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Economic Policy Uncertainty, Energy and Sustainable Cryptocurrencies: Investigating Dynamic Connectedness during the COVID-19 Pandemic

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Abstract: The purpose of the research is to explore the dynamic multiscale linkage between economic policy uncertainty, equity market volatility, energy and sustainable cryptocurrencies during the COVID-19 period. We use a multiscale TVP-VAR model considering level (EPUs and IDEMV) and returns series (cryptocurrencies) from 1 December 2019 to 30 September 2022. The data are then decomposed into six wavelet components, based on the wavelet MODWT method. The TVP-VAR connectedness approach is used to uncover the dynamic connectedness among EPUs, energy and sustainable cryptocurrency returns. Our findings reveal that CNEPU (USEPU) is the strongest (weakest) NET volatility transmitter. IDEMV is the most consistent volatility NET transmitter among all uncertainty indices across the original returns and wavelet scales (D1~D6). Energy cryptocurrencies, i.e., GRID, POW and SNC, are more likely to receive volatility spillovers than sustainable cryptocurrencies during a turbulent period (COVID-19). XLM (XNO) is least (most) affected by volatility spillover in system-wide connectedness, and XLM (ADA and MIOTA) showed a consistent (heterogeneous) non-recipient behavior across the six wavelet (D1~D6) scales and original return series. This study uncovers the dynamic connectedness across multiscale, which will support investors considering different investment horizons (D1~D6).

Keywords: energy and sustainable cryptocurrencies; EPU; equity market volatility; multiscale TVP-VAR; safe-haven

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1. Introduction

Uncertainty has been considered one of the major concerns among investors and policymakers. Regarding investors and academics, uncertainty started with the analysis of standard deviation as a risk measure and evolved to the analysis of variables such as the Chicago Board Options Exchange Volatility Index (VIX) (Baker et al. 2016), the economic policy uncertainty index (EPU) (Al-Thaqeb and Algharabali 2019), cryptocurrency policy uncertainty index (UCRY policy) (Lucey et al. 2022) or index of cryptocurrency environmental attention (ICEA) (Wang et al. 2022). Importantly, financial crises are key predictors of volatility and uncertainty in financial markets (Karaömer 2022; Karim et al. 2022). Due to global interconnectedness, financial crises cause spillovers for the different economies and transmit to international financial markets country-wide (Gulzar et al. 2019).

These events shake the trust of individual and institutional investors in financial institutions (Haq and Bouri 2022) and are considered major reasons to avoid or delay investments during these periods, considering potential losses and high uncertainty levels. Due to this, it is crucial to study the impact of uncertainty or volatility on the cryptocurrency market, focusing on energy and sustainable cryptocurrencies during the period of COVID-19.

Starting with Bitcoin, the first cryptocurrency introduced in 2009, there are already more than 19,850 cryptocurrencies, with more than 70 having a market value higher than $1 billion (Yousaf et al. 2022). Traditional cryptocurrency mining uses a tremendous amount of energy, which has drawn a lot of criticism (Gallersdörfer et al. 2020). Initially, studies on cryptocurrencies regarded all of them equally, but with time, some crypto assets have come to be seen as intrinsically different, especially in terms of sustainability. For instance, Haq and Bouri (2022) investigate the time-frequency co-movement between bitcoin, sustainable cryptocurrencies and sustainable financial markets and find that conventional cryptocurrencies, i.e., Bitcoin, have an adverse effect on sustainability. Contrarily, sustainable cryptocurrencies show a favorable impact on sustainability and sustainable financial assets. Likewise, Ren and Lucey (2022b) analyze clean and dirty cryptocurrencies, claiming that the clean energy crypto markets do not often exhibit herding behavior while the dirty energy crypto markets exhibit asymmetric and severe herding tendencies in negative markets. Ren and Lucey (2022a) explore the linkage of clean energy with green and dirty cryptocurrencies, finding that clean energy has weak connectedness with dirty and green cryptocurrencies, suggesting weak hedging or safe-haven properties of clean energy, regarding sustainable cryptocurrencies. Green cryptocurrencies are weakly connected with Bitcoin and Ethereum, while financial and macro-economic factors influence the tail dependence of carbon, dirty and green cryptocurrency markets (Pham et al. 2022). Policy and price uncertainty might influence the returns of sustainable and conventional (dirty) cryptocurrencies (Haq and Bouri 2022). However, how economic policy uncertainty and COVID-19 affect equity market volatility and the capacity to predict the returns of energy and sustainable cryptocurrencies is still a key question for sustainable policymakers and investors.

Interests in the cryptocurrency market have evolved during the last few years and crypto traders (amateur and informed investors) are now more concerned about the environmental and social effects of the conventional cryptocurrency market (Lucey et al. 2022; Wang et al. 2022). For instance, Elon Musk, the CEO of Tesla Corporation expressed that traditional cryptocurrency (Bitcoin) consumes large amounts of electricity and fossil fuel and produces a carbon footprint that makes the global environment dirty and unclean, and this could affect investors' trust. Meanwhile, crypto investors are revising their priorities, with an increased preference for sustainable, green or clean cryptocurrencies (Haq and Bouri 2022; Pham et al. 2022; Ren and Lucey 2022a; Haq et al. 2022a). Generally, three well-known cryptocurrencies support energy trades in the renewable energy sector: Powerledger (POWR), GridPlus (GRID+) and SunContract (SNC) (Yousaf et al. 2022). Additionally, SolarCoin (SLR), Bitcoin Green (BITG), Cardano (ADA), Steller (XLM) and Ripple (XRP) are recognized as committed to sustainability (Haq and Bouri 2022; Haq et al. 2022a). In this research, we study the dynamic multiscale connectedness between economic policy uncertainty, energy and sustainable cryptocurrencies. Additionally, we explore the linkage between the Daily Infectious Disease Equity Market Volatility Tracker (IDEMV) and cryptocurrencies.

Previous research has investigated the connectedness between EPU and conventional cryptocurrencies from several methodological and empirical perspectives. A first strand of research analyzes the connectedness and the impact of EPU in traditional cryptocurrencies using different time series and empirical approaches (Bouri and Gupta 2021; Chen et al. 2021; Cheng and Yen 2020; Koumba et al. 2020; Papadamou et al. 2021; Wang et al. 2019; Wu et al. 2021; Yen and Cheng 2021). A second strand of literature is focused on the impact of EPU or risk measures on the time-varying relationship between cryptocurrency and financial markets, through the use of GARCH family models (Fang et al. 2017, 2019; Li et al.

2022; Mokni et al. 2020; Xiong et al. 2018; Zhao and Wang 2022). A third strand of research examines the connectedness between economic/financial risk measures and cryptocurrencies across time-and frequency domains (Ah Mand 2021; Al-Yahyaee et al. 2019; Haq and Bouri 2022; Jiang et al. 2021; Rubbaniy et al. 2021; Wu et al. 2021; Zhu et al. 2022). This area of research studies the impact of risk measures such as EPU, index of cryptocurrency environmental attention (ICEA), UCRY policy, UCRY price and cryptocurrency implied volatility index (VCRIX), and conventional cryptocurrencies. A final strand of research investigates the linkage (impact) between EPU and the cryptocurrency market (Chen et al. 2021; Jiang et al. 2021; Mokni et al. 2022; Wu et al. 2021).

To the best of our knowledge, no research has investigated the impact of EPU and IDEMV on energy and sustainable cryptocurrencies during the fragile economic and crisis period associated with COVID-19. The rest of the paper is designed as follows. Section 2 reviews related studies. Section 3 explains the data and TVP-VAR method. Section 4 presents the empirical findings and relates them to previous research. Finally, the last section concludes and presents the implications.

2. Literature Review and Related Studies

Several studies have investigated the relationship between EPU and conventional cryptocurrencies, i.e., Bitcoin and Ethereum, considering different perspectives. One of those perspectives analyzes the connectedness/impact of EPU on traditional cryptocurrencies (Bouri and Gupta 2021; Chen et al. 2021; Cheng and Yen 2020; Koumba et al. 2020; Papadamou et al. 2021; Wang et al. 2019; Wu et al. 2021; Yen and Cheng 2021). For instance, Wang et al. (2019) studied the risk spillover effect from EPU to Bitcoin using MVQM-CAViaR and the Granger causality method, finding that the spillover from EPU to Bitcoin is marginal and Bitcoin is a safe-haven or diversifier during the time of EPU shocks. Similarly, Cheng and Yen (2020) investigated the impact of EPUs on traditional cryptocurrencies using a predictive regression model and concluded that China-EPU predicts Bitcoin returns, while Koumba et al. (2020) investigated the dependence between EPU indices and traditional cryptocurrencies through the use of a D-Vince Copula approach, finding that US-EPU predicts Ethereum better than Bitcoin returns. Moreover, Ethereum has a higher effective hedge for EPU than Bitcoin. Bouri and Gupta (2021) studied the predictive power of news-based and internet-based EPU risk measures concerning Bitcoin returns, with both measures predicting Bitcoin returns positively. Notably, it is evident that not only does EPU predict Bitcoin returns positively but also the volatility of Bitcoin negatively (Yen and Cheng 2021). In this debate, Wu et al. (2021) found that the EPU Twitter-based index is also positively connected with returns of the top four cryptocurrencies (Bitcoin, Ethereum, Litecoin, and Ripple), considering the use of the Granger Causality test. However, more cryptocurrencies are linked to EPU in bearish market and less in bullish market conditions (Papadamou et al. 2021). The country-wide EPU shows a consistent volatility spillover effect on the cryptocurrency market, based on the DCC-GARCH model (Foglia and Dai 2021). A number of studies have validated that EPU has mixed (positive/negative) predicting ability of Bitcoin returns (Chen et al. 2021; Demir et al. 2018; Shaikh 2020; Wang et al. 2020).

Another research path focuses on the impact of EPU or risk measures on the time-varying relationship between cryptocurrency and financial markets (Fang et al. 2019; Li et al. 2022; Mokni et al. 2020). For example, Fang et al. (2019) studied the impact of EPU on the correlation patterns of Bitcoin-bond, using a GARCH-MIDAS approach, concluding that the global EPU index shows a negative impact on Bitcoin–bond pair correlations, but a positive impact on Bitcoin–commodities and Bitcoin–equities correlation patterns, reflecting the limited hedging ability of Bitcoin returns. With a similar objective, Mokni et al. (2020) studied the impact of EPU on Bitcoin–US stock correlation using the DDC-GARCH model, concluding that EPU has a positive effect on Bitcoin–SP500 before the crash and low-EPU periods, while having a negative impact on the conditional correlation, raising the possibility of using Bitcoin as a hedging tool when high uncertainty occurs. Additionally, Li et al. (2022) documented that EPU shows heterogenous effects on Bitcoin–SP500 and

Bitcoin–Gold pairs (correlations), indicating that stock and cryptocurrency markets are sensitive to domestic and global economic and fiscal events. Therefore, it is relevant to investigate the volatility spillover effect of EPU and volatility measures on energy and sustainable cryptocurrencies.

The connectedness of economic or financial risk measures and cryptocurrencies across time and frequency domains has also originated several studies (Ah Mand 2021; Al-Yahyaee et al. 2019; Haq and Bouri 2022; Jiang et al. 2021; Rubbaniy et al. 2021; Wu et al. 2021; Zhu et al. 2022). For instance, Al-Yahyaee et al. (2019) investigated the co-movement between VIX and Bitcoin returns and the impact of EPU on the Bitcoin–VIX correlation, based on bivariate and multivariate wavelet coherence approaches in time and frequency domains. Those authors find heterogenous co-movement across time and investment horizons and conclude that VIX could be used to predict Bitcoin returns, at the same time as Bitcoin-uncertainty indices are time and frequency dependent. Ah Mand (2021) investigated the co-movement in both time and frequency domains between cryptocurrency uncertainties and cryptocurrency returns, concluding that cryptocurrency uncertainties predict cryptocurrency returns in all investment horizons. However, EPU and VIX failed to influence the co-movement between cryptocurrency returns and uncertainties. Jiang et al. (2021) analyzed the interconnectedness between EPU, COVID-19-induced equity market volatility index and traditional cryptocurrency market returns, based on a quantile coherency analysis approach. According to those authors, most traditional cryptocurrencies are effective hedges for high EPU and COVID-19-induced equity market volatility index during the COVID-19 pandemic. Focusing on COVID-19, Rubbaniy et al. (2021) explored the co-movement between financial and non-financial risk proxies and the returns of Bitcoin, Ethereum, and Ripple, using a wavelet coherence approach, finding that cryptocurrencies are safe-haven assets for non-financial market-based proxies, but acting like traditional assets against financial market-based proxies. Wu et al. (2021) studied the co-movement between EPU and four cryptocurrencies (Bitcoin, Ethereum, Ripple and Litecoin), using a wavelet coherence approach, and did not find a causal relationship between EPU and cryptocurrency returns during the COVID-19 pandemic.

Another strand of research investigated the nexus of energy, sustainable cryptocurrencies, and stock markets. For example, Haq et al. (2022a) consider the financial market and sustainability perspectives, studying the co-movement of green bonds, sustainable and traditional cryptocurrencies and major sustainability indices in both time and frequency domains, concluding that green bonds and sustainable cryptocurrencies are sustainable investment and risk management avenues for sustainable crypto traders and investors. Similarly, Pham et al. (2022) analyze the tail dependence between carbon prices and green and non-green cryptocurrencies, using quantile connectedness. In contrast to low-volatility times, they observe increased dependency during high-volatility periods. At times of low volatility, the relationship between carbon prices and cryptocurrencies returns is basically inexistent, while the interconnectedness between green cryptocurrencies and Bitcoin and Ethereum is marginal. Finally, those authors noticed that macroeconomic and financial uncertainties significantly affect the tail dependence between these variables. Ren and Lucey (2022a) investigated the relationship of clean energy with green and dirty cryptocurrencies using the DCC-GARCH model and found that clean energy is not a suitable hedge for both types of cryptocurrencies, but a weak safe haven. Additionally, clean energy is a more suitable safe haven for dirty cryptocurrencies than for clean cryptocurrencies. Haq and Bouri (2022) investigated the co-movement of sustainable and conventional cryptocurrencies and cryptocurrency uncertainty indices, using a wavelet coherence method and considering multiple investment horizons, finding that sustainable and conventional cryptocurrencies have a positive correlation with both cryptocurrency uncertainty indices (UCRY Price and UCRY Policy) in short-term investment horizons, showing a short-lived hedging ability of cryptocurrencies regarding cryptocurrency uncertainty indices.

The above discussion considers the idea that national and global economic factors are vulnerable to the stability of financial and cryptocurrency markets (Fang et al. 2019;

Li et al. 2022), with the volatility spillover of EPU and IDEMV on energy and sustainable cryptocurrencies not being analyzed in previous research. Moreover, previous research is also scarce on the empirical evidence of multiscale analysis of EPU on energy and sustainable cryptocurrencies, considering the heterogeneity of investors and investment horizons (Haq and Bouri 2022; Haq et al. 2022b). Based on this, our research has two motivations: firstly, crypto institutional/individual investors and traders are turning toward sustainable cryptocurrencies due to both social and economic benefits, making it relevant to investigate the impact of economic and financial variables; secondly, investors have heterogeneous investment interests considering multiple investment horizons such as D1~D6, so it is crucial to investigate this connectedness considering six wavelet scales.

3. Methodology

3.1. Data

This study considers the daily data of three EPU indices (USA, China and the UK) as well as a Daily Infectious Disease Equity Market Volatility Tracker (IDEMV), sourced from https://www.policyuncertainty.com. Additionally, three energy cryptocurrencies (Powerledger—POWR, GridPlus—GRID, and SunContract—SNC) and five sustainable cryptocurrencies (SolarCoin—SLR, Bitcoin Green—BITG, Cardano—ADA, Steller—XLM and Ripple—XRP) were considered, due to their sustainable mechanisms and mining processes. The daily closing prices for cryptocurrencies were sourced from coinmarketcap.com. The closing prices of energy and sustainable cryptocurrencies were transformed into returns with the daily return as $R_{i,t} = (\ln(P_{i,t}) - (P_{i,t-1}))$. The dataset starts on 1 December 2019 and ends on 30th September 2022, covering the period of turmoil related to the COVID-19 pandemic, and the returns of energy and sustainable cryptocurrencies are found in Figure 1.

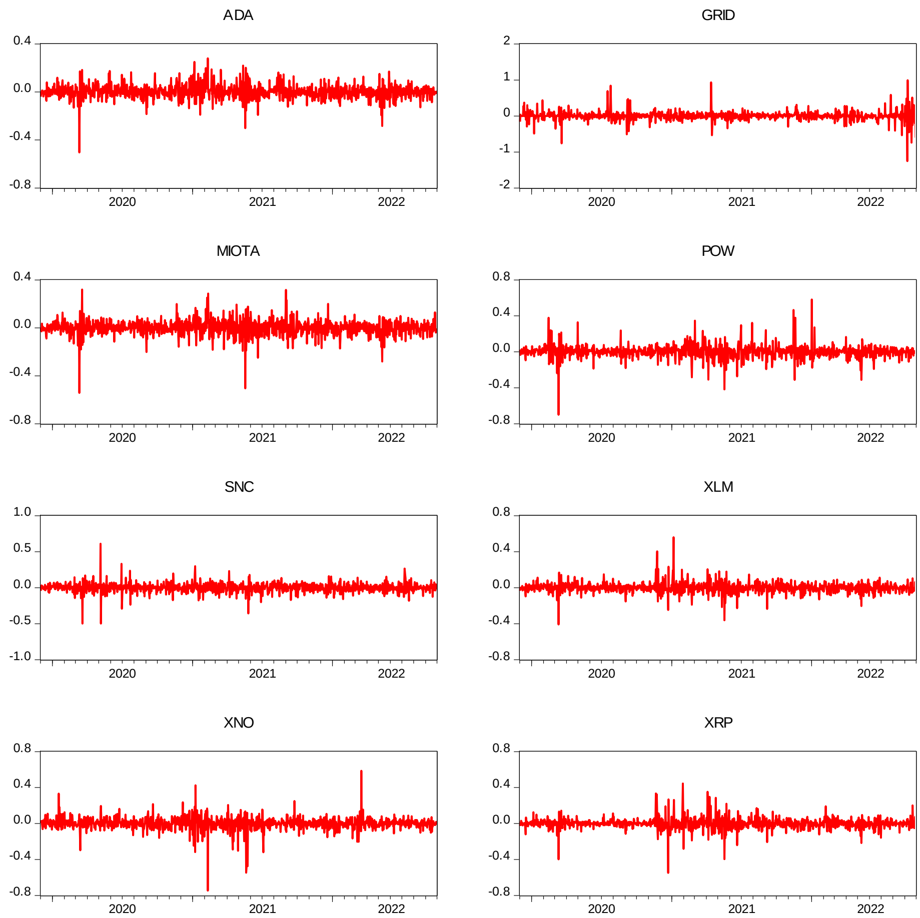

Figure 1. Returns of energy and sustainable cryptocurrencies.

3.2. Maximum Overlap Discrete Wavelet Transform Method

We used the Percival and Walden (2000) maximum overlap discrete wavelet transform (MODWT) in order to decompose the original EPU and cryptocurrency return series into six wavelet components (i.e., D1, D2 ... D6), focusing on the multiscale analysis and considering the importance of investment horizons (short-term, medium-term and long-term). This wavelet technique can distinguish between the main types of variability and examine each wavelet component at a resolution according to its scale (Maghyereh et al. 2019). The MODWT, a non-orthogonal transform, outperforms the discrete wavelet transform (DWT) in several ways, including non-specific sample length, constant conversion process, incremental resolution at larger scales, and a more asymptotically efficient wavelet variance estimate (Cui et al. 2021). In numerous existing research studies, the MODWT has been used to divide the original return series into various wavelet components as part of the wavelet-based analytic framework (Cui et al. 2021; Maghyereh et al. 2019).

Equations (1)–(4) can be used to get the wavelet coefficients $V_{j,t}$ and scaling coefficients $S_{j,t}$ of the return series $(R_{i,t})$ at the jth level:

$$\widetilde{V}_{i,j} = \sum_{I=0}^{L_j-1} \widetilde{x}_{j,l}\, R_{t-j \ mod \ T} \ t = 0, 1, \ldots, T-1 \tag{1}$$

$$\widetilde{S}_{i,j} = \sum_{I=0}^{L_j-1} \widetilde{y}_{j,l}\, R_{t-j \ mod \ T} \ t = 0, 1, \ldots, T-1 \tag{2}$$

Considering the wavelet filter length represented by L, and $\widetilde{x}_{j,l} = {}^{x_{j,l}}/_{2^{j/2}}$ and $\widetilde{y}_{j,l} = {}^{y_{j,l}}/_{2^{j/2}}$ as the wavelet filter and the scale filter, respectively. We have the following properties (Khalfaoui et al. 2015):

$$\begin{gathered} \sum_{l=0}^{L_j-1} \widetilde{x}_l = 0, \sum_{l=0}^{L_j-1} \widetilde{y}_l = 0; \sum_{l=0}^{L_j-1} \widetilde{x}^2{}_l = \sum_{l=0}^{L_j-1} \widetilde{y}^2{}_l = \frac{1}{2^l}; \\ \sum_{-\infty}^{+\infty} \widetilde{y}_l \widetilde{y}_{l+2n} = \sum_{-\infty}^{+\infty} \widetilde{x}_l \widetilde{x}_{l+2n} \end{gathered} \tag{3}$$

Following Cui et al. (2021) and Maghyereh et al. (2019), we employed the MODWT wavelet filter for decomposition, due to its linear phase and symmetric properties. The MODWT can be expressed as follows:

$$R(t) = A_j(t) + \sum_{j-1}^{J} B_j(t) \tag{4}$$

where $A_j(t) = \sum_{I=-\infty}^{+\infty} x(l) A_{J-1}\left(t + 2^{j-1} \times l\right)$ represents the smoothed form of the return series $R(t)$ at the scale J. Furthermore, $B_j(t) = \sum_{I=-\infty}^{+\infty} y(l) A_{J-1}\left(t + 2^{j-1} \times l\right)$ expresses the detailed wavelet components that can capture the local dynamics of $R(t)$ over the sample period at each scale j, where $J = (1, 2, \ldots, J)$. The wavelet decomposition of the level series for EPUs is found in Figure 2. In addition, the level and return series of IDEMV and cryptocurrencies are decomposed into D1~D6 as presented in Figure A2.

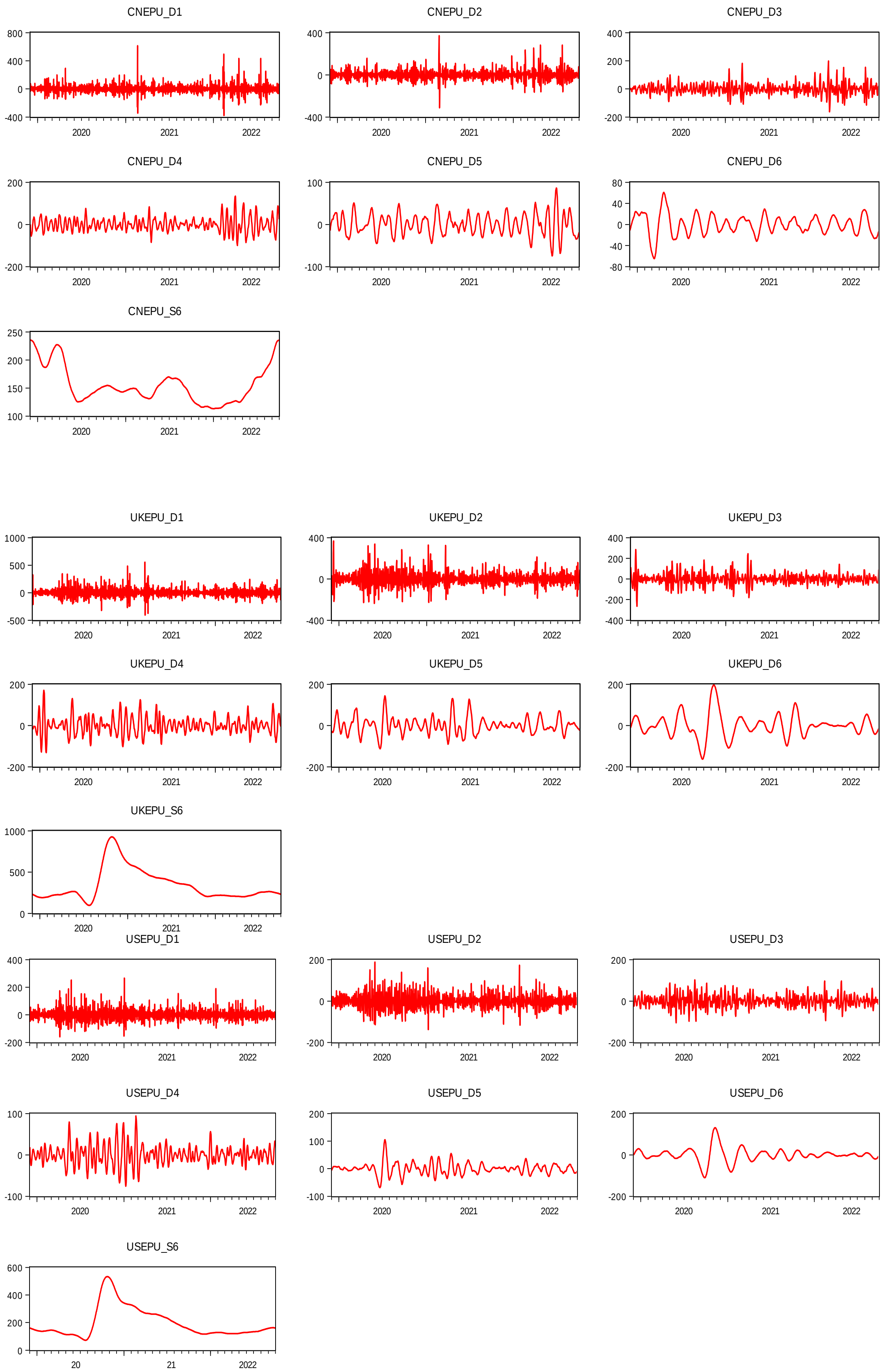

Figure 2. Wavelet decomposition graphs.

3.3. TVP-VAR Approach

The TVP-VAR approach is the combination of Time-Varying Parameters (TVP) and Vector Autoregressive (VAR). Considering the entire dataset, the static approach considers the use of a vector autoregressive model, whereas the dynamics are estimated using a rolling-window VAR method. Initially proposed by Primiceri (2005), the TVP-VAR has been applied by Antonakakis et al. (2020) and developed by Diebold and Yilmaz (2009, 2012) and Diebold and Yilmaz (2014), being used in this study to assess the dynamic connectedness among economic policy uncertainty indices, energy and sustainable cryptocurrencies. Generally, it is a widely adopted approach to track and assess spillovers in a specified network (Bouri et al. 2021) because it offers researchers and practitioners both a static and a dynamic approach to time series network analysis. This model estimates potential changes in the degree to which EPUs and cryptocurrencies are interconnected in order to demonstrate whether the linear structure is derived from the likelihood of shocks or from the extension of the change mechanism response (Karim and Naeem 2022). The model also offers odd characteristics to spot probable structural breaks and offers compelling explanations to understand the relationship between EPU indices and cryptocurrencies.

Previous research highlighted several additional benefits of using this approach, which are key motivations behind using the TVP-VAR model (Adekoya and Oliyide 2021; Bouri et al. 2021; Haq et al. 2022a). First, it enables the variance to change via a Kalman Filter estimation with forgetting components. Second, it eliminates the need to arbitrarily select the rolling-window size. Third, it does not cause a loss of observations during the estimation process. Finally, it can be applied to low-frequency datasets.

The model equation can be written as follows:

$$C_t = \beta_{0,t} + \beta_{1,tYt-1} + \ldots + \beta_{p,tYt-p} + u_t + X_t''\Theta_t + u_t \tag{5}$$

with C_t indicating the vector of the dependent variable with dimension $n \times 1$ and $\beta_{0,t \ldots p,t}$ as $n \times n$ dynamic coefficients varying over time, which are rewritten as the Θ_t matrix (Haq et al. 2022a; Karim and Naeem 2021) and with u_t representing structural shocks and $n \times 1$ has zero mean with a heteroskedastic distribution.

It is also possible to represent

$$D_t' = \left[1, C_{t-1}', \ldots, C_{t-p}'\right] \tag{6}$$

with D_t' as an $n \times k$ matrix that incorporates both the intercept and the lags of time-varying variables and

$$\Omega_t = M_t^{-1} H_t \left(M_t^{-1}\right) \tag{7}$$

with the term Ω_t indicating the time-varying variance-covariance matrix. Therefore, the variance-covariance matrix of cryptocurrencies and green financial assets returns series can be written as in Equation (7), where M_t^{-1} and H_t represent the simultaneous relationship between time series and stochastic connectedness, respectively.

The transition in dynamic parameters over time is assumed to be as follows:

$$\Theta_t = \Theta_{t-1} + v_t, v_t \approx N(0, S) \tag{8}$$

$$\alpha_t = \alpha_{t-1} + \xi_t, \xi_t \approx N(0, Q) \tag{9}$$

Here, the time-varying parameters are estimated through Equations (8) and (9) by following the random walk process (Kamal and Hassan 2022).

Finally, we can get

$$\ln\, h_{it-1} = \ln h_{i,t-1} + \sigma_t \mu_{i,t}, \mu_{i,t} \approx N(0, 1) \tag{10}$$

to estimate the stochastic connectedness using the random walk process. Overall, the error term is determined to be independent of the transition equation. Therefore, the variables' coefficients vary independently to maintain efficient and simplified estimates (Haq et al. 2022a; Karim and Naeem 2021; Primiceri 2005).

4. Results and Discussion

4.1. Summary Statistics

Figure A2 indicates the evolution of economic policy uncertainty and cryptocurrency prices during the COVID-19 pandemic period. The IDEMV, UKEPU and USEPU indices followed a dynamic pattern over time, and a sharp hike can be noticed near the COVID-19 outbreak, from the start of 2020 to the end of 2021. However, policy uncertainty became slightly more stable after 2021 except for the CHEPU whose fluctuations were homogenous and followed more dispersion in 2022. The prices of energy and sustainable cryptocurrencies followed a spike at the start of 2021, and cryptocurrency prices were always high during COVID-19. However, GRID and POW prices increased in 2022. These findings suggest that at times of high policy uncertainty and equity market volatility, investors prefer the cryptocurrency market as an attractive investment avenue, increasing the demand for cryptocurrencies and their prices. These findings are consistent with Huynh et al. (2021a), who documented the relationship between financial markets and uncertainty during the coronavirus period.

Table 1 reports the output of descriptive statistics, which includehte mean, standard deviation, skewness, kurtosis, and the Jarque–Bera and Augmented Dickey–Fuller test. In Panel A (original return series), UKEPU (CNEPU and USEPU) remains the most (least) volatile EPU index. Mean returns of all cryptocurrencies are positive with ADA and POW (XLM, XRP, GRID) showing the highest (lowest) positive returns. Among all cryptocurrencies, GRID (XLM) is the most (least) volatile. Additionally, returns of cryptocurrencies have negative skewness coefficients (with the exception of the XLM returns) and kurtosis values above three, indicating negative skewness and leptokurtic characteristics. By using the Jarque–Bera (JB) statistic, we rejected the normal hypothesis of the return (cryptocurrency) and level (EPU) distributions at the 1% level of significance, confirming that the original return series have non-normal distributions. Applying the Augmented Dickey– Fuller test, we conclude that all return (cryptocurrency) and level (EPU) series are stationary.

Table 1. Descriptive statistics.

Panel A: Descriptive statistics (Original data)								
	M	**SD**	**Skew.**	**Kurt.**	**JB**	**Prob.**	**ADF**	**Obs.**
CNEPU	155.2620	110.1860	3.0840	20.4490	14,770.9500	0.0000	−26.7720	1035
UKEPU	340.9980	239.1110	1.7060	6.2180	948.6390	0.0000	−12.0300	1035
USEPU	196.4830	133.6060	1.7170	6.1290	930.8360	0.0000	−11.2390	1035
IDEMV	16.3420	13.1670	2.0660	10.2690	3014.9220	0.0000	−15.8360	1035
ADA	0.0020	0.0600	−0.3830	10.0720	2182.2890	0.0000	−26.7720	1035
MIOTA	0.0000	0.0650	−0.8510	13.1330	4553.0520	0.0000	−12.030	1035
XLM	0.0010	0.0590	0.6120	17.4090	9018.2740	0.0000	−11.2390	1035
XNO	0.0000	0.0750	−1.4040	23.9060	19,187.9800	0.0000	−15.8360	1035
XRP	0.0010	0.0640	−0.1710	17.2390	8748.0520	0.0000	−14.5541	1035
GRID	0.0010	0.1340	−0.1630	21.3500	14,525.6100	0.0000	−29.8821	1035
POW	0.0020	0.0760	−0.0190	18.1780	9934.9530	0.0000	−12.9171	1035
SNC	0.0000	0.0670	−0.0720	17.4840	9048.4440	0.0000	23.2812	1035
Panel B: Descriptive statistics of D1 (2 to 4 days)								
	M	**SD**	**Skew.**	**Kurt.**	**JB**	**Prob.**	**ADF**	**Obs.**
ADA.D1	0.0000	0.0440	0.0700	8.5780	1342.7030	0.0000	−29.4492	1035
CNEPU.D1	0.0000	70.1520	1.3270	16.0230	7618.3180	0.0000	−13.2330	1035
GRID.D1	0.0000	0.1010	0.5120	20.5090	13,266.4500	0.0000	−12.3629	1035

Table 1. *Cont.*

Panel B: Descriptive statistics of D1 (2 to 4 days)								
	M	**SD**	**Skew.**	**Kurt.**	**JB**	**Prob.**	**ADF**	**Obs.**
IDEMV.D1	0.0000	5.6050	0.9590	7.2120	923.7150	0.0000	−17.4196	1035
MIOTA.D1	0.0000	0.0480	−0.2190	9.7040	1946.4830	0.0000	−29.4492	1035
POW.D1	0.0000	0.0550	−0.0140	12.4460	3847.7960	0.0000	−13.2330	1035
SNC.D1	0.0000	0.0520	−0.4090	19.0450	11,131.7500	0.0000	−12.3629	1035
UKEPU.D1	0.0000	82.1900	0.8060	8.6860	1506.4220	0.0000	−17.4196	1035
USEPU.D1	0.0000	42.7660	0.8620	7.1400	867.3040	0.0000	−16.0095	1035
XLM.D1	0.0000	70.1520	1.3270	16.0230	7618.3180	0.0000	−32.8703	1035
XNO.D1	0.0000	0.0540	−0.4020	14.4600	5691.8620	0.0000	−14.2088	1035
XRP.D1	0.0000	0.0460	0.1030	13.3670	4637.0130	0.0000	25.6093	1035
Panel C: Descriptive statistics of D2 (4 to 8 days)								
	M	**SD**	**Skew.**	**Kurt.**	**JB**	**Prob.**	**ADF**	**Obs.**
ADA.D2	0.0000	0.0280	0.0710	4.6100	112.6090	0.0000	−32.3941	1035
CNEPU.D2	0.0000	51.5500	0.7220	9.5640	1947.8710	0.0000	−14.5563	1035
GRID.D2	0.0000	0.0690	−0.1270	15.2150	6437.3630	0.0000	−13.5992	1035
IDEMV.D2	0.0000	5.2250	0.6520	4.9590	238.9820	0.0000	−19.1616	1035
MIOTA.D2	0.0000	0.0310	−0.1260	6.5520	546.8900	0.0000	−32.3941	1035
POW.D2	0.0000	0.0400	0.0110	10.4360	2384.7470	0.0000	−14.5563	1035
SNC.D2	0.0000	0.0320	0.0420	6.6630	578.8200	0.0000	−13.5992	1035
UKEPU.D2	0.0000	69.0410	0.6710	6.7170	673.6270	0.0000	−19.1616	1035
USEPU.D2	0.0000	36.4110	0.4520	5.0450	215.5060	0.0000	−17.6105	1035
XLM.D2	0.0000	51.5500	0.7220	9.5640	1947.8710	0.0000	−36.1573	1035
XNO.D2	0.0000	0.0380	−0.6420	15.9670	7322.7660	0.0000	−15.6297	1035
XRP.D2	0.0000	0.0320	−0.0550	11.5610	3161.2370	0.0000	28.1703	1035
Panel D: Descriptive statistics of D3 (8 to 16 days)								
	M	**SD**	**Skew.**	**Kurt.**	**JB**	**Prob.**	**ADF**	**Obs.**
ADA.D3	0.0000	0.0200	−0.0050	4.0790	50.2510	0.0000	−35.6335	1035
CNEPU.D3	0.0000	38.2350	0.5000	6.2650	502.8990	0.0000	−16.0119	1035
GRID.D3	0.0000	0.0410	0.1000	7.5040	876.6810	0.0000	−14.9591	1035
IDEMV.D3	0.0000	3.4260	0.2440	4.1820	70.5470	0.0000	−21.0777	1035
MIOTA.D3	0.0000	0.0210	0.0720	5.3750	244.0840	0.0000	−35.6335	1035
POW.D3	0.0000	0.0240	0.0000	4.9870	170.3290	0.0000	−16.0119	1035
SNC.D3	0.0000	0.0190	0.2360	5.3950	257.0310	0.0000	−14.9591	1035
UKEPU.D3	0.0000	52.3780	0.3790	6.8730	671.6150	0.0000	−21.0777	1035
USEPU.D3	0.0000	28.5890	0.1380	4.0920	54.7430	0.0000	−19.3715	1035
XLM.D3	0.0000	38.2350	0.5000	6.2650	502.8990	0.0000	−39.7731	1035
XNO.D3	0.0000	0.0250	−0.6020	9.8640	2094.2210	0.0000	−17.1927	1035
XRP.D3	0.0000	0.0200	0.1080	5.9760	383.8930	0.0000	30.9873	1035
Panel E: Descriptive statistics of D4 (16 to 32 days)								
	M	**SD**	**Skew.**	**Kurt.**	**JB**	**Prob.**	**ADF**	**Obs.**
ADA.D4	0.0000	0.0140	−0.0580	3.9300	37.8890	0.0000	−39.1969	1035
CNEPU.D4	0.0000	32.4780	0.4440	4.2620	102.7110	0.0000	−17.6131	1035
GRID.D4	0.0000	0.0270	−0.0940	5.8560	353.3490	0.0000	−16.4550	1035
IDEMV.D4	0.0000	2.5440	0.1400	3.2750	6.6410	0.0360	−23.1855	1035
MIOTA.D4	0.0000	0.0160	0.1340	4.6480	120.2100	0.0000	−39.1969	1035
POW.D4	0.0000	0.0170	0.0810	4.9000	156.8720	0.0000	−17.6131	1035
SNC.D4	0.0000	0.0140	−0.0310	4.7100	126.2750	0.0000	−16.4550	1035
UKEPU.D4	0.0000	41.7260	0.4060	4.4650	120.8910	0.0000	−23.1855	1035
USEPU.D4	0.0000	23.6930	0.3200	4.6310	132.2880	0.0000	−21.3087	1035
XLM.D4	0.0000	32.4780	0.4440	4.2620	102.7110	0.0000	−43.7504	1035
XNO.D4	0.0000	0.0170	−0.3760	7.4700	885.8810	0.0000	−18.9119	1035
XRP.D4	0.0000	0.0160	−0.0190	6.2760	462.9490	0.0000	34.0860	1035

Table 1. *Cont.*

Panel F: Descriptive statistics of D5 (32 to 64 days)								
	M	**SD**	**Skew.**	**Kurt.**	**JB**	**Prob.**	**ADF**	**Obs.**
ADA.D5	0.0000	0.0100	0.1860	3.2850	9.4620	0.0090	−39.5889	1035
CNEPU.D5	0.0000	25.0480	0.0550	3.1880	2.0470	0.0590	−17.7893	1035
GRID.D5	0.0000	0.0170	0.2640	4.3790	94.0520	0.0000	−16.6196	1035
IDEMV.D5	0.0000	2.8530	0.5490	8.1990	1217.6600	0.0000	−23.4173	1035
MIOTA.D5	0.0000	0.0110	0.2810	4.9150	171.7250	0.0000	−39.5889	1035
POW.D5	0.0000	0.0120	−0.1500	3.6190	20.4050	0.0000	−17.7893	1035
SNC.D5	0.0000	0.0090	0.0020	3.7460	24.0240	0.0000	−16.6196	1035
UKEPU.D5	0.0000	40.2270	0.5540	4.3690	133.9040	0.0000	−23.4173	1035
USEPU.D5	0.0000	21.0890	0.6510	7.2240	842.5880	0.0000	−21.5217	1035
XLM.D5	0.0000	25.0480	0.0550	3.1880	2.0470	0.0510	−44.1879	1035
XNO.D5	0.0000	0.0120	−0.2490	5.4370	266.7420	0.0000	−19.1010	1035
XRP.D5	0.0000	0.0110	0.4170	4.5430	132.6840	0.0000	34.4269	1035
Panel G: Descriptive statistics of D6 (64 to 128 days)								
	M	**SD**	**Skew.**	**Kurt.**	**JB**	**Prob.**	**ADF**	**Obs.**
ADA.D6	0.0000	0.0080	−0.1520	3.1660	5.1540	0.0760	−39.9847	1035
GRID.D6	0.0000	0.0120	0.0900	2.8940	1.8930	0.0880	−17.9671	1035
IDEMV.D6	0.0000	3.7780	1.6250	11.7650	3768.2920	0.0000	−16.7858	1035
MIOTA.D6	0.0000	0.0070	−0.0650	3.1270	1.4150	0.0930	−23.6515	1035
POW.D6	0.0000	0.0080	−0.2310	3.6250	26.0700	0.0000	−39.9847	1035
SNC.D6	0.0000	0.0070	−0.1230	3.0090	2.6250	0.0690	−17.9671	1035
UKEPU.D6	0.0000	56.2440	0.4910	5.1430	239.6660	0.0000	−16.7858	1035
USEPU.D6	0.0000	33.2920	0.3300	7.4570	875.2530	0.0000	−23.6515	1035
XLM.D6	0.0000	19.1440	−0.1650	4.1250	59.3260	0.0000	−21.7370	1035
XNO.D6	0.0000	0.0090	−0.1760	2.7970	7.1220	0.0280	−44.6298	1035
XRP.D6	0.0000	0.0100	−0.0400	4.0180	44.9700	0.0000	−19.2921	1035
CNEPU.D6	0.0000	19.1440	−0.1650	4.1250	59.3260	0.0000	34.7711	1035

Note: For abbreviations, M = Mean, SD = Standard deviation, Skew. = Skewness, Kurt. = Kurtosis, JB = Jarque–Bera, Prob. = Probability, ADF = Augmented Dickey–Fuller test, Obs. = Observations.

Further descriptive statistics of wavelet components are also presented in Table 1. The results of wavelet components are homogenous to the original returns. In particular, the crypto returns and EPU indices have mean values of zero over all time horizons, indicating that positive and negative shocks balance one another over longer investment horizons (Cui et al. 2021; Maghyereh et al. 2019). The lower the scales, the greater the unconditional volatility as measured by the standard deviation (high-frequency components). Wavelet components of cryptocurrency returns exhibit larger swings at several scales. Additionally, we see that the wavelet scales for crypto returns and EPU indices are all skewed and leptokurtic. The non-normality of the wavelet components was also confirmed by the JB statistic results. Interestingly, the returns of cryptocurrencies and EPU indices are closer to normality and follow somewhat non-normal distribution at higher wavelet scales, which is consistent with earlier research (Cui et al. 2021; Maghyereh et al. 2019). Additionally, we use the ADF unit root test to check if each wavelet component is stationary. The returns and level series of cryptocurrencies and EPU level series are stationary considering a 1% level of significance, respectively.

Table 2 reports the unconditional correlation between EPUs, IDEVM, energy and sustainable cryptocurrencies. The results of Panel A show that the correlation coefficients of CNEPU and IDEVM with MIOTA, GRID and POW are negative. Contrarily, the coefficient signs of UKEPU and USEPU with energy and sustainable cryptocurrencies are predominantly positive for the original return series, meaning that we could find safe-haven properties of energy and sustainable cryptocurrencies for UKEPU and USEPU. The unconditional correlation coefficients of EPUs and IDEVM are mostly negative with both types of cryptocurrencies at D1 (2 to 4 days), D2 (4 to 8 days) and D3 (8 to 16 days) scales, indicating lower safe-haven avenues across very short and short wavelet scales. For the D4 (16 to 32 days) scale, XLM shows positive correlation coefficients with EPUs and IDEVM, suggesting that an increase in EPUs leads to an increase in XLM returns. However, conditional correlation coefficients of SNC are negative and other cryptocurrencies show heterogeneous signs. These findings suggest mixed safe-haven properties of energy and sustainable cryptocurrencies during the COVID-19 period for EPUs and IDEVM. Noticeably, in a medium-term investment horizon, the correlation coefficients show positive signs between EPUs/energy and EPUs/sustainable cryptocurrencies. However, IDEVM shows predominantly negative signs with both classes of cryptocurrency. These findings reveal that energy and sustainable cryptocurrencies could be seen as having a safe-haven behavior for policy uncertainty.

Table 2. Correlation Matrix.

Panel A: Correlation Matrix (Original data)

	CNEPU	UKEPU	USEPU	IDEMV	ADA	MIOTA	XLM	XNO	XRP	GRID	POW	SNC
CNEPU	1											
UKEPU	−0.0145	1										
USEPU	0.0122	0.7150	1									
IDEMV	−0.0186	0.4967	0.4699	1								
ADA	0.0294	0.0809	0.0478	0.0034	1							
MIOTA	−0.0056	0.0281	0.0355	−0.0291	0.7121	1						
XLM	0.0129	0.0842	0.0501	0.0346	0.7523	0.7051	1					
XNO	−0.0117	0.0225	0.0516	0.0127	0.0443	0.0338	0.0726	1				
XRP	−0.0212	0.0120	0.0160	0.0119	0.5667	0.6183	0.7176	0.1232	1			
GRID	−0.0401	0.0103	0.0097	−0.0143	0.0500	0.0263	0.0098	0.0087	0.0283	1		
POW	−0.0003	0.0246	0.0174	−0.0278	0.4607	0.5529	0.4692	−0.0201	0.4350	0.0046	1	
SNC	0.0075	0.0180	0.0126	−0.0473	0.0255	0.0479	0.0009	0.0369	0.0224	0.1751	−0.0141	1

Panel B: Correlation Matrix of D1 (2 to 4 days)

	CNEPU.D1	UKEPU.D1	USEPU.D1	IDEMV.D1	ADA.D1	MIOTA.D1	XLM.D1	XNO.D1	XRP.D1	GRID.D1	POW.D1	SNC.D1
CNEPU.D1	1											
UKEPU.D1	−0.0665	1										
USEPU.D1	−0.0363	−0.0765	1									
IDEMV.D1	−0.0638	−0.2423	0.0655	1								
ADA.D1	0.0263	0.0344	−0.0494	−0.0015	1							
MIOTA.D1	−0.0009	−0.0345	−0.0230	−0.0038	0.7163	1						
XLM.D1	1.0000	−0.0665	−0.0363	−0.0638	0.0263	−0.0009	1					
XNO.D1	−0.0406	−0.0273	0.0381	0.0112	0.0925	0.1261	−0.0406	1				
XRP.D1	−0.0354	−0.0552	−0.0309	0.0233	0.5801	0.6313	−0.0354	0.1752	1			
GRID.D1	−0.0310	0.0180	0.0212	−0.0495	0.0387	0.0367	−0.0310	−0.0117	0.0212	1		
POW.D1	−0.0043	−0.0407	−0.0503	−0.0009	0.4613	0.5146	−0.0043	0.0515	0.4558	0.0143	1	
SNC.D1	0.0276	0.0126	−0.0554	−0.0429	0.0316	0.0613	0.0276	0.0087	0.0119	0.1554	−0.0283	1

Panel C: Correlation Matrix of D2 (4 to 8 days)

	CNEPU.D2	UKEPU.D2	USEPU.D2	IDEMV.D2	ADA.D2	MIOTA.D2	XLM.D2	XNO.D2	XRP.D2	GRID.D2	POW.D2	SNC.D2
CNEPU.D2	1											
UKEPU.D2	0.0088	1										
USEPU.D2	0.0693	−0.2164	1									
IDEMV.D2	−0.0700	0.2066	−0.3051	1								
ADA.D2	0.0720	0.0086	−0.0528	−0.0227	1							
MIOTA.D2	−0.0023	−0.0510	0.0120	−0.0908	0.6994	1						
XLM.D2	1.0000	0.0088	0.0693	−0.0700	0.0720	−0.0023	1					
XNO.D2	−0.0642	−0.0519	−0.0123	0.0221	−0.0437	−0.0892	−0.0642	1				
XRP.D2	−0.0134	−0.0354	−0.0367	0.0206	0.5174	0.5594	−0.0134	0.0772	1			
GRID.D2	−0.0118	0.0371	−0.0331	0.0747	0.0763	0.0006	−0.0118	0.0177	0.0207	1		
POW.D2	0.0330	−0.0244	−0.0051	−0.0494	0.4325	0.5644	0.0330	−0.1551	0.3635	0.0065	1	
SNC.D2	−0.0263	−0.0574	0.0467	−0.0227	−0.0140	0.0241	−0.0263	−0.0070	0.0096	0.1361	0.0153	1

Panel D: Correlation Matrix of D3 (8 to 16 days)

	CNEPU.D3	UKEPU.D3	USEPU.D3	IDEMV.D3	ADA.D3	MIOTA.D3	XLM.D3	XNO.D3	XRP.D3	GRID.D3	POW.D3	SNC.D3
CNEPU.D3	1											
UKEPU.D3	−0.0077	1										
USEPU.D3	0.0689	0.2153	1									
IDEMV.D3	−0.0302	0.2510	−0.2141	1								
ADA.D3	0.0023	0.0607	−0.0403	−0.0648	1							
MIOTA.D3	−0.0307	0.0362	−0.0460	−0.0821	0.7110	1						
XLM.D3	1.0000	−0.0077	0.0689	−0.0302	0.0023	−0.0307	1					
XNO.D3	0.0364	0.0153	0.0844	0.0441	−0.0815	−0.1698	0.0364	1				
XRP.D3	−0.0425	0.0196	−0.0193	−0.0606	0.6126	0.6645	−0.0425	−0.0217	1			
GRID.D3	−0.0577	−0.0616	−0.0840	0.1329	0.0546	−0.0091	−0.0577	0.0371	−0.0106	1		
POW.D3	−0.0570	0.0987	0.0334	−0.0583	0.4948	0.6393	−0.0570	−0.1178	0.5094	−0.0538	1	
SNC.D3	−0.0333	−0.0273	−0.0433	−0.0552	−0.0498	−0.0225	−0.0333	0.1122	0.0262	0.2389	−0.0261	1

Table 2. *Cont.*

Panel E: Correlation Matrix of D4 (16 to 32 days)												
	CNEPU.D4	**UKEPU.D4**	**USEPU.D4**	**IDEMV.D4**	**ADA.D4**	**MIOTA.D4**	**XLM.D4**	**XNO.D4**	**XRP.D4**	**GRID.D4**	**POW.D4**	**SNC.D4**
CNEPU.D4	1											
UKEPU.D4	0.0377	1										
USEPU.D4	0.0246	0.5767	1									
IDEMV.D4	0.0573	0.4240	0.3213	1								
ADA.D4	−0.0257	0.1910	0.2215	0.1134	1							
MIOTA.D4	−0.0479	0.0832	0.0837	−0.0215	0.6842	1						
XLM.D4	1.0000	0.0377	0.0246	0.0573	−0.0257	−0.0479	1					
XNO.D4	0.1715	−0.0270	−0.0220	0.1363	0.0478	−0.0933	0.1715	1				
XRP.D4	0.0515	0.1429	0.1177	0.2156	0.5977	0.6139	0.0515	0.0848	1			
GRID.D4	−0.1291	−0.1520	−0.0707	−0.1619	−0.1811	−0.0952	−0.1291	−0.0038	−0.0228	1		
POW.D4	0.0161	0.1861	0.1796	0.0496	0.4447	0.6418	0.0161	−0.0818	0.4472	−0.2194	1	
SNC.D4	−0.0599	−0.0032	−0.0389	−0.0987	−0.1717	−0.2078	−0.0599	0.2532	−0.0714	0.3751	−0.3160	1
Panel F: Correlation Matrix of D5 (32 to 64 days)												
	CNEPU.D5	**UKEPU.D5**	**USEPU.D5**	**IDEMV.D5**	**ADA.D5**	**MIOTA.D5**	**XLM.D5**	**XNO.D5**	**XRP.D5**	**GRID.D5**	**POW.D5**	**SNC.D5**
CNEPU.D5	1											
UKEPU.D5	0.2362	1										
USEPU.D5	0.1491	0.7446	1									
IDEMV.D5	0.1037	0.3586	0.2483	1								
ADA.D5	0.2004	0.3614	0.3775	−0.0349	1							
MIOTA.D5	0.1455	0.2209	0.2542	−0.0077	0.6688	1						
XLM.D5	1.0000	0.2362	0.1491	0.1037	0.2004	0.1455	1					
XNO.D5	−0.0399	0.1917	0.2314	0.0439	0.2103	0.1229	−0.0399	1				
XRP.D5	0.1377	0.2259	0.3021	0.0409	0.6273	0.6313	0.1377	0.2086	1			
GRID.D5	−0.2158	−0.0389	0.1027	−0.3333	0.1395	0.0483	−0.2158	0.1384	0.176	1		
POW.D5	0.0469	0.3454	0.3602	−0.1501	0.5562	0.6174	0.0469	0.1403	0.4111	0.0791	1	
SNC.D5	0.0358	0.2228	0.1838	−0.2568	0.3663	0.2990	0.0358	0.0896	0.1881	0.3785	0.2425	1
Panel G: Correlation Matrix of D6 (64 to 128 days)												
	CNEPU.D6	**UKEPU.D6**	**USEPU.D6**	**IDEMV.D6**	**ADA.D6**	**MIOTA.D6**	**XLM.D6**	**XNO.D6**	**XRP.D6**	**GRID.D6**	**POW.D6**	**SNC.D6**
CNEPU.D6	1											
UKEPU.D6	0.2430	1										
USEPU.D6	0.2069	0.8863	1									
IDEMV.D6	−0.0642	0.3183	0.2964	1								
ADA.D6	0.1342	0.1510	0.3172	−0.2643	1							
MIOTA.D6	0.1553	0.2226	0.4256	−0.2364	0.7796	1						
XLM.D6	1.0000	0.2430	0.2069	−0.0642	0.1342	0.1553	1					
XNO.D6	0.0370	0.2293	0.1289	−0.3077	0.0898	0.1526	0.0370	1				
XRP.D6	0.0856	0.1270	0.2658	−0.1230	0.5016	0.7188	0.0856	0.0993	1			
GRID.D6	0.2328	0.0628	0.2984	−0.3565	0.5516	0.5557	0.2328	0.2601	0.4831	1		
POW.D6	0.1843	0.1970	0.1554	−0.4575	0.4921	0.5083	0.1843	0.2345	0.4091	0.4882	1	
SNC.D6	0.2735	0.3326	0.3623	−0.2980	0.6015	0.5755	0.2735	0.1740	0.4137	0.5097	0.5622	1

Note: All unconditional correlation coefficients are significant at 1% or 0.001 significance level.

4.2. Evidence from TVP-VAR Approach

Table 3 reports the output of the TVP-VAR dynamic connectedness approach. We investigate the connectedness between EPU level series and cryptocurrency returns (energy and sustainable cryptocurrencies) from 1st December 2019 to 30th September 2022. Generally, the output of TVP-VAR across multiple scales shows heterogeneous connectedness. Notably, the total connectedness index followed an increasing trajectory from a low-frequency scale to a high-frequency scale. Table 3 shows the total connectedness indices or system-wide connectedness for Panel A (40.41%), Panel B (42.13%), Panel C (47.66%), Panel D (54.78%), Panel E (63.86%), Panel F (63.91%) and Panel G (65.12%). These findings suggest that the connection became stronger with the frequency of scale. They also show that the connectedness is stronger in the medium-term than in the very short and short term. These findings are consistent with previous research (Cui et al. 2021).

Table 3. Return Connectedness.

Panel A: Return Connectedness (Original data)													
	CNEPU	**UKEPU**	**USEPU**	**IDEMV**	**ADA**	**MIOTA**	**XLM**	**XNO**	**XRP**	**GRID**	**POW**	**SNC**	**FROM**
CNEPU	88.320	4.300	3.000	2.030	0.350	0.220	0.250	0.290	0.450	0.340	0.200	0.250	11.680
UKEPU	1.270	53.530	17.830	24.020	0.430	0.410	0.350	0.490	0.360	0.510	0.250	0.530	46.470
USEPU	0.950	22.610	56.060	17.070	0.340	0.320	0.250	0.620	0.220	0.500	0.240	0.810	43.940

Table 3. *Cont.*

	CNEPU	UKEPU	USEPU	IDEMV	ADA	MIOTA	XLM	XNO	XRP	GRID	POW	SNC	FROM
Panel A: Return Connectedness (Original data)													
IDEMV	0.870	8.980	7.510	77.350	0.630	0.660	0.390	0.810	0.300	0.980	0.710	0.810	22.650
ADA	0.750	0.920	0.630	0.500	35.530	17.860	20.400	0.560	14.050	0.270	8.130	0.400	64.470
MIOTA	0.300	0.940	0.660	0.400	17.570	34.830	17.750	0.750	15.150	0.250	11.000	0.410	65.170
XLM	0.390	0.840	0.460	0.370	19.260	17.290	33.550	0.450	18.750	0.190	8.200	0.260	66.450
XNO	0.990	1.450	1.980	1.150	1.020	1.330	0.810	86.330	2.150	0.510	1.490	0.790	13.670
XRP	0.540	0.950	0.550	0.250	14.610	16.110	20.580	0.640	37.390	0.180	7.880	0.300	62.610
GRID	0.930	1.610	1.330	1.570	1.060	1.480	0.930	1.240	1.150	81.810	1.410	5.480	18.190
POW	0.600	0.710	0.700	0.540	10.820	15.170	11.480	0.500	9.960	0.260	48.460	0.800	51.540
SNC	0.730	1.750	2.160	1.510	0.870	1.330	0.970	0.550	0.760	6.030	1.450	81.890	18.110
TO	8.320	45.060	36.810	49.410	66.970	72.170	74.170	6.930	63.310	10.000	40.940	10.860	484.960
NET	−3.370	−1.400	−7.130	26.760	2.500	7.000	7.710	−6.740	0.700	−8.180	−10.590	−7.250	TCI = 40.41
Panel B: Return Connectedness (2 to 4 days)													
CNEPU.D1	47.310	0.870	0.530	1.410	0.340	0.350	47.310	0.590	0.240	0.440	0.250	0.340	52.690
UKEPU.D1	1.350	68.990	8.400	14.120	0.930	0.450	1.350	0.930	0.750	1.600	0.480	0.660	31.010
USEPU.D1	1.990	21.820	59.510	7.770	1.040	0.880	1.990	1.100	0.770	1.500	0.720	0.900	40.490
IDEMV.D1	2.190	5.930	2.230	80.300	1.090	0.900	2.190	1.090	0.730	1.170	0.980	1.200	19.700
ADA.D1	1.590	0.830	0.840	0.840	40.720	22.210	1.590	1.130	16.050	0.630	12.170	1.400	59.280
MIOTA.D1	0.970	0.660	0.500	0.670	20.150	41.950	0.970	1.470	17.540	0.640	13.600	0.880	58.050
XLM.D1	47.310	0.870	0.530	1.410	0.340	0.350	47.310	0.590	0.240	0.440	0.250	0.340	52.690
XNO.D1	3.450	1.450	2.600	1.170	2.920	4.190	3.450	68.490	4.660	1.310	4.220	2.100	31.510
XRP.D1	1.460	1.050	0.780	0.630	16.750	20.090	1.460	1.240	43.440	0.910	11.290	0.900	56.560
GRID.D1	2.470	2.130	2.260	2.310	1.920	2.610	2.470	2.070	2.370	73.090	1.720	4.580	26.910
POW.D1	1.790	0.790	1.180	1.300	11.220	15.720	1.790	1.150	10.650	0.640	52.680	1.120	47.320
SNC.D1	2.200	1.360	3.120	1.870	2.650	3.030	2.200	1.690	1.570	7.210	2.460	70.640	29.360
TO	66.770	37.750	22.980	33.500	59.340	70.780	66.770	13.060	55.570	16.500	48.150	14.420	505.580
NET	14.080	6.730	−17.510	13.800	0.060	12.720	14.080	−18.450	−1.000	−10.410	0.820	−14.940	TCI = 42.13
Panel C: Return Connectedness (4 to 8 days)													
CNEPU.D2	41.120	2.650	2.250	1.580	1.270	1.880	41.120	0.840	2.880	3.460	0.250	0.700	58.880
UKEPU.D2	2.560	63.380	10.470	10.610	1.320	1.860	2.560	0.960	2.330	2.080	0.800	1.070	36.620
USEPU.D2	2.390	17.900	57.140	6.380	1.400	2.860	2.390	1.020	2.560	3.920	0.980	1.060	42.860
IDEMV.D2	2.220	10.300	7.640	60.970	1.540	3.000	2.220	1.050	3.490	4.830	1.480	1.250	39.030
ADA.D2	2.470	2.110	2.200	2.200	41.160	19.760	2.470	1.560	13.510	2.990	8.360	1.200	58.840
MIOTA.D2	2.130	1.900	2.970	2.430	17.840	36.210	2.130	1.520	15.700	5.630	10.200	1.330	63.790
XLM.D2	41.120	2.650	2.250	1.580	1.270	1.880	41.120	0.840	2.880	3.460	0.250	0.700	58.880
XNO.D2	3.150	2.930	3.040	2.640	2.170	3.790	3.150	66.670	3.130	3.920	2.890	2.530	33.330
XRP.D2	3.060	2.650	2.910	2.700	13.970	17.630	3.060	0.830	41.240	5.990	5.030	0.920	58.760
GRID.D2	4.040	2.610	4.130	3.440	1.780	6.320	4.040	1.210	6.510	61.810	0.990	3.120	38.190
POW.D2	1.210	1.250	1.760	1.700	13.050	15.780	1.210	2.680	7.920	2.240	49.270	1.920	50.730
SNC.D2	2.570	2.850	3.870	3.820	0.970	2.070	2.570	1.820	2.980	6.100	2.470	67.930	32.070
TO	66.930	49.800	43.490	39.070	56.570	76.840	66.930	14.330	63.890	44.600	33.690	15.810	571.960
NET	8.050	13.180	0.630	0.040	−2.260	13.050	8.050	−18.990	5.130	6.420	−17.040	−16.270	TCI = 47.66
Panel D: Return Connectedness (8 to 16 days)													
CNEPU.D3	42.440	1.200	0.990	1.530	0.550	1.200	42.440	2.590	1.100	1.070	1.420	3.470	57.560
UKEPU.D3	2.320	54.630	7.770	15.970	2.690	3.590	2.320	2.530	1.440	2.120	1.950	2.680	45.370
USEPU.D3	3.130	16.340	45.660	9.900	2.340	1.470	3.130	2.620	1.270	8.080	2.360	3.690	54.340
IDEMV.D3	2.700	7.440	6.550	55.350	4.600	5.630	2.700	2.890	1.880	3.470	2.530	4.270	44.650
ADA.D3	3.720	2.480	2.420	2.130	33.890	15.950	3.720	9.630	9.000	3.870	9.320	3.890	66.110
MIOTA.D3	3.620	2.060	1.800	2.550	15.170	32.910	3.620	9.930	8.030	3.120	13.110	4.080	67.090
XLM.D3	42.440	1.200	0.990	1.530	0.550	1.200	42.440	2.590	1.100	1.070	1.420	3.470	57.560
XNO.D3	4.560	2.060	3.150	3.470	5.690	6.930	4.560	51.670	3.600	3.940	5.710	4.670	48.330
XRP.D3	3.270	1.590	1.530	2.200	15.590	14.710	3.270	5.540	33.290	4.200	10.310	4.500	66.710
GRID.D3	2.680	2.240	2.360	3.610	4.680	4.740	2.680	5.490	4.960	54.280	5.530	6.770	45.720
POW.D3	2.830	1.460	1.400	2.720	12.030	15.140	2.830	6.900	8.000	3.150	39.400	4.130	60.600
SNC.D3	2.800	2.800	2.530	3.780	3.870	5.020	2.800	7.210	2.570	5.650	5.350	55.620	44.380
TO	74.060	40.860	31.490	49.380	67.760	75.550	74.060	57.940	42.960	39.760	59.000	45.620	658.420
NET	16.490	−4.510	−22.840	4.730	1.650	8.460	16.490	9.600	−23.750	−5.960	−1.600	1.240	TCI = 54.87
Panel E: Return Connectedness (16 to 32 days)													
CNEPU.D4	40.360	2.240	4.400	2.960	1.620	1.550	40.360	1.450	0.990	1.930	0.780	1.370	59.640
UKEPU.D4	5.910	46.850	11.680	12.560	2.090	0.780	5.910	2.650	3.370	5.060	1.540	1.590	53.150
USEPU.D4	4.730	27.440	34.630	13.410	3.680	0.870	4.730	1.990	2.980	2.300	1.920	1.330	65.370
IDEMV.D4	8.930	10.060	6.790	43.830	1.790	1.470	8.930	3.150	8.050	2.730	2.670	1.590	56.170
ADA.D4	5.700	6.130	3.670	2.960	29.450	10.740	5.700	5.920	12.230	3.790	7.160	6.550	70.550
MIOTA.D4	4.070	2.710	3.030	3.430	14.180	25.230	4.070	5.190	12.460	2.630	13.070	9.940	74.770
XLM.D4	40.360	2.240	4.400	2.960	1.620	1.550	40.360	1.450	0.990	1.930	0.780	1.370	59.640
XNO.D4	4.670	3.010	3.860	5.090	3.660	5.490	4.670	45.610	5.090	3.520	7.740	7.600	54.390
XRP.D4	2.400	4.320	3.680	5.130	13.710	12.670	2.400	5.080	32.110	1.680	8.480	8.350	67.890
GRID.D4	4.000	3.910	5.660	5.950	7.560	7.880	4.000	5.260	9.460	31.460	7.230	7.630	68.540
POW.D4	3.990	4.250	3.500	3.720	6.250	12.290	3.990	8.030	9.120	4.280	29.640	10.950	70.360
SNC.D4	6.000	5.440	4.920	3.760	10.010	4.620	6.000	8.120	5.730	3.540	7.750	34.100	65.900
TO	90.750	71.740	55.600	61.910	66.160	59.910	90.750	48.290	70.470	33.390	59.130	58.260	766.370
NET	31.110	18.590	−9.770	5.750	−4.390	−14.860	31.110	−6.100	2.580	−35.150	−11.220	−7.640	TCI = 63.86

Table 3. *Cont.*

Panel F: Return Connectedness (32 to 64 days)													
CNEPU.D5	38.410	2.630	2.140	3.500	1.520	2.040	38.410	2.250	0.880	3.170	2.910	2.130	61.590
UKEPU.D5	3.610	40.610	18.480	17.390	5.000	1.670	3.610	1.790	2.330	1.610	2.410	1.500	59.390
USEPU.D5	2.680	25.040	36.250	13.280	4.730	1.940	2.680	2.050	3.670	1.850	2.870	2.970	63.750
IDEMV.D5	3.680	11.820	10.200	46.550	2.800	2.810	3.680	4.380	2.000	5.560	3.330	3.200	53.450
ADA.D5	4.540	6.910	7.690	3.230	29.070	11.240	4.540	4.640	15.390	3.290	6.380	3.070	70.930
MIOTA.D5	2.630	4.610	4.860	3.570	14.660	30.730	2.630	3.920	14.030	1.440	11.870	5.050	69.270
XLM.D5	38.410	2.630	2.140	3.500	1.520	2.040	38.410	2.250	0.880	3.170	2.910	2.130	61.590
XNO.D5	3.240	6.400	6.830	6.870	3.200	4.110	3.240	46.390	6.110	3.260	6.810	3.540	53.610
XRP.D5	2.810	5.570	8.390	3.360	15.910	9.860	2.810	3.820	32.300	5.720	6.480	2.970	67.700
GRID.D5	4.780	4.850	10.080	8.870	4.350	6.120	4.780	4.080	6.690	32.060	5.470	7.890	67.940
POW.D5	5.290	6.110	5.980	2.150	9.480	14.130	5.290	2.840	6.950	6.160	30.690	4.920	69.310
SNC.D5	3.540	7.410	9.600	2.180	11.670	9.130	3.540	2.160	6.270	4.780	6.660	33.060	66.940
TO	75.210	83.980	86.390	67.900	74.830	65.100	75.210	34.180	65.190	40.030	58.090	39.350	765.470
NET	13.620	24.590	22.640	14.450	3.900	−4.170	13.620	−19.430	−2.510	−27.920	−11.220	−27.590	TCI = 63.91
Panel G: Return Connectedness (64 to 128 days)													
CNEPU.D6	33.110	4.200	4.090	4.020	2.950	2.140	33.110	2.140	1.990	3.140	2.800	6.320	66.890
UKEPU.D6	3.380	42.430	27.290	9.800	1.440	2.160	3.380	2.270	1.290	2.010	0.820	3.720	57.570
USEPU.D6	2.200	30.070	39.430	7.710	3.080	4.310	2.200	1.080	2.810	1.710	1.550	3.840	60.570
IDEMV.D6	3.270	5.500	3.080	45.670	4.500	4.460	3.270	4.840	2.490	8.660	9.050	5.210	54.330
ADA.D6	4.100	5.000	7.400	3.150	30.510	11.890	4.100	1.480	10.480	6.370	3.650	11.900	69.490
MIOTA.D6	2.330	5.320	9.000	3.610	17.100	25.890	2.330	2.650	15.210	5.640	5.090	5.840	74.110
XLM.D6	33.110	4.200	4.090	4.020	2.950	2.140	33.110	2.140	1.990	3.140	2.800	6.320	66.890
XNO.D6	5.640	10.700	9.260	4.980	4.520	4.510	5.640	41.380	4.350	2.310	3.020	3.690	58.620
XRP.D6	3.230	3.890	5.610	1.830	15.200	15.480	3.230	1.670	30.620	6.500	4.370	8.370	69.380
GRID.D6	3.350	3.730	5.070	5.430	10.230	6.600	3.350	3.860	10.810	30.790	6.810	9.970	69.210
POW.D6	2.520	4.840	6.580	5.160	8.720	12.630	2.520	2.920	9.180	6.250	32.490	6.200	67.510
SNC.D6	5.450	7.540	7.690	5.580	10.460	6.060	5.450	3.080	5.690	5.290	4.520	33.190	66.810
TO	68.570	84.990	89.150	55.280	81.140	72.380	68.570	28.150	66.290	51.010	44.470	71.390	781.400
NET	1.680	27.420	28.580	0.950	11.650	−1.730	1.680	−30.470	−3.090	−18.200	−23.050	4.570	TCI = 65.12

The results of Panel A (original returns) reveal that EPU failed to act as a spillover transmitter. However, COVID-19-induced equity market volatility remains the strongest volatility transmitter as the NET spillover coefficient is 26.76%. Interestingly, energy cryptocurrencies (GRID, POW and SNC) are major volatility recipients among cryptocurrencies with NET connectedness values of −8.18%, −10.59% and −7.25%, respectively. However, only one sustainable cryptocurrency (XNO) is a recipient of volatility transmission, with a NET connectedness coefficient of 6.74%. Results of Panel B (2 to 4 days scale) demonstrate that CNEPU, UKEPU and IDEMV are NET volatility transmitters regarding uncertainty measures, with NET connectedness values of 14.08%, 6.73%, and 13.80%, respectively. Among energy and sustainable cryptocurrencies, XNO (−18.45%) and XRP (−1.00%) are NET volatility recipients, as well as GRID and SNC, with NET connectedness coefficients of 10.41% and 14.94%, respectively. For wavelet scales of 4–8 days (Panel C), all considered uncertainties are NET volatility transmitters, with UKEPU being the leading transmitter, followed by CNEPU, with NET connectedness values of 13.18 and 8.05%, respectively. Among energy cryptocurrencies (sustainable), POW and SNC (ADA and XNO) are higher (lower) NET volatility receivers, with NET connectedness coefficients of −17.04% and −16.27% (−2.26% and −18.99%). Considering the results of Panel D (8 to 16 days), only CNEPU and USEPU are NET volatility transmitters, with NET connectedness values of 16.49% and 4.73%, respectively. Among cryptocurrencies, only XRP is the highest NET recipient, showing a NET connectedness of −23.75%, while two other energy cryptocurrencies have negative values: GRID (−5.96%) and POW (−1.60%). Notably, Panel D is the only wavelet scale where more than three cryptocurrencies are volatility recipients. Focusing on the output of Panel E (16 to 32 days), all uncertainty indices are volatility transmitters, CNEPU being the leading volatility transmitter with a value of 31.11% of NET connectedness, followed by UKEPU (18.59%), and with IDEMV as the weakest volatility transmitter (5.75%).

Among cryptocurrencies, all energy cryptocurrencies (GRID, POW and SNC) are volatility recipients, with values of −35.15%, −11.22% and −7.64%, with sustainable cryptocurrencies (ADA, MIOTA, XNO) also as volatility recipients, with NET connectedness values of −4.39%, −14.86% and −6.10%. The results of Panel F (scales from 32 to 64) confirm that EPUs (CNEPU, UKEPU and USEPU) and IDEMV indices are major transmitters, while all energy cryptocurrencies (GRID, POW and SNC) are NET volatility receivers and MIOTA, XNO and XRP returns are also volatility recipients with sustainable cryptocurrencies (−4.10%, −19.43% and −2.51%).

Finally, the results of Panel G (64 to 128 days) show that all EPUs (CNEPU, USKEPU, USEPU), as well as IDEMV, are NET volatility transmitters. More specifically, the NET connectedness values are 1.68%, 27.42% and 28.58%, for CNEPU, USKEPU and USEPU, with IDEMV showing the least volatility spillover effect, with a NET connectedness value of 0.95%. Among sustainable cryptocurrencies, MIOTA, XNO and XRP are volatility recipients (NET connectedness values of −1.73%, −30.47% and −3.09%), with two energy cryptocurrencies (GRID and POW) also as significant volatility receivers, with NET connectedness values of −18.20% and −23.05%, respectively (see Figure 3).

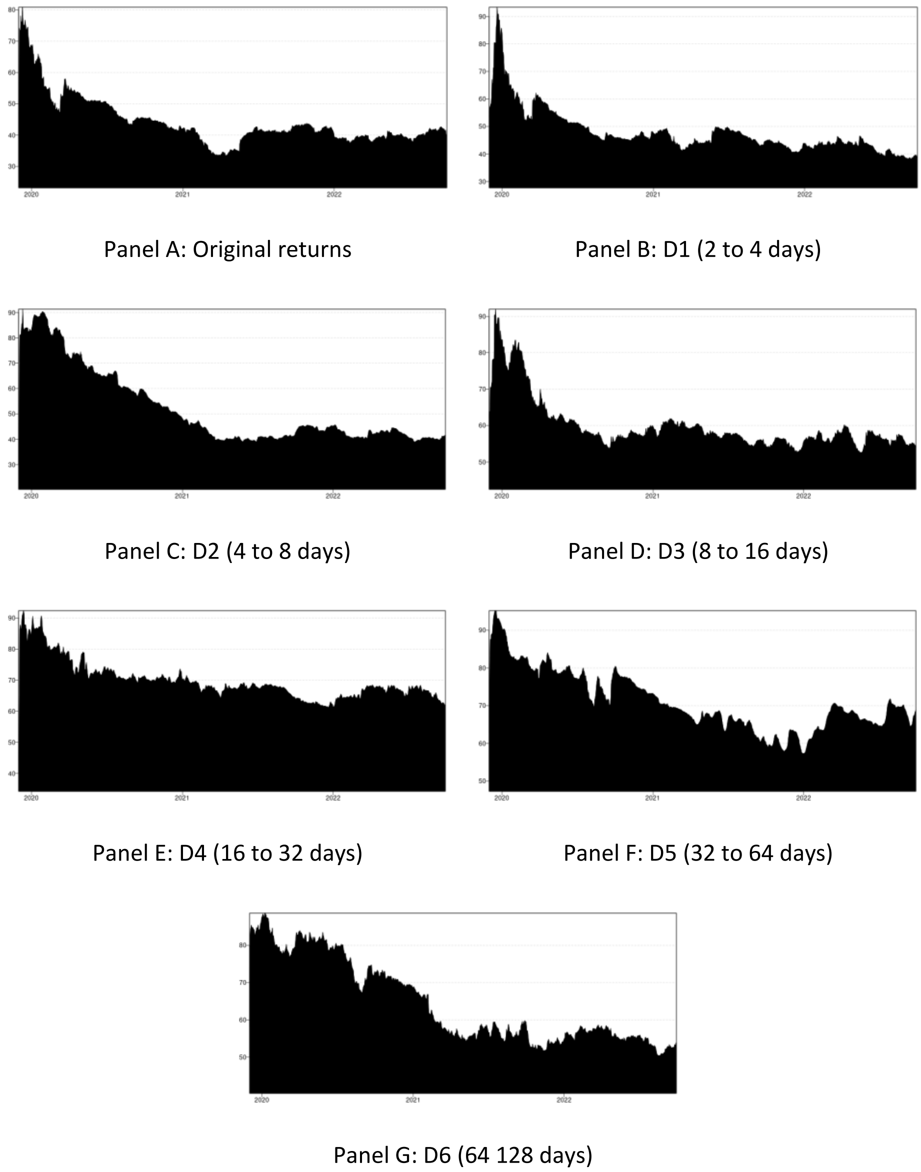

Figure 3. Dynamic return connectedness.

Generally, we find that EPUs and COVID-19 induced equity market volatility are consistent with the results of Foglia and Dai (2021), who concluded that the cryptocurrency market is a NET volatility receiver from EPU, with a peak in 2015, and dropping down gradually. The role of UKEPU and CNEPU in volatility transmission is supported by previous research (Cheng and Yen 2020; Foglia and Dai 2021) which found that Chinese restrictions influence the cryptocurrency market and that the UK is a net source of volatility contribution. These findings are particularly corroborated by earlier research, which found that the spillover from EPU to Bitcoin is marginal and Bitcoin is a safe-haven or diversifier during the time of EPU shocks (Wang et al. 2019). Moreover, more cryptocurrencies are linked to EPU in bearish market and less in bullish market conditions (Papadamou et al. 2021).

On the other hand, only XLM shows consistent non-recipient behavior of volatility from EPU and IDEMV across all wavelet components and original return series, also consistent with previous research, which documented negative connectedness between cryptocurrencies, EPU and IDEMV, while traditional cryptocurrencies are effective hedges for high EPU. Additionally, Ah Mand (2021) documented that EPU and VIX failed to influence traditional cryptocurrency returns and uncertainties. Nor did Wu et al. (2021) find a causal relationship between EPU and traditional cryptocurrency returns during the COVID-19 pandemic. Therefore, the cryptocurrency market generally has low hedging and safe-haven properties. Our study confirmed that only XLM can be considered a safe-haven sustainable cryptocurrency during the turbulent period of COVID-19. Finally, our findings show that few sustainable cryptocurrencies (MIOTA and ADA) were not volatility recipients from EPUs and IDEMV, although showing scale-dependent safe-haven properties. These findings are consistent with Al-Yahyaee et al. (2019), who found that Bitcoin-uncertainty co-movement indices are time and frequency dependent.

5. Conclusions and Implications

Using the TVP-VAR technique from 1 December 2019 to 30 September 2022, our paper provides evidence of the connectedness between national economic policy uncertainty, energy, and sustainable cryptocurrencies during the turbulent period of the COVID-19 pandemic. Furthermore, we looked into how the COVID-19 equities market volatility, energy, and sustainable cryptocurrencies are interconnected. In general, focusing on the volatility transmission perspective, our findings reveal that CNEPU (USEPU) is the strongest (weakest) NET volatility transmitter, followed by UKEPU, among the EPUs. Additionally, IDEMV is the most volatile NET transmitter among all uncertainty indices across the original returns and wavelet scales (D1~D6). Considering volatility recipients, energy cryptocurrencies (GRID, POW and SNC) are more likely to receive volatility spillovers than sustainable cryptocurrencies during the period under analysis. Notably, XLM (XNO) is the least (most) affected by volatility spillover in system-wide connectedness, and XLM showed a consistent behavior as non-recipient, across the six wavelet (D1~D6) scales. Moreover, the additional least effected sustainable cryptocurrencies are ADA and MIOTA as summarized in Table 4.

Table 4. Summary of NET Volatility Transmitters and Recipients based on TVP-VAR.

	Volatility Transmitters				Volatility Recipients							
Variables	**CNEPU**	**UKEPU**	**USEPU**	**IDEMV**	**ADA**	**MIOTA**	**XLM**	**XNO**	**XRP**	**GRID**	**POW**	**SNC**
Original Returns	No	No	No	Yes	No	No	No	Yes	No	Yes	Yes	Yes
D1:(2–4 days)	Yes	Yes	No	Yes	No	No	No	Yes	Yes	Yes	No	Yes
D2:(4–8 days)	Yes	Yes	Yes	Yes	Yes	No	No	Yes	No	No	Yes	Yes
D3:(8–16 days)	Yes	No	No	Yes	No	No	No	No	Yes	Yes	Yes	No
D4:(16–32 days)	Yes	Yes	No	Yes	Yes	Yes	No	Yes	No	Yes	Yes	Yes
D5:(32–64 days)	Yes	Yes	Yes	Yes	No	Yes	No	Yes	Yes	Yes	Yes	Yes
D6:(64–128 days)	Yes	Yes	Yes	Yes	No	Yes	No	Yes	Yes	Yes	Yes	No

Note: The highlighted box with "Yes" (No) in the volatility transmitters column confirms EPUs and IDEMV are the NET transmitters (non-transmitters). The highlighted box with "Yes" (No) in the volatility recipients column confirms energy and sustainable cryptocurrencies are the NET recipients (non-recipients).

These findings have several relevant implications. Firstly, cryptocurrency traders and sustainable investors should exercise caution when diversifying their portfolios between traditional assets, which are impacted by equity-economic news and political uncertainties, with the returns of cryptocurrencies showing consistent fluctuation throughout the period.

Secondly, in the case of participants, institutional investors can choose energy and sustainable cryptos in the cryptocurrency market that offer greater diversification and reduce higher risks following periods of economic instability. Along with considering the potential advantages of diversifying their portfolios while focusing on the multiscale findings, portfolio managers can also acquire a variety of investment options to prevent significant losses. Our analysis identifies a variety of cryptocurrencies with various levels of risk absorption and diversification and their corresponding ramifications. Thirdly, because we discovered pass-through mechanisms between the economy and digital markets, cryptocurrencies are also regarded as a component of traditional investment channels. The results suggest that those who plan to invest in or trade on the cryptocurrency market should keep a watch on the volatility of the equity market as well as regular news coverage of issues such as economic growth, political shifts, and catastrophes. In a similar line, stabilizing the financial system and monetary policies should also include stabilizing the cryptocurrency markets. The role of government is crucial in protecting the environment from fund inflows through effective supervision (Tran et al. 2022). Finally, policymakers must promote energy and sustainable investments for portfolio diversification since the cryptocurrency market has faced various concerns. Regulators and investors should consider this investment opportunity when constructing a risk-free portfolio, according to implications drawn from the fact that high EPUs and the COVID-19 equity market volatility index also transmitted volatility spillovers. Sustainable and crypto investors can also look at a number of energy-related and sustainable cryptocurrencies with the lowest risk and highest return, which exhibit less volatility throughout the COVID-19 period.

There are a few limitations to our study. Firstly, we considered the COVID-19 period to study the multiscale relationship. These findings inherit the pandemic flavor. Secondly, we employed the multiscale TVP-VAR approach to examine the dynamic connectedness, indicating TVP-VAR-specific output. Finally, our study focused on energy/sustainable cryptocurrencies and daily EPU measures. Future research needs to uncover the connectedness with other country-level EPU indices on a monthly or investigate the impact of financial and economic uncertainties on the sectoral level (Huynh et al. 2021b). Another extension to the current study is employing dynamic connectedness models, i.e., LASSO-VAR.

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Appendix A

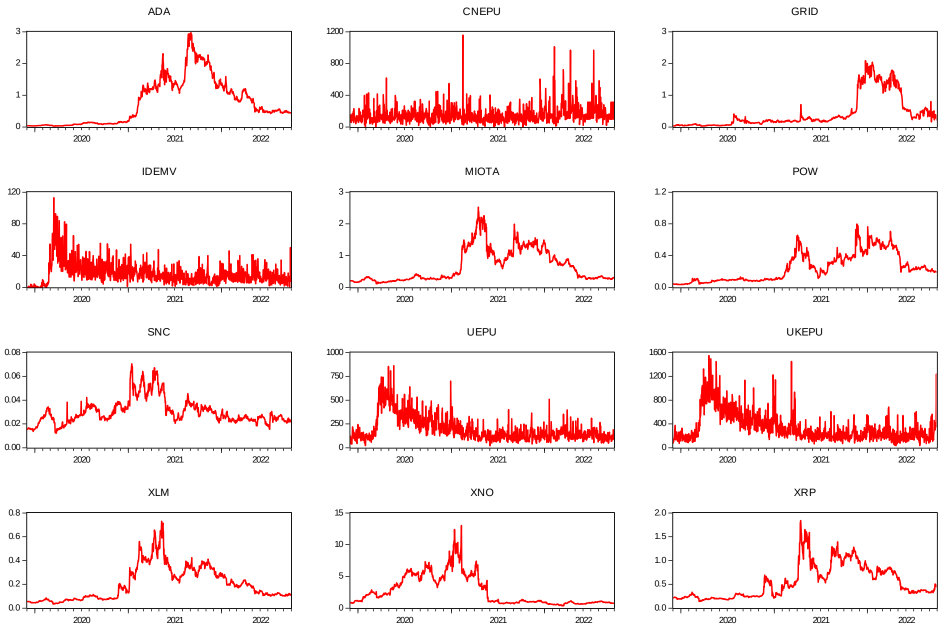

Figure A1. Evolution of EPU and cryptocurrencies.

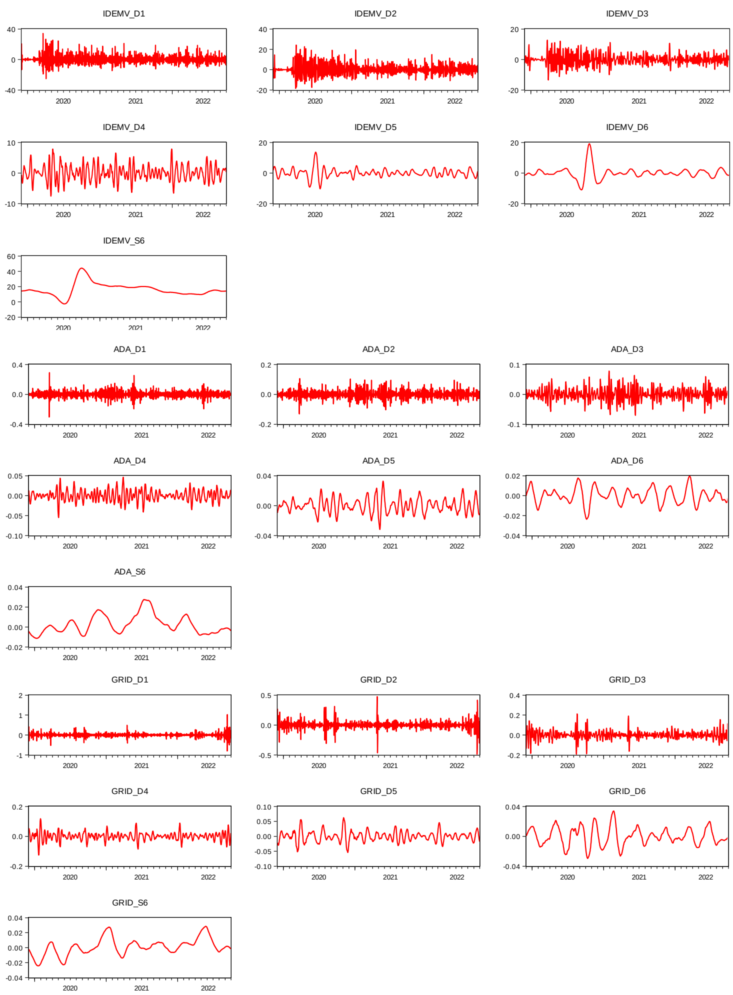

Figure A2. *Cont.*

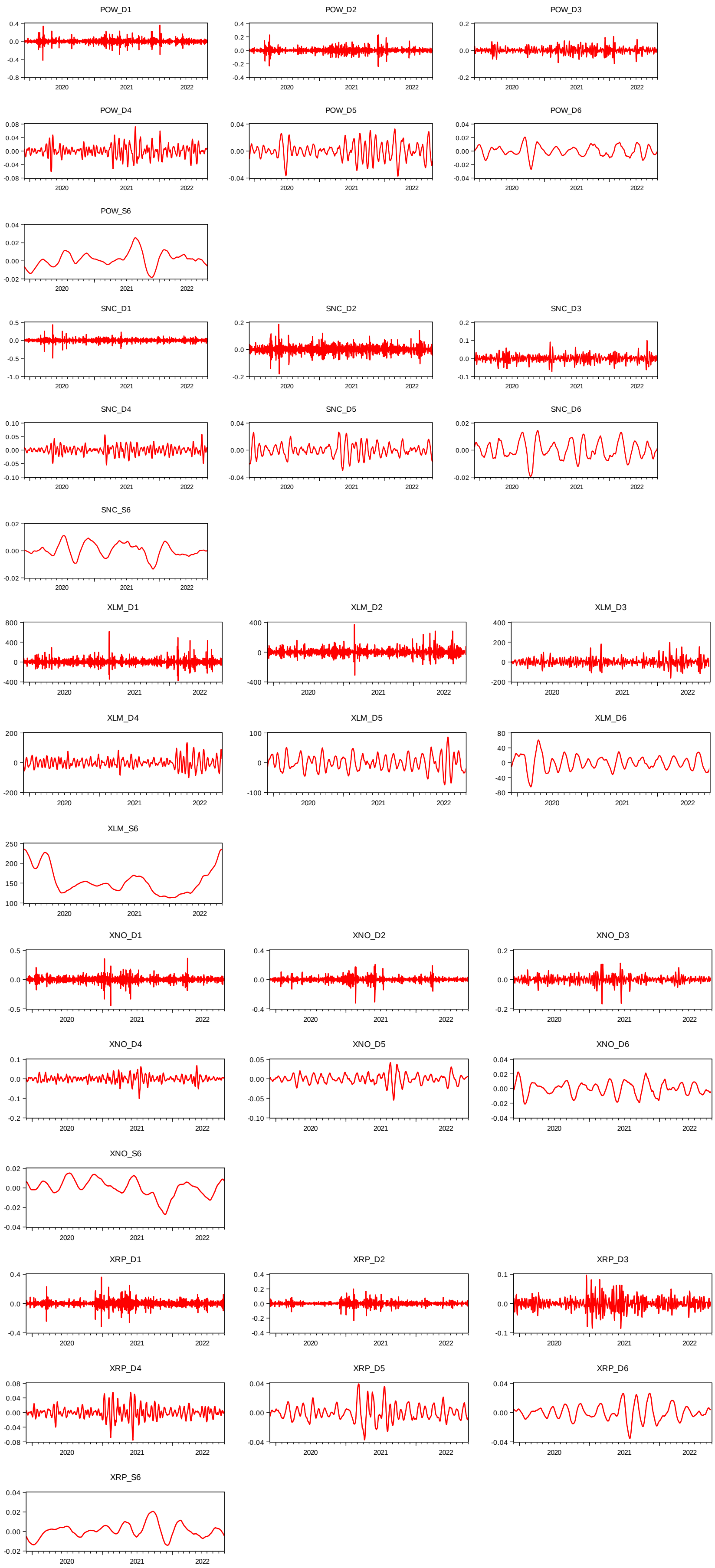

Figure A2. Wavelet decomposition graphs for all assets.

References

Adekoya, Oluwasegun, and Johnson Oliyide. 2021. How COVID-19 drives connectedness among commodity and financial markets: Evidence from TVP-VAR and causality-in-quantiles techniques. *Resources Policy* 70: 101898. [CrossRef] [PubMed]

Ah Mand, Abdollah. 2021. Cryptocurrency Returns and Cryptocurrency Uncertainty: A Time-Frequency Analysis. Available online: https://ssrn.com/abstract=3950087 (accessed on 25 October 2022).

Al-Thaqeb, Saud, and Barrak Algharabali. 2019. Economic policy uncertainty: A literature review. *The Journal of Economic Asymmetries* 20: e00133. [CrossRef]

Al-Yahyaee, Khamis, Mobeen Rehman, Walid Mensi, and Idries Al-Jarrah. 2019. Can uncertainty indices predict Bitcoin prices? A revisited analysis using partial and multivariate wavelet approaches. *The North American Journal of Economics and Finance* 49: 47–56. [CrossRef]

Antonakakis, Nikolaos, Ioannis Chatziantoniou, and David Gabauer. 2020. Refined Measures of Dynamic Connectedness based on Time-Varying Parameter Vector Autoregressions. *Journal of Risk and Financial Management* 13: 84. [CrossRef]

Baker, Scott, Nicholas Bloom, and Steven Davis. 2016. Measuring economic policy uncertainty. *The Quarterly Journal of Economics* 131: 1593–636. [CrossRef]

Bouri, Elie, and Rangan Gupta. 2021. Predicting Bitcoin returns: Comparing the roles of newspaper-and internet search-based measures of uncertainty. *Finance Research Letters* 38: 101398. [CrossRef]

Bouri, Elie, Oguzhan Cepni, David Gabauer, and Rangan Gupta. 2021. Return connectedness across asset classes around the COVID-19 outbreak. *International Review of Financial Analysis* 73: 101646. [CrossRef]

Chen, Tiejun, Chi Lau, Sadaf Cheema, and Chun Koo. 2021. Economic policy uncertainty in China and bitcoin returns: Evidence from the COVID-19 period. *Frontiers in Public Health* 9: 651051. [CrossRef]

Cheng, Hui-Pei, and Kuang-Chueh Yen. 2020. The relationship between the economic policy uncertainty and the cryptocurrency market. *Finance Research Letters* 35: 101308. [CrossRef]

Cui, Jinxin, Mark Goh, and Huiwen Zou. 2021. Information spillovers and dynamic dependence between China's energy and regional CET markets with portfolio implications: New evidence from multi-scale analysis. *Journal of Cleaner Production* 289: 125625. [CrossRef]

Demir, Ender, Giray Gozgor, Chi Lau, and Samuel A. Vigne. 2018. Does economic policy uncertainty predict the Bitcoin returns? An empirical investigation. *Finance Research Letters* 26: 145–49. [CrossRef]

Diebold, Francis, and Kamil Yilmaz. 2009. Measuring financial asset return and volatility spillovers, with application to global equity markets. *The Economic Journal* 119: 158–71. [CrossRef]

Diebold, Francis, and Kamil Yilmaz. 2012. Better to give than to receive: Predictive directional measurement of volatility spillovers. *International Journal of Forecasting* 28: 57–66. [CrossRef]

Diebold, Francis, and Kamil Yilmaz. 2014. On the network topology of variance decompositions: Measuring the connectedness of financial firms. *Journal of Econometrics* 182: 119–34. [CrossRef]

Fang, Libing, Honghai Yu, and Lei Li. 2017. The effect of economic policy uncertainty on the long-term correlation between US stock and bond markets. *Economic Modelling* 66: 139–45. [CrossRef]

Fang, Libing, Elie Bouri, Rangan Gupta, and David Roubaud. 2019. Does global economic uncertainty matter for the volatility and hedging effectiveness of Bitcoin? *International Review of Financial Analysis* 61: 29–36. [CrossRef]

Foglia, Matteo, and Peng-Fei Dai. 2021. "Ubiquitous uncertainties": Spillovers across economic policy uncertainty and cryptocurrency uncertainty indices. *Journal of Asian Business and Economic Studies* 29: 35–49. [CrossRef]

Gallersdörfer, Ulrich, Lena Klaaßen, and Christian Stoll. 2020. Energy consumption of cryptocurrencies beyond bitcoin. *Joule* 4: 1843–46. [CrossRef]

Gulzar, Saqib, Ghulam Mujtaba Kayani, Hui Xiaofen, Usman Ayub, and Amir Rafique. 2019. Financial cointegration and spillover effect of global financial crisis: A study of emerging Asian financial markets. *Economic Research-Ekonomska Istraživanja* 32: 187–218. [CrossRef]

Haq, Inzamam Ul, and Elie Bouri. 2022. Sustainable versus Conventional Cryptocurrencies in the Face of Cryptocurrency Uncertainty Indices: An Analysis across Time and Scales. *Journal of Risk and Financial Management* 15: 442. [CrossRef]

Haq, Inzamam Ul, Apichit Maneengam, Supat Chupradit, and Chunhui Huo. 2022a. Are green bonds and sustainable cryptocurrencies truly sustainable? Evidence from a wavelet coherence analysis. *Economic Research-Ekonomska Istraživanja* 36: 807–26. [CrossRef]

Haq, Inzamam Ul, Paulo Ferreira, Apichit Maneengam, and Worakamol Wisetsri. 2022b. Rare Earth Market, Electric Vehicles and Future Mobility Index: A Time-Frequency Analysis with Portfolio Implications. *Risks* 10: 137. [CrossRef]

Huynh, Nhan, Anh Dao, and Dat Nguyen. 2021a. Openness, economic uncertainty, government responses, and international financial market performance during the coronavirus pandemic. *Journal of Behavioral and Experimental Finance* 31: 100536. [CrossRef] [PubMed]

Huynh, Nhan, Dat Nguyen, and Anh Dao. 2021b. Sectoral performance and the government interventions during COVID-19 pandemic: Australian evidence. *Journal of Risk and Financial Management* 14: 178. [CrossRef]

Jiang, Yonghong, Lanxin Wu, G. Tian, and He Nie. 2021. Do cryptocurrencies hedge against EPU and the equity market volatility during COVID-19?—New evidence from quantile coherency analysis. *Journal of International Financial Markets, Institutions and Money* 72: 101324. [CrossRef]

Kamal, Javed, and Mohammad Hassan. 2022. Asymmetric connectedness between cryptocurrency environment attention index and green assets. *The Journal of Economic Asymmetries* 25: e00240. [CrossRef]

Karaömer, Yunus. 2022. The time-varying correlation between cryptocurrency policy uncertainty and cryptocurrency returns. *Studies in Economics and Finance* 39: 297–310. [CrossRef]

Karim, Sitara, and Muhammad Naeem. 2021. Clean Energy, Australian Electricity Markets, and Information Transmission. *Energy Research Letters* 3: 29973. [CrossRef]

Karim, Sitara, and Muhammad Naeem. 2022. Do global factors drive the interconnectedness among green, Islamic and conventional financial markets? *International Journal of Managerial Finance* 18: 639–60. [CrossRef]

Karim, Sitara, Muhammad Naeem, Nawazish Mirza, and Jessica Paule-Vianez. 2022. Quantifying the hedge and safe-haven properties of bond markets for cryptocurrency indices. *The Journal of Risk Finance* 23: 191–205. [CrossRef]

Khalfaoui, Rabeh, Mohamed Boutahar, and Heni Boubaker. 2015. Analyzing volatility spillovers and hedging between oil and stock markets: Evidence from wavelet analysis. *Energy Economics* 49: 540–49. [CrossRef]

Koumba, Ur, Calvin Mudzingiri, and Jules Mba. 2020. Does uncertainty predict cryptocurrency returns? A copula-based approach. *Macroeconomics and Finance in Emerging Market Economies* 13: 67–88. [CrossRef]

Li, Zheng-Zheng, Chi-Wei Su, and Meng Zhu. 2022. How Does Uncertainty Affect Volatility Correlation between Financial Assets? Evidence from Bitcoin, Stock and Gold. *Emerging Markets Finance and Trade* 58: 2682–94. [CrossRef]

Lucey, Brian, Samuel Vigne, Larisa Yarovaya, and Yizhi Wang. 2022. The cryptocurrency uncertainty index. *Finance Research Letters* 45: 102147. [CrossRef]

Maghyereh, Aktham, Basel Awartani, and Hussein Abdoh. 2019. The co-movement between oil and clean energy stocks: A wavelet-based analysis of horizon associations. *Energy* 169: 895–913. [CrossRef]

Mokni, Khaled, Ahdi Ajmi, Elie Bouri, and Xuan Vo. 2020. Economic policy uncertainty and the Bitcoin-US stock nexus. *Journal of Multinational Financial Management* 57: 100656. [CrossRef]

Mokni, Khaled, Manel Youssef, and Ahdi Ajmi. 2022. COVID-19 pandemic and economic policy uncertainty: The first test on the hedging and safe haven properties of cryptocurrencies. *Research in International Business and Finance* 60: 101573. [CrossRef]

Papadamou, Stephanos, Nikolaos Kyriazis, and Panayiotis Tzeremes. 2021. Non-linear causal linkages of EPU and gold with major cryptocurrencies during bull and bear markets. *The North American Journal of Economics and Finance* 56: 101343. [CrossRef]

Percival, Donald, and Andrew Walden. 2000. *Wavelet Methods for Time Series Analysis*. Cambridge: Cambridge University Press.

Pham, Linh, Sitara Karim, Muhammad Naeem, and Cheng Long. 2022. A tale of two tails among carbon prices, green and non-green cryptocurrencies. *International Review of Financial Analysis* 82: 102139. [CrossRef]

Primiceri, Giorgio. 2005. Time varying structural vector autoregressions and monetary policy. *The Review of Economic Studies* 72: 821–52. [CrossRef]

Ren, Boru, and Brian Lucey. 2022a. A clean, green haven?—Examining the relationship between clean energy, clean and dirty cryptocurrencies. *Energy Economics* 109: 105951. [CrossRef]

Ren, Boru, and Brian Lucey. 2022b. Do clean and dirty cryptocurrency markets herd differently? *Finance Research Letters* 47: 102795. [CrossRef]

Rubbaniy, Ghulame, Ali Khalid, and Aristeidis Samitas. 2021. Are cryptos safe-haven assets during covid-19? Evidence from wavelet coherence analysis. *Emerging Markets Finance and Trade* 57: 1741–56. [CrossRef]

Shaikh, Imlak. 2020. Policy uncertainty and Bitcoin returns. *Borsa Istanbul Review* 20: 257–68. [CrossRef]

Tran, Quang Thien, Nhan Huynh, and Nhu An Huynh. 2022. Trading-off between being contaminated or stimulated: Are emerging countries doing good jobs in hosting foreign resources? *Journal of Cleaner Production* 379: 134649. [CrossRef]

Wang, Gang-Jin, Chi Xie, Danyan Wen, and Longfen Zhao. 2019. When Bitcoin meets economic policy uncertainty (EPU): Measuring risk spillover effect from EPU to Bitcoin. *Finance Research Letters* 31. [CrossRef]

Wang, Pengfei, Xiao Li, Dehua Shen, and Wei Zhang. 2020. How does economic policy uncertainty affect the bitcoin market? *Research in International Business and Finance* 53: 101234. [CrossRef]

Wang, Yizhi, Brian Lucey, Samuel Vigne, and Larisa Yarovaya. 2022. An index of cryptocurrency environmental attention (ICEA). *China Finance Review International* 12: 378–414. [CrossRef]

Wu, Wansah, Aviral Tiwari, Giray Gozgor, and Huang Leping. 2021. Does economic policy uncertainty affect cryptocurrency markets? Evidence from Twitter-based uncertainty measures. *Research in International Business and Finance* 58: 101478. [CrossRef]

Xiong, Xiong, Yuxiang Bian, and Dehua Shen. 2018. The time-varying correlation between policy uncertainty and stock returns: Evidence from China. *Physica A: Statistical Mechanics and Its Applications* 499: 413–19. [CrossRef]

Yen, Kuang-Chieh, and Hui-Pei Cheng. 2021. Economic policy uncertainty and cryptocurrency volatility. *Finance Research Letters* 38: 101428. [CrossRef]

Yousaf, Imran, Yasir Riaz, and John Goodell. 2022. Energy cryptocurrencies: Assessing connectedness with other asset classes. *Finance Research Letters* 103389. [CrossRef]

Zhao, Wen, and Yu-Dong Wang. 2022. On the time-varying correlations between oil-, gold-, and stock markets: The heterogeneous roles of policy uncertainty in the US and China. *Petroleum Science* 19: 1420–32. [CrossRef]

Zhu, Huiming, Yiwen Chen, Yinghua Ren, Zhanming Xing, and Liya Hau. 2022. Time-frequency causality and dependence structure between crude oil, EPU and Chinese industry stock: Evidence from multiscale quantile perspectives. *The North American Journal of Economics and Finance* 61: 101698. [CrossRef]