972
Panel B:					
Return Scales					
D1	0.5375	0.0000	0.2277	0.1682	0.7652
D2	**0.2453**	**0.0023**	**0.6544**	**0.0000**	**0.8997**
D3	0.4548	0.0000	-0.0000	0.9999	0.4548
D4	**0.9855**	**0.0000**	**0.0143**	**0.0000**	**0.9998**

Table 5. includes the analysis findings of Fear index (VIX) and Bitcoin raw data and different time scales. According to the findings, it can be concluded that the α and β coefficients of Bitcoin raw data returns are not significant, and that the shocks and dynamic conditional correlations in the past period have no effect on the dynamic conditional correlations of VIX and Bitcoin returns in the current period. This result is also an indication that there is no dynamic relationship or volatility interaction between the Fear index and Bitcoin returns. When the predictions of wavelet-based DCC-GARCH(1,1) models (from to) are examined; It took values of $\alpha+\beta<1$ at all time scales. However, it was concluded that $\alpha+\beta<1$ was statistically significant in the D_2 and D_4 time scales. This finding shows that dynamic correlations fluctuate around a fixed level in 4-8 month and 16-32 month investment cycles and have a process that tends to return to the mean.

The α coefficient estimates of the DCC-GARCH(1,1) models at all time scales are statistically significant at the 1% significance level, but the statistical significance of the β coefficients is significant at the 1% significance level in D_2 and D_4, but the β coefficients are not significant at the D_1 and D_3 time scales. has been observed. When these findings are evaluated, it can be said that past period conditional correlations on D_1 and D_3 time scales do not have an effect on current period correlations, in other words, volatility shocks do not show permanence in 2-4 month and 8-16 month investment cycles. It can even be stated that there is no volatility interaction in these investment cycles. On the other hand, it can be stated that there are time-varying correlations between VIX and Bitcoin returns on the D_2 and D_4 time scales, and that past volatility shocks and conditional correlations are effective on these correlations. In other words, volatility shocks are permanent in both 4-8 month and 16-32 month investment cycles. In addition, in the 4-8 and 16-32 month investment cycles, although $\alpha+\beta<1$, it is very close to 1 (one); with VIX, it can be stated that conditional volatility for Bitcoin is more likely to be permanent.

Table 6. Analysis Results for GEPU-Bitcoin Raw Data and Return Scales

Panel A:					
Raw Data	α	p	β	p	$\alpha+\beta$
Bitcoin	-0.0000	0.9999	0.0891	0.7611	0.0891
Panel B:					
Return Scales					
D1	0.5647	0.0000	0.1465	0.1721	0.7103
D2	**0.4292**	**0.0000**	**0.4567**	**0.0000**	**0.8859**
D3	0.2816	0.0000	-0.0000	0.9999	0.2816
D4	0.2295	0.0000	-0.0000	0.9999	0.2295

Table 6. shows the findings regarding GEPU and Bitcoin raw data and different time scales. According to the findings, the α and β parameter coefficients regarding Bitcoin raw data returns are not statistically significant. Therefore, shocks and dynamic conditional correlations in the past period are an indication that GEPU and Bitcoin returns in the current period have no effect on dynamic conditional correlations. In other words, it can be stated that there is neither a dynamic relationship nor a volatility interaction between the global economic political index and Bitcoin returns. When the predictions of wavelet-based DCC-GARCH(1,1) models (from D_1 to D_4) are examined; The α coefficient estimates of the DCC-GARCH(1,1) models at all time scales are positive and statistically significant at the 1% significance level, but the statistical significance of the β coefficients is only significant at the 1% significance level; However, it was concluded that the β coefficients were not significant at the time scales D_1, D_3 and D_4.

When these findings are evaluated; In the investment cycle periods of 2-4 months, 8-16 months and 16-32 months, past period conditional correlations do not have an effect on current period correlations, in other words, volatility shocks are affected according to the investment cycle periods of 2-4 months, 8-16 and 16-32 months. It can be stated that it is not permanent. It can even be stated that there is no volatility interaction during these investment cycle periods. On the other hand, it can be stated that there are time-varying correlations between GEPU and Bitcoin returns during , that is, the 4-8 month investment cycle period, and that past volatility shocks and conditional correlations are effective on these correlations. In other words, volatility shocks are permanent in the 4-8 month investment cycle. In addition, in the investment cycle period of 4-8 months, although $\alpha+\beta<1$, it is very close to 1 (one); with GEPU, it can be stated that conditional volatility for Bitcoin is more likely to be permanent.

Table 7. Analysis Results for VIX-Ethereum Raw Data and Return Scales

Panel A:					
Raw Data	α	p	β	p	$\alpha+\beta$
Ethereum	-0.0000	0.9999	0.3350	0.1654	0.3350
Panel B:					
Return Scales					
D1	0.3251	0.0469	0.3188	0.4781	0.6439
D2	0.1792	0.2102	0.6596	0.0169	0.8388
D3	-0.0013	0.9589	0.1807	0.0000	0.1794
D4	0.8100	0.0000	-0.0000	0.9999	0.8100

Table 7. includes the Fear index (VIX) and Ethereum raw data and analysis findings for different time scales. According to these findings, the α and β parameter estimation coefficients of Ethereum raw data returns are not statistically significant. According to this result, volatility shocks and dynamic conditional correlations in the past period show that there is no effect on the fear index and Ethereum returns dynamic conditional correlations in the current period. In other words, it is an indication that there is no volatility interaction between the fear index and Ethereum returns. When the estimates of the wavelet-based DCC-GARCH(1,1) models (from D_1 to D_4) were examined, it was determined that the α coefficient estimates of the DCC-GARCH (1,1) models were not statistically significant at all time scales. When the β coefficient estimates are examined, it is not statistically significant in the 2-4 month and 16-32 month investment cycles, but it is statistically significant in the 4-8 month and 8-16 month investment cycles. According to these findings, it has been determined that there is no relationship between the fear index and volatility shocks and dynamic correlations in the past period, volatility shocks and dynamic conditional correlations in the current period in Ethereum returns according to different time scales.

Table 8. Analysis Results for GEPU-Ethereum Raw Data and Return Scales

Panel A:					
Raw Data	α	p	β	p	$\alpha+\beta$
Ethereum	-0.0000	0.9999	0.4132	0.3956	0.4132
Panel B:					
Return Scales					
D1	0.3023	0.0139	0.2152	0.2535	0.5175
D2	**0.3271**	**0.0112**	**0.4845**	**0.0020**	**0.8116**
D3	0.3239	0.0000	-0.0000	0.9999	0.3239
D4	**0.8268**	**0.0000**	**0.0883**	**0.0000**	**0.9151**

Table 8. includes the Global Economic Political Uncertainty Index (GEPU) and Ethereum raw data and analysis findings for different time scales. According to the findings, it can be concluded that the α and β coefficients of Ethereum raw data returns are not significant, and that the shocks and dynamic conditional correlations in the past period have no effect on the global economic political uncertainty index and Ethereum returns dynamic conditional correlations in the current period. This result is also an indication that there is no dynamic relationship or volatility interaction between the global economic political uncertainty index and Ethereum returns. When the predictions of wavelet-based DCC-GARCH(1,1) models (from D_1 to D_4) are examined; It took values of $\alpha+\beta<1$ at all time scales. However, it was concluded that $\alpha+\beta<1$ was statistically significant in the D_2 and D_4 time scales. This finding shows that dynamic correlations fluctuate around a fixed level in the 4-8 month and 16-32 month investment cycles and have a process that tends to return to the mean. The α coefficient estimates of the DCC-GARCH(1,1) models at all time scales are positive and statistically significant at the 1% significance level, but the statistical significance of the β coefficients is significant at the 1% significance level in D_2 and D_4, but the β coefficients are significant at D_1 and D_3 time scales. It was observed that it was not significant.

When these findings are evaluated, it can be said that past period conditional correlations have no effect on current period correlations in and time scales, in other words, volatility shocks do not show permanence in 2-4 month and 8-16 month investment cycles. It can even be stated that there is no volatility interaction in these investment cycles. On the other hand, it can be stated that there are time-varying correlations between GEPU and Ethereum returns on the D_2 and D_4, time scales, and past volatility shocks and conditional correlations are effective on these correlations. In other words, volatility shocks are permanent in both 4-8 month and 16-32 month investment cycles. In addition, in the 4-8 and 16-32 month investment cycles, although $\alpha+\beta<1$, it is very close to l (one); with GEPU, it can be said that conditional volatility for Ethereum is more likely to be permanent.

5. CONCLUSION

Cryptocurrencies have recently become an alternative investment tool and an area of regulation that attracts the attention of both individual investors and corporate authorities. However, the high volatility in cryptocurrencies and the impact of some international developments on cryptocurrencies worry investors. In this context, the relationship between crypto currencies and developments involving global economic and political uncertainty has become a matter of curiosity. Whether there is a dynamic interaction between crypto currencies and the global economic political uncertainty index and fear index, and the direction of the relationship, is a phenomenon that should be carefully evaluated by both investors and policy makers. Therefore, the purpose of this study is to examine the impact of price movements in the Global Economic Political Uncertainty Index (GEPU) and the Fear Index (VIX) on crypto currencies. Thus, it is aimed to contribute new empirical findings to the literature examining the volatility interaction between crypto currencies, global economic political uncertainty and the fear index, and to reveal important findings for investors and policy makers. For this purpose, firstly, index and crypto currencies (Bitcoin, Ethereum) return series were separated into different time scales by wavelet decomposition analysis and then examined with the DCC-GARCH method between these series. In the study, the period between GEPU, VIX and Bitcoin was April 2012-April 2024; monthly data for Ethereum between April 2016 and April 2024 used. While creating the data set of the study, these dates were determined due to data constraints for the variables.

As a result of the analysis; Findings were obtained in terms of the volatility interaction between cryptocurrencies and GEPU and VIX and four different time scales representing the short, medium and long term. The findings obtained based on raw data and disaggregated return series were evaluated separately. As a result of the analyzes carried out based on raw data; Analyzes based on raw data have obtained evidence that there is no volatility interaction between cryptocurrencies (Bitcoin, Ethereum) and GEPU and VIX returns. According to this finding, it is an indication that the shocks and dynamic conditional correlations between Bitcoin and Ethereum returns and GEPU and VIX returns in the past period have no effect on the dynamic conditional correlations between Bitcoin and Ethereum returns and GEPU and VIX returns in the current period. This result can also be expressed as there is no dynamic relationship or volatility interaction between Bitcoin and Ethereum returns and GEPU and VIX returns. When the predictions of the wavelet-based DCC-GARCH(1,1) models were evaluated, it was concluded that $\alpha+\beta<1$ in the D_2 and D_4 time scales of Bitcoin and VIX returns was statistically significant. This finding shows that dynamic correlations fluctuate around a fixed level in the 4-8 month and 16-32 month investment cycles and have a process that tends to return to the mean. Both α coefficient estimates of DCC-GARCH(1,1) models at all time scales are statistically significant; However, the statistical significance of the β coefficients was found to be significant at the D_2 and D_4 time scales. According to these findings, it is an indicator of the persistence of volatility shocks in both 4-8 month and 16-32 month investment cycles. In addition, in the 4-8 and 16-32 month investment cycles, although $\alpha+\beta<1$, it is very close to l (one); With VIX, it can be said that conditional volatility for Bitcoin is more likely to be permanent. In other words, there is a positive and strong relationship between returns that varies over time.

When the time scales between Bitcoin and GEPU are examined, it is concluded that there are time-varying correlations between GEPU and Bitcoin returns only in D_2 , that is, the 4-8 month investment cycle period, and that past volatility shocks and conditional correlations are effective on these correlations. In other words, volatility shocks are permanent in the 4-8 month investment cycle. In addition, in the investment cycle period of 4-8 months, although $\alpha+\beta<1$, it is very close to l (one); With GEPU, it can be stated that conditional volatility for Bitcoin is more likely to be permanent. It has been determined that $\alpha+\beta<1$ on the and time scales of Ethereum and GEPU returns is statistically significant. This finding shows that dynamic correlations fluctuate around a fixed level in the 4-8 month and 16-32 month investment cycles and have a process that tends to return to the mean.

Both α coefficient estimates of DCC-GARCH(1,1) models at all time scales are statistically significant; However, the statistical significance of the β coefficients was found to be significant at the D_2 and D_4 time scales. According to these findings, it is an indicator of the persistence of volatility shocks in both 4-8 month and 16-32 month investment cycles. In addition, in the 4-8 and 16-32 month investment cycles, although $\alpha+\beta<1$, it is very close to l (one); It can be said that conditional volatility for Ethereum and GEPU is more likely to persist. On the other hand, it has been determined that there is no relationship between the fear index and the volatility shocks and dynamic correlations in the past period and the volatility shocks and dynamic conditional correlations in the current period in Ethereum returns according to different time scales.

In conclusion, these findings have practical implications for both investors and policy makers. As both the economic and political uncertainty index and the fear index are the volatility interaction between global currencies, this study shows that this affects the cryptocurrencies Bitcoin and Ethereum. Therefore, investors need to have comprehensive information about changes in the global economy and politics. Information-related policy changes should be factored into portfolio selection to avoid random market fluctuations. In addition, investors can obtain comprehensive information about the global economy and policy changes in the market, which is more turbulent and subject to sudden changes in the short term due to its unregulated structure. It is thought that these results will provide insight for both investors and policy makers.

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