# The Dynamic Linkage Among Bitcoin, Clean Energy and Stock Market: Evidence by TVP-VAR

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## Credit author statement

**Amirreza Attarzadeh**: Conceptualization, Methodology, Formal Analysis, Writing - Original draft preparation, Reviewing and Editing, Data Curation, and Software. **Mehmet Balcilar**: Writing - Reviewing and Editing**,** Original draft preparation, and Software.

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## Abstract

This paper analyses the return and realized volatility spillovers among Bitcoin, wilder hill clean energy index (ECO), S&P 500 as conventional stocks and West Texas Intermediate (WTI) from 11/11/2013 to 30/09/2021. We investigate the transmission mechanism with Time-Varying Parameter Vector Auto regression (TVP-VAR). Our findings indicate that stock markets such as clean energy and conventional transmit return shocks to Bitcoin and oil and receive volatility shocks from Bitcoin and oil. In addition, during non-crisis periods, Bitcoin and other financial markets are weakly related; but, during crisis periods, such as the great cryptocurrency crash in 2018 and the coronavirus pandemic in 2020, their connection increases significantly.


**Keywords**: Clean energy, Bitcoin, Realized Volatility, Connectedness, TVP-VAR, Transmitters, Receivers

## Introduction

Intermarket linkage is a significant component of international finances as assessed by spillovers of returns and volatility and has key implications for portfolio and hedging decision-making. The empirical literature has attracted great attention with the signs of increased integration into the market led by market openness, globalization, finance, and technology advancement. For example, during crises, the volatility of the financial market grows dramatically and spills across markets. Of course, one would prefer to measure and control such outbreaks, both providing 'early warning' for emerging crises and monitoring the progress of existing crises.

Cryptocurrency markets have gotten considerably more popular in recent years so that cryptocurrencies can be shifted to the investment asset category. As Bitcoin emerged as the first and most popular crypto-currency, this new asset received attention, Bitcoin use block-chain technology to enable decentralized systems to safely and equitably issue new Bitcoins and confirm transactions by resolving a puzzle. As the number of Bitcoin transactions grows, more miners compete in the Bitcoin network, and the crypto algorithm that validates blocks and rewards miners becomes more complicated therefore the need for assessing the volatility of power and energy grows. According to the BBC, Cambridge academics estimate that Bitcoin consumes around 121.36 terawatt-hours (TWh) of electricity every year, which is more than Argentina's consumption with 46 million population. According to the Digiconomist, Bitcoin Energy Consumption Index, one Bitcoin transaction consumes 53 days of electricity for the average US family. These reports highlight the importance of financial and energy markets in the future of cryptocurrencies.

The need of checking the role of Bitcoin started in 2016, which became highly prominent in the investment and financial press. Bitcoin prices rose by more than 1300 percent in 2017, giving the entire market worth exceeding USD 215 Billion and this amount reached more than one trillion dollars in 2021. Therefore, for investment and policymakers' sake, it is necessary to study and evaluate the returns and volatility links between Bitcoin and other asset classes. Any proof of substantial returns and volatility spillages between Bitcoin and other asset classes possibly influences not just asset selection, allocation, and decision-making on risk management but also regulatory measures that aim to ensure global financial system stability. It is also significant for politicians that consider Bitcoin part of their foreign reserves or experiment with their own crypto-monetary equivalents.

This research is linked to the strand that looks into energy commodity Sadorsky (2012), despite their substantial interconnection, the dynamics and economic links between energy, Bitcoin, and the financial market have not been investigated sufficiently. This study fills the gap by contributing the TVP-VAR method and the comparison of realized volatility results with return spillovers among Bitcoin, clean energy, stock price, and fossil fuel. Our research expands the literature that analyzes the relationship between cryptocurrencies and financial markets. Our research is close to Dyhrberg (2016); Katsiampa (2017); Balcilar et al. (2017); Symitsi and Chalvatzis (2018); Akyildirim et al. (2020); Naeem and Karim (2021). Our findings indicate that return and realized volatility spillovers among Bitcoin, stock, and energy markets are time varying. Although During non-crisis periods, Bitcoin and other financial markets are weakly related; but, during crisis periods, such as the great cryptocurrency crash in 2018 and the coronavirus pandemic in 2020, their connection increases significantly. Furthermore, the spillover effects between Bitcoin and other markets are asymmetric. Furthermore, we discovered that cryptocurrency investors' environmental awareness has a considerable impact on the spillovers between cryptocurrency and green investments, particularly at the times when Bitcoin prices peaked, such as in 2018 and 2021.

The following is a breakdown of our paper's structure. Literature review is presented in section 2, the data, and methodology are presented in Section 3. The empirical findings are discussed in Section 4 and the main conclusions are presented in Section 5.

## Literature Review

The enormous volume of Bitcoin trading is well known to consume a significant amount of energy. As a result, while cryptocurrency has economic benefits, it also has the potential to hasten environmental destruction (Krause and Tolaymat 2018)**.**The multidimensional evolution of financial technology paints a beautiful picture of current trading while simultaneously warning about the negative repercussions on our future environment (Truby 2018; Corbet et al. 2021).

The current literature looks into how Bitcoin trading affects the financial market and environmental sustainability. According to a recent analysis by Jiang et al. (2021), maintaining the Bitcoin block chain in 2024 will require 296.59 Twh, leading to producing 130.50 million metric tons of carbon. Polemis and Tsionas (2021) conducted an investigation in 50 countries to find the causal relationship among Bitcoin usage and Co2 emissions. Surprisingly, lower Bitcoin miner returns have a rapid effect on environmental circumstances. This study emphasizes the impact

of renewable energy and long-term mining hardware disposal in reducing Bitcoin's carbon emissions at the regional level.

The financial linkages between Bitcoin and energy investments have been established in the literature due to cryptocurrency's strong reliance on energy. On average, Ji et al. (2019) show a weak link between cryptocurrencies and energy commodities such as heating oil, crude oil, natural gas although this link varies over time. The bidirectional and unidirectional spillover between cryptocurrency and crude oil spot prices is investigated by Okorie & Lin (2020), Bitcoin represents a bidirectional spillover of volatility. Jareño et al. (2021), report that that oil shocks have a significant linkage with cryptocurrencies return. They also point out how, in 2020, during the first wave of the COVID-19 pandemic, oil and cryptocurrency became more intertwined. Continuing efforts to find relationships between digital currencies and the financial market, to account for the bivariate reliance between Bitcoin and other markets, Naeem and Karim (2021) uses the bivariate copula model. Baur et al. (2015) found that Bitcoin could be used as a diversifier. Low correlation with bonds and equities was the evidence of this conclusion and Ji et al. (2018) reached the same conclusion by using the directed acyclic graph approach. On the other hand, they did not take into account the relationship between return and volatility in different markets. However, there is limited empirical research of Bitcoin to other-markets returns and volatility spillovers. Balcilar et al. (2017) use trade volume data to predict Bitcoin returns and volatility. They claim that while transaction volume can assist anticipate returns in some cases, it does not provide information on volatility. Katsiampa (2017) applies multiple GARCH models to Bitcoin volatility and discovers the importance of integrating both long and short-run components of conditional variance. According to Bouri et al. (2017) Bitcoin can be used to hedge against commodity indices and uncertainty indicators. Bouri et al. (2018) employed a smooth transition model of VARGARCH-in-mean; the findings imply that spillovers between Bitcoin and the asset classes analyzed are affected by the time and market conditions under which they were utilized. Bitcoin is linked to other assets primarily through return rather than volatility.

The literature focuses primarily on studying volatility connectivity. However, this may be misleading to investors because the dynamics of return and volatility frequency connectivity may differ, and both may provide significant information to investors. The purpose of this research is to look at the total and frequency connectedness of Bitcoin, S&P500, Clean Energy, and crude oil on both the return and volatility levels.

## Data and Methodology

### Data Analysis

This research examines the return and realized volatility spillover effects of four significant assets (i.e., S&P500, Bitcoin, Wilder Hill Clean Energy Index, and West Texas Intermediate (WTI)) utilizing the expanded Time-Varying Parameter Vector Auto Regression (TVP-VAR) method presented by Diebold and Yilmaz (2009; 2012). The shortcomings of the generalized VAR approach are overcome by this methodology. It addresses the question of which potential outcomes are affected by lag order because of Cholesky factor orthogonalization.

The data are used on a daily basis for both the return and volatility series from 11/11/2013 until 30/09/2021. The data for WTI, which assesses crude oil spot price and Bitcoin price as well as the S&P500 composite index as common stocks that illustrate the overall market performance, are extracted from Investing.com. In addition, the performance of clean energy is measured through the Wilder Hill CE Index (ECO) extracted from DataStream.

In this article Volatility is calculated as the realized volatility by employing Christopher Rogers and Satchell (1991), Leonard Rogers et al. (1994) suggestions for High, Low, Open, and Close price of each variable by following the formula:

$$V_{j,t} = 100 * \sqrt{N * ln\left(\frac{H_t}{O_t}\right) * ln\left(\frac{H_t}{C_t}\right) + ln\left(\frac{L_t}{O_t}\right) * ln(\frac{L_t}{C_t})}$$

$V_{j,t}$ present Realized Volatility, N is the number of trading days, H and L represent the High and Low price respectively. O and C represent the Open and Close price. The daily return calculate as follows, $R_{j,t}$ is the percentage log return of and $P_{j,t}$ is the close price. $R_{j,t} = \ln\left(P_{j,t}/P_{j,t-1}\right) * 100$.

According to Tables 1 and 2, Bitcoin has the highest average daily return in terms of both return and volatility, with 0.249 and 60.566, respectively, and oil has the lowest average daily return in terms of return. The latter realized volatility index, like BTC and OIL, has a lot of volatility. Furthermore, all realized volatility series have excess kurtosis and are positively skewed. At last, as demonstrated by the Jarque-Bera test, all series are not normally

distributed. Stock and Watson (1996) proposed the ERS test (also known as the ADF-GLS test), which is significant for all series, implying that all returns and realized volatility series are stationary.

**Table 1** Statistical report of return

| | S&P500 | CE | WTI | BTC |
|---|---|---|---|---|
| Mean | 0.047 | 0.046 | 0.019 | 0.249 |
| Variance | 1.187 | 4.046 | 8.764 | 25.374 |
| Skewness | -1.050*** | -0.596*** | 0.225*** | -0.483*** |
| Ex.Kurtosis | 22.303*** | 7.495*** | 26.106*** | 10.195*** |
| JB | 41486.151*** | 4761.451*** | 56357.036*** | 8668.772*** |
| ERS | -19.888*** | -8.023*** | -17.653*** | -8.166*** |

**Table 2** Statistical report of realized volatility

| | S&P500 | CE | WTI | BTC |
|---|---|---|---|---|
| Mean | 10.953 | 22.998 | 40.202 | 60.566 |
| Variance | 88.646 | 316.103 | 1245.594 | 3542.784 |
| Skewness | 3.601*** | 3.437*** | 6.730*** | 3.969*** |
| Ex.Kurtosis | 22.282*** | 21.416*** | 74.065*** | 27.101*** |
| JB | 45330.422*** | 41821.257*** | 468453.830*** | 65924.493*** |
| ERS | -6.565*** | -8.970*** | -5.893*** | -12.292*** |

As previously stated, we are investigating the transmission mechanism in a time-varying manner using the methodology outlined in Antonakakis and Gabauer (2017) The Bayesian Information Criterion (BIC) dictates that we use a TVP-VAR (8) with time-varying volatility.

**Total Connectedness Index**

$$y_t = \omega_t y_{t-1} + \sigma_t \qquad \sigma_t \sim T(0, \eta_t) \tag{1}$$
$$\mathrm{vec}(\omega_t) = \mathrm{vec}(\omega_{t-1}) + \mathrm{J}_t \qquad \mathrm{J}_t \sim T(0, \Xi_t) \tag{2}$$

Where $y_t$, $\sigma_t$ and $\mathrm{J}_t$ are T*1 vectors and $\eta_t$, $\Xi_t$ and $\omega_t$ are T*T dimensional matrices. TVP-VAR Wold represent by; $y_t = \sum_{i=1}^{p} \omega_{it} y_{t-i} + \sigma_t = \sum_{j=1}^{\infty} A_{jt} \sigma_{t-j} + \sigma_t$.

The fundament of time-varying coefficients of vector moving average (VMA) model is presented by Diebold & Yilmaz (2012) using generalized impulse response functions $GIRF$ and generalized forecast error variance decompositions $GFEVD$ , $\varphi_{ij,t}^{h}(J)$ ,developed by Koop et al. (1996); Pesaran and Shin (1998). The GFEVD, which can be understood as the variance share variable $i$ explains on variable j, is more interesting for us and we can calculate it as follow;

$$\varphi_{ij,t}^{h}(J) = \frac{S_{ii,t}^{-1} \sum_{t=1}^{J-1} \left(\Omega_i' A_t S_t \Omega_j\right)^2}{\sum_{j=1}^{N} \sum_{t=1}^{J-1} \left(\Omega_i A_t S_t A_t' \iota_i\right)} \tilde{\varphi}_{ij,t}^{h}(J) = \frac{\varphi_{ij,t}^{h}(J)}{\sum_{j=1}^{N} \varphi_{ij,t}^{h}(J)} \quad (3)$$

Where $\Omega_i$ is a zero vector with unity on the $i$ position, $\sum_{j=1}^{N} \varphi_{ij,t}^{N}(J)$=1 and $\sum_{j.i=1}^{N} \varphi_{ij,t}^{N}(J)$=N.

Total connectedness index (TCI) construct by generalized forecast error variance decompositions and is calculated by the following formula:

$$c_t^h(J) = \frac{\sum_{i,j=1,i\neq j}^{N} \tilde{\varphi}_{ijt}^{h}(J)}{\sum_{i,j=1}^{N} \tilde{\varphi}_{ijt}^{g}(J)} \quad (4)$$

Intuitively, it can be defined as the average spillover from all other markets to a given asset, ignoring the effect that the market has on itself due to lags. Firstly, we are curious about the spillovers of variable i to all others j, which indicate the total directional connectedness to others (equation 5) and secondly we calculate total directional connectedness from others by equation 6.

$$c_{i\rightarrow jt}^{h}(J) = \sum_{j=1,i\neq j}^{N} \tilde{\varphi}_{jit}^{h}(J) \quad (5)$$

$$c_{i\leftarrow jt}^{h}(J) = \sum_{j=1,i\neq j}^{N} \tilde{\varphi}_{jit}^{h}(J) \quad (6)$$

In addition, net directional connectedness (equation 7) can be calculated by subtracting equation 5 from 6.

$$c_{it}^{h} = c_{i\rightarrow jt}^{h}(J) - c_{i\leftarrow jt}^{h}(J) \quad (7)$$

Finally, by computing net pairwise directional connectedness from equation 8, we may infer bidirectional linkages and demonstrate that variable $i$ has an effect on variable $j$ or vice versa.

$$NPDC_{ij}(H) = \widetilde{\varphi}_{jit}(H) - \widetilde{\varphi}_{ijt}(H) \quad (8)$$

# Empirical results

### Averaged Dynamic connectedness

Table 3 presents the calculation of whole sample return and volatility spillover indices, as well as their decomposition as receivers and transmitters among oil, stocks, and Bitcoin. Total connectedness index (TCI) is almost close for both estimations with 25.13% and 23.96% for return and volatility respectively, which means around 25% of the return FEVD is obtained from other markets on average, also around 24% for realized volatility obtained from other assets on average.

The results show that oil and Bitcoin are net receivers with -4.31% and -0.08% for return and stocks (clean energy and conventional) are net transmitters. In contrast to the return results, oil and Bitcoin became net transmitters with 2.07% and 2.15% in realized volatility estimations, and the role of stocks changed to net receivers with -2.13% for S&P500 and -2.09% for the clean energy index. By considering table 3 panel (a), the largest contributor is conventional stocks with 40.26% and is followed by clean energy index, oil, and Bitcoin.

The net spillover for S&P500 is 30.44 to CE and its 7.08% and 2.75% for oil and Bitcoin. Additionally, clean energy contributes 2.2% for Bitcoin, 8.69%, and 30.70% for oil and S&P500. Overall spillover between oil and Bitcoin is the lowest amount for both return and realized volatility by 0.85% and 1.87% respectively, which implies that there exist lower pass-through among them also spillovers between Bitcoin, S&P 500 is 2.2%, and it followed by clean energy and oil. The analysis confirms that shocks from other assets to Bitcoin are so small; however, there is net return, transmission to the Bitcoin the impact is small.

With respect to the results of realized volatility in table 3, TCI is 23.96% and it is quite the same as return results. In addition, the VS&P 500 index spillovers are 23.96%, 8.79%, and 1.77% for VCE, VOIL, and VBTC. Moreover, the lowest spills are VCE to VBTC by 1.75% and the highest is VS&P500 with 24.25. The finding from Bitcoin to other

markets has the same intensity; although, it is greater than return results. The bidirectional volatility spillover from oil to other markets is larger in comparison to return spillover.

In terms of risk spillover, we can conclude that Bitcoin can be safe haven on average for investors from 2013 to 2021 because the volatility spillover to Bitcoin is quite small and its net sender than recipient. In addition, the shocks from oil and other assets do not have a significant effect on Bitcoin in this period.

**Table 3** Dynamic connectedness of related assets

| Return (a) | S&P500 | CE | OIL | BTC | Received |
|---|---|---|---|---|---|
| S&P500 | 61.57 | 30.70 | 5.52 | 2.20 | 38.43 |
| CE | 30.44 | 60.96 | 6.59 | 2.01 | 39.04 |
| OIL | 7.08 | 8.69 | 82.73 | 1.50 | 17.27 |
| BTC | 2.75 | 2.20 | 0.85 | 94.20 | 5.80 |
| Transmitted | 40.26 | 41.60 | 12.96 | 5.72 | 100.54 |
| Including own | 101.83 | 102.56 | 95.69 | 99.92 | TCI |
| NET spillovers | 1.83 | 2.56 | -4.31 | -0.08 | **25.13%** |
| Volatility (b) | VS&P500 | VCE | VOIL | VBTC | Received |
| VS&P500 | 63.36 | 24.25 | 10.09 | 2.30 | 36.64 |
| VCE | 23.96 | 64.74 | 8.67 | 2.63 | 35.26 |
| VOIL | 8.79 | 7.17 | 81.44 | 2.61 | 18.56 |
| VBTC | 1.77 | 1.75 | 1.87 | 94.60 | 5.40 |
| Transmitted | 34.51 | 33.17 | 20.63 | 7.54 | 95.86 |
| Including own | 97.87 | 97.91 | 102.07 | 102.15 | TCI |
| NET spillovers | -2.13 | -2.09 | 2.07 | 2.15 | **23.96%** |

Note: In return and volatility spillovers, the underlying variance decompositions are produced using the TVP-VAR model with a 10-day-ahead forecast window. S&P500= conventional stocks index, CE = Wilder Hill Clean Energy Index, OIL= West Texas Intermediate crude oil and BTC= Bitcoin. (V) Represent Volatility.

**Dynamic total connectedness**

Passing from the TCI to the time-varying version shown in Figure 1 clearly shows that the total connectedness index across the sample period based on the TVP-VAR model changes over time between 16-55% for return and 11-49% in realized volatility. The overall images indicate similar prominent peaks in early 2020, which were caused by the coronavirus pandemic. In January 2020-world, a health organization (WHO) issues a global health emergency and in March, they declare COVID-19 is Pandemic (peak level).

The results in realized volatility do obviously illustrate six main occurrences first peak related to the oil crash which oil drop to 44$ from the highest price in June 2014 with 107$ per barrel second peak related to stock market selloff in August 2015 and the third peak is related to Syrian Civil War. In the following, we will refer to the fourth peak, which has the election of a new president in the United States and then to the two main peaks, namely, the great crypto crash in January 2018 and the beginning of the Pandemic in January 2020.

(a) Returns (b) Volatility

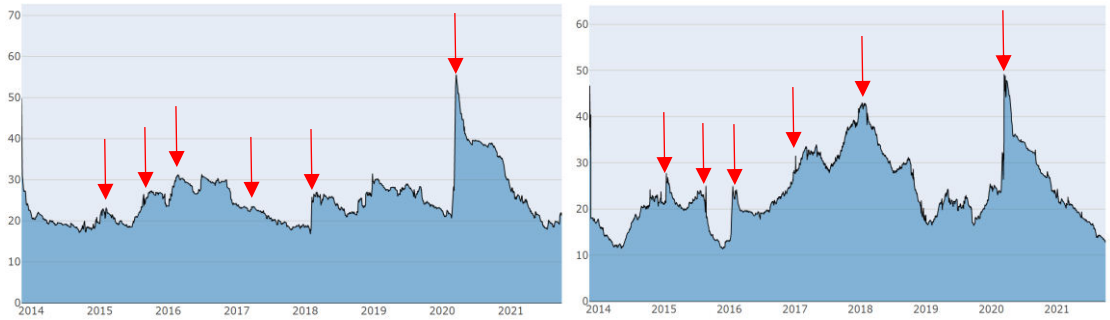


**Fig. 1 a** Total return spillover indices of four asstes (s&p500, clean energy, oil and Bitcoin), **b** Total realized volatiliy spillover of these four markets

**Net total directional connectedness**

We calculate net total directional connectedness by subtracting the equation [5] from [6].Figure two-panel (a) shows that both conventional stocks and clean energy stocks are net transmitters in reverse oil and Bitcoin are net receivers which confirm our results in table 3.

By considering panel (b) in figure two we understand that S&P500 is net receivers before 2019 and then it becomes net transmitters in our sample period. After 2018 clean energy mostly is net receivers. The result confirms that Bitcoin and oil are net transmitters in most of the sample period. Overall, this finding supports the results in table 3 and it suggests that stock markets such as clean energy and conventional transmit return shocks to Bitcoin and oil and receive volatility shocks from Bitcoin and oil.

(a) Return (b) Volatility

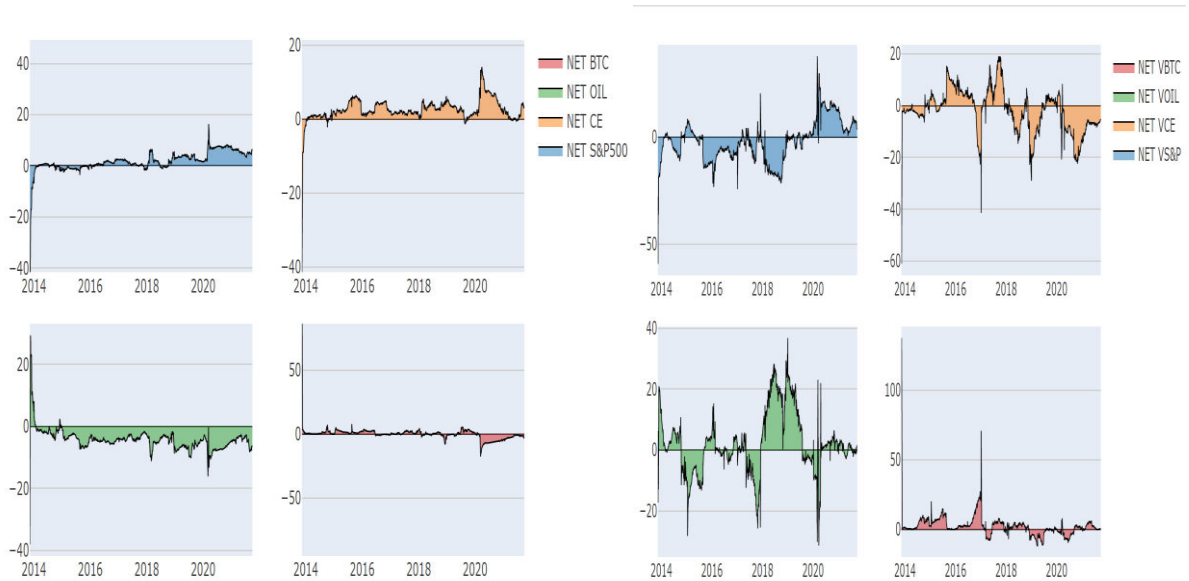


**Fig. 2 a** Net total directional connectedness in return for four asstes (s&p500, clean energy, oil and Bitcoin), **b** Net total directional connectedness in realized volatiliy for these four markets Note: Negative (Positive) indicates the reciver (trasmitter) of the spillover

**Net Pairwise Directional Connectedness (NPDC)**

We focused on the net pairwise directional connectedness in order to better separate the propagation processes between the return and realized volatilities of Bitcoin and the remaining assets. NPDC determined the net

transmitters and net receivers among pairs of markets. NPDC, which is shown in figure 3 panel (a) for return and panel (b) for realized volatility.

As seen in figure 3 panel (a), we get six different combinations from our four variables. Bitcoin is a transmitter of the shocks to oil and its receivers of the shocks from the conventional stock market. From early 2014, Bitcoin was a contributor to shocks from clean energy but after the pandemic, it became receiver of the shocks from clean energy in return. According to figure three panel (b), Bitcoin remains as transmitters of the shocks to clean energy and it had the same trend as the conventional stock market. Oil become net receivers shock in all major crises such as the oil crash in 2015, the great crypto crash in 2018, and the covid-19 pandemic in comparison to clean energy and conventional stock markets. In addition, clean energy was a shocks contributor to S&P500 in most of the samples before the pandemic.

(a) Return (b) Volatility

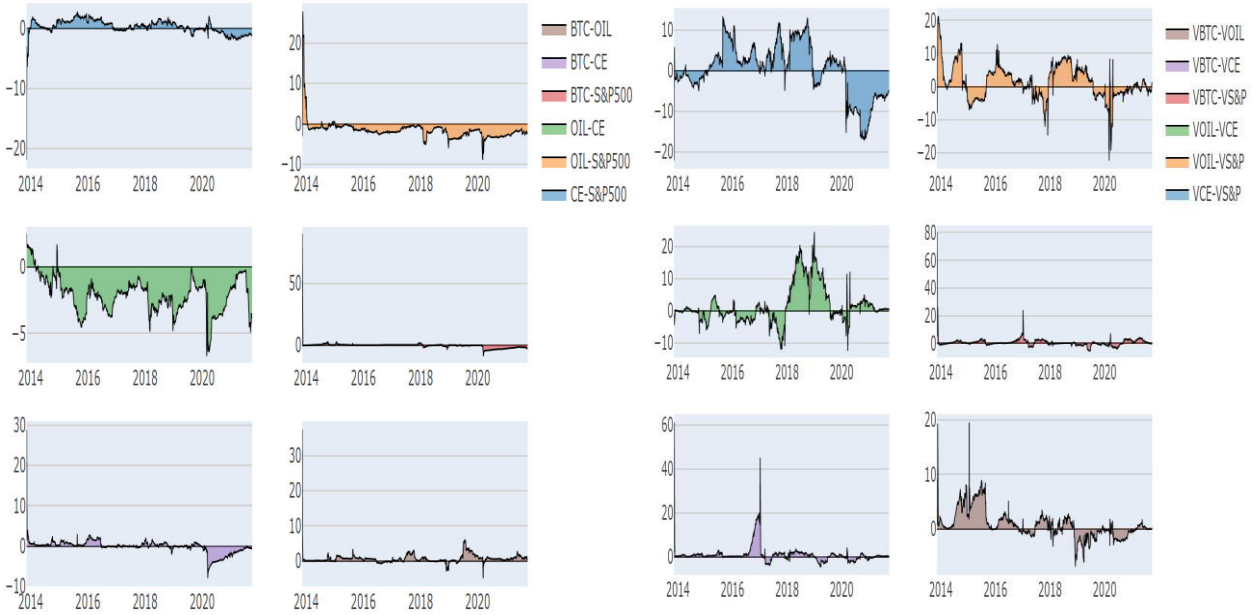


**Fig. 3** Net Pairwise Directional Connectedness of related markets in return (a) and realized volatility (b) Note: Negative (positive) indicates the reciver (trasmitter) of the spillover

**Network plot**

Figure 4 illustrates the network plot among S&P500; CE, OIL, and BTC, Yellow (Blue) nodes represent the net shock receiver (transmitter). Averaged net pairwise directional connectedness measurements are used to weight vertices. The size of the nodes is the weighted average of the net total directional connectedness.

(a) Return (b) Volatility

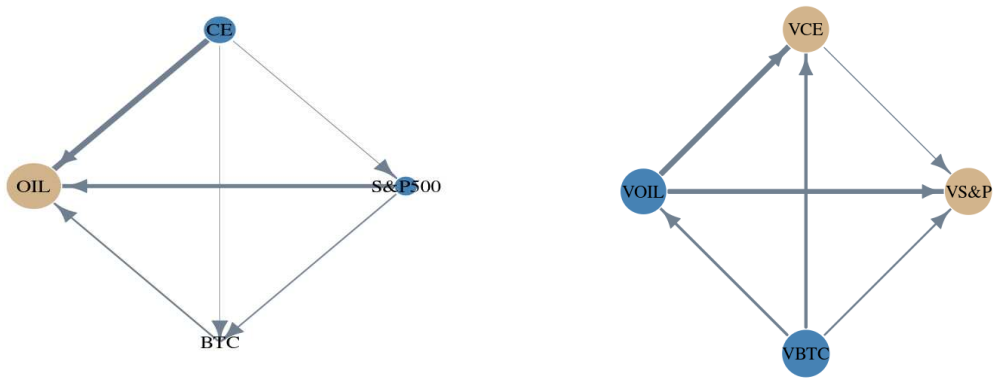


**Fig. 4** Network plot in return and volatiliy spillovers

Finally, figure four confirms our results in table 3, as it shows oil was the major net receiver and the weighted average of Bitcoin is quite small in panel (a). By contrast, to the return results, oil and Bitcoin are net contributors of the shocks and clean energy and conventional stocks are net receivers in realized volatility.

## Conclusion

The TVP-VAR-based spillover index Diebold and Yilmaz (2012)**;** Antonakakis and Gabauer (2017) approach is used to determine the dynamic linkage among Bitcoin, S&P500, Wilder hill clean energy index, and WTI in both return and realized volatility. We used this novel method to overcome the shortcomings of the generalized VAR. we used daily data from 11 November 2013 until 30 September 2021. In terms of return results, clean energy and

conventional stocks are net transmitters so it can be defined that stocks price can be well thought out as an exogenous source of shocks. However, the return total net spillover is around 25%. In contrast to the return results, in terms of realized volatility analysis, oil and Bitcoin price are net transmitters of the shocks.

Our findings suggest that stock markets such as clean energy and conventional transmit return shocks to Bitcoin and oil price during this period and they received volatility shocks from Bitcoin and oil price. In addition, the results of the realized volatility show well the great shocks caused by economic and political issues such as the covid-19 pandemic and cryptocurrencies crash during this period.

This research extends the empirical findings on information transmission among cryptocurrencies and energy markets. In summary, this study demonstrates that the volatility of Bitcoin and financial markets is greater than their connection in terms of returns.

Bitcoin has the potential to be a hedging tool against any uncertainty policy. The exploration of the primary reasons for this phenomenon is left to future research. We believe our results are noteworthy and may be valuable to researchers and Bitcoin market players in evaluating the impact of Bitcoin in the energy and financial markets. It would be useful to expand on this paper by focusing on various methodologies, such as VAR models, which are the vector smooth transition autoregressive, vector threshold autoregressive and vector Markov-switching autoregressive models. We leave that to future studies.

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