On the dynamic return and volatility connectedness of cryptocurrency, crude oil, clean energy, and stock markets: a time-varying analysis

Amirreza Attarzadeh1 · Mehmet Balcilar1,2

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Abstract
The high energy consumption of cryptocurrency transactions has raised concerns about the environment and sustainability among green investors and regulatory authorities. The current study examines the connectedness among clean energy, Bitcoin, the stock market, and crude oil empirically. The time-varying parameter vector autoregression (TVP-VAR) is used to estimate the dynamics of connectedness in a daily dataset spanning the period November 11, 2013 to September 30, 2021. We find that the clean energy and traditional stock markets transmit shocks to Bitcoin and oil in terms of return, and they receive shocks in terms of volatility from Bitcoin and oil. Additionally, Bitcoin and other financial markets are only tenuously linked during non-crisis periods. Nonetheless, their connection strengthens substantially during times of crisis, such as the great cryptocurrency crash of 2018 and the COVID-19 pandemic of 2020. We believe that these findings can help explain how clean energy and cryptocurrency markets are linked during times of crisis.

Keywords Cryptocurrency · Bitcoin · Clean energy · TVP-VAR · Dynamic connectedness · Realized volatility

Introduction
Intermarket linkage is a substantial component of international finance, as measured by returns and volatility spillovers, and has significant implications for portfolio and hedging decision-making. The empirical literature has received considerable attention as a result of evidence of increased market integration facilitated by market openness, globalization, financial integration, and technological advancement. For example, during times of crisis, financial market volatility increases dramatically, resulting in spillovers across markets. Naturally, one would prefer to quantify and control such outbreaks, providing an ‘early warning’ system for emerging crises and monitoring the progress of ongoing crises.

Cryptocurrency markets have grown significantly in popularity in recent years, elevating cryptocurrencies to the level of investment assets. As the first and most popular cryptocurrency, Bitcoin, this new asset garnered considerable attention. By resolving puzzles, Bitcoin enables decentralized systems to safely and equitably issue new coins and confirm transactions. As Bitcoin transactions increase in volume, the Bitcoin network becomes more competitive. The crypto algorithm that validates blocks and compensates miners becomes more complicated, making it more difficult to forecast the volatility of power and energy. According to the British Broadcasting Channel (BBC), Cambridge academics estimate that Bitcoin consumes approximately 121.36 terawatt-hours (TWh) of electricity each year, which is more than Argentina’s consumption with a population of 46 million. According to the Digiconomist’s Bitcoin Energy Consumption Index, a single Bitcoin transaction consumes the equivalent of 53 days of electricity for an average American family. These reports demonstrate the critical role of financial and energy markets in the future of cryptocurrencies.

The need to check the role of Bitcoin started in 2016, which became highly prominent in the investment and financial press. In 2017, Bitcoin prices increased by more than...
1300%, valuing the entire market at more than 215 billion dollars, with this figure expected to exceed one trillion dollars by 2022. As a result, investigating and assessing the relationships between the returns and volatility of Bitcoin and other asset classes is significant for investors and policymakers. Any evidence of significant returns and volatility spillovers between Bitcoin and other asset classes may influence asset selection, allocation, risk management decisions, and regulatory measures designed to ensure global financial system stability. It is also significant for politicians who consider cryptocurrencies as part of their foreign reserves or experiment with their crypto-monetary equivalents.

Despite the Bitcoin mining process's heavy reliance on energy, practical information on how Bitcoin is related to energy investments, particularly clean energy stock investments, is limited. Furthermore, despite their substantial interconnectedness (especially Bitcoin's reliance on energy), the dynamics and economic links between clean energy, Bitcoin, and the financial market have not been sufficiently investigated. Against this backdrop, the purpose of this study is to determine the degree to which Bitcoin is interconnected with clean energy, fossil fuels, and the broad stock market. Additionally, as the Bitcoin mining industry grows, this study sheds light on the strategy investors should employ when constructing a portfolio of these assets. Additionally, the study examines whether diversifying a Bitcoin portfolio with environmentally friendly assets such as green energy stocks is beneficial. This study fills the gap by estimating dynamic connectedness among these assets using a TVP-VAR model. The study estimates both return and volatility spillovers among Bitcoin, clean energy, stock prices, and fossil fuels. In addition, we compare the TVP-VAR results with results from a rolling window VAR (RW-VAR) in terms of total connectedness indexes for robustness analysis. Naeem and Karim (2021) and Hung (2021) have investigated the relationship between cryptocurrencies and green financial markets. They make use of the bivariate copula model, the quantile-on-quantile regression, as well as Granger causality-in-quantiles. Our study contributes in a variety of ways to a better understanding of Bitcoin, oil, clean energy, and the stock market connectedness. We define multivariate market reliance, which reflects the network of direct and indirect shock transmission between markets. Thus, our research identifies the shock transmitters and receivers explicitly within a network of Bitcoin, oil, clean energy, and stock market investments.

This study extends the literature that analyzes the relationship between cryptocurrencies and financial markets. The focus of the study is close to Dyhrberg (2016), Katsiampa (2017), Balcilar et al. (2017), Symitsi and Chalvatzis (2018), Akyildirim et al. (2020), and Naeem and Karim (2021). Our findings indicate that return and realized volatility spillovers among Bitcoin, stocks, and energy markets are time-varying. Additionally, the study’s findings indicate the existence of a negligible spillover between Bitcoin and clean energy investment during non-crisis periods. The conclusion suggests that investing in Bitcoin and clean energy may provide investors with diversification benefits. However, during times of crisis, such as a Bitcoin crash or an energy crisis, this investment strategy may be ineffective, as the spillovers between cryptocurrency and clean energy investments increase significantly. The extreme fluctuations in connectedness that occur during a crisis show that constant dependencies are implausible. Additionally, Bitcoin’s low correlation with stock indices during non-crisis periods demonstrates its investment potential. Additionally, we discovered that cryptocurrency investors’ environmental consciousness has a significant effect on the spillovers between cryptocurrency and green investments, particularly during times of high Bitcoin prices, such as 2018 and 2021.

The following is a breakdown of our paper’s structure. A literature review is presented in the “Literature review” section, and the data and methodology are presented in the “Data and empirical methodology” section. The empirical findings are discussed in the “Empirical results” section. The “Discussion” section contains discussion, and the main conclusion and policy recommendation are presented in the “Conclusion and policy recommendation” section.

**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 can 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 investigates the impact of Bitcoin trading on the financial market and environmental sustainability. According to a recent analysis by Jiang et al. (2021), maintaining the Bitcoin blockchain in 2024 will require 296.59 Twh, which will lead to the production of 130.50 million metric tons of carbon. Polemis and Tsionas (2021) investigated 50 countries to find the causal relationship between 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, and natural gas, although this link varies over time. The bidirectional and unidirectional spillover between cryptocurrency and crude oil spot prices were investigated by Okorie and Lin (2020). Bitcoin represents a bidirectional spillover of volatility. Jareño et al. (2021) report that oil shocks are linked significantly with cryptocurrency returns. They also point out that oil and cryptocurrency became more intertwined in 2020, during the first wave of the COVID-19 pandemic. 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) use the bivariate copula model. Baur et al. (2015) find that Bitcoin could be a diversifier. Low correlation with bonds and equities was the evidence of this conclusion, and Ji et al. (2018a, b) reach the same conclusion using the directed acyclic graph approach.

On the other hand, they did not consider the relationship between return and volatility in different markets. However, there is limited empirical research on Bitcoin’s return and volatility spillovers to other markets. Balci lar et al. (2017) use trade volume data to predict Bitcoin returns and volatility. They claim that while transaction volume can assist in anticipating returns in some cases, it does not provide information on volatility. Katsiampa (2017) applies multivariate generalized autoregressive conditional heteroskedasticity (GARCH) to estimate Bitcoin volatility and discovers the importance of integrating conditional variance’s long-run and short-run components. According to Bouri et al. (2017), Bitcoin can be used to hedge against commodity indices and uncertainty indicators. Bouri et al. (2018) employ a smooth transition VAR-GARCH in mean model. Their 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.

Concerning the literature that investigates the dynamic connectedness of assets. Ji et al. (2018a, b) examine the risk and return connectedness of carbon and energy markets, especially the green sector, using a systematic time-series approach. According to their findings, the volatility connectedness among the underlying markets is stronger than the return connection. Ferrer et al. (2018) investigate the short-term volatility spillovers among renewable energy stocks, crude oil prices, and various financial variables. Nasreen et al. (2020) investigate the time–frequency relationship between crude oil and the stock prices of renewable energy and technology businesses. The results show that the underlying markets have weak connectedness in the frequency and time domain. Using the Diebold-Yilmaz (DY) index (Diebold and Yilmaz 2009, 2012), Naeem et al. (2020) investigate the temporal and frequency connectivity between oil price shocks and other energy markets such as electricity, clean energy, and carbon. The study’s findings show a rise in connectedness across the underlying markets during the shale oil revolution. Dutta et al. (2020) investigate the effect of implied volatility in the energy sector on the returns of green investments. According to their findings, an increase in the implied volatility of energy companies leads to a fall in green stock returns. The evidence also shows that the underlying variables have an asymmetric influence. Elsayed et al. (2020) investigate the time pattern of volatility connectivity between oil prices and seven markets. The study’s key findings indicate that oil price volatility has an insignificant effect on those markets. More crucially, the findings show that global stock and energy indices are transmitters of shocks to the green market. According to Foglia and Angelini (2020), the static and dynamic volatility of the oil prices and the renewable market intensified during the pandemic crisis.

The literature focuses primarily on studying volatility connectivity. However, this may be misleading because the dynamics of return and volatility connectivity may differ, and both may provide meaningful information to investors. Additionally, the connectedness might be time-varying and one needs to estimate this using an optimal estimator. Therefore, this study aims to examine the time-varying connectedness of Bitcoin, S&P 500, clean energy, and crude oil prices in return and volatility using a TVP-VAR model, which is an optimal estimator of time-variation in parameters.

**Data and empirical methodology**

**Data**

The four asset classes examined in the study are the S&P 500 (S&P500), Bitcoin (BTC), the Wilder Hill Clean Energy Index (CE), and the West Texas Intermediate (WTI) crude oil price (OIL). The data used is at daily frequency for both the return and volatility series, covering the period from November 11, 2013 to September 30, 2021. Oil is the most commonly traded commodity, and any volatility in oil prices impacts other markets. The oil price we use is the spot WTI crude oil price. The Bitcoin spot price was chosen based on market capitalization and trading frequency, and the S&P 500 composite index was chosen as a common stock representing overall market performance and sentiment. In addition, the Wilder Hill Clean Energy Index was chosen to follow the performance of green investments. The data was extracted from Fusion Media (www.investing.com) and Datastream.

The time variations of daily data across the sample period are depicted in Fig. 1. While the dynamics of the clean energy index, Bitcoin price, and S&P 500 show an upward trend, the
The path taken by oil has fluctuated in the last 7 years. The oil price recovered from the lowest price in 2020 to $75 at the end of this period. Bitcoin and clean energy prices rose significantly during the COVID-19 epidemic and reached a new all-time high. The S&P500 index is shown in Fig. 1, fluctuating around a steadily increasing curve. Furthermore, S&P500 reached a new high (around 4500).

We calculate the daily realized volatility by employing the method proposed by Rogers and Satchell (1991) and Rogers et al. (1994) which uses High (H), Low (L), Open (O), and Close (C) prices of the asset in the following formula:

\[
V_j = 100 \times \sqrt{\frac{N}{\sum \left( \ln \left( \frac{H_i}{O_j} \right) \times \ln \left( \frac{H_i}{C_j} \right) + \ln \left( \frac{L_i}{O_j} \right) \times \ln \left( \frac{L_i}{C_j} \right) \right)}},
\]

where \(V_j\) presents realized volatility of at day \(t\) and \(N\) is the number of trading days. The daily returns, \(R_j\), are calculated as the percentage of log returns is the closing price \(P_{jt}\), that is \(R_j = \ln \left( \frac{P_{jt}}{P_{j(t-1)}} \right) \times 100\).

Figure 2(a) shows the return series of all four markets, which shows an increased fluctuation after 2019 due market’s negative sentiment caused by the COVID-19 pandemic. Figure 2(b) shows the realized volatility of the four markets: S&P 500 (VS&P500), Bitcoin (VBTC), the Wilder Hill Clean Energy Index (VCE), and oil price (VOIL). Realized volatility in the oil price increased between 2014 and 2016 when the oil price fell. Also, the COVID-19 pandemic crisis in early 2020 increased realized volatility significantly. Moreover, realized volatility rose markedly for clean energy and conventional stocks during the pandemic.

According to statistics given in Table 1, 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 returns. The Bitcoin also has the highest average realized volatility. Furthermore, all realized volatility series have excess kurtosis and are positively skewed. As demonstrated by the Jarque–Bera test, all series are not normally distributed. Elliot et al. (1996) the generalized least squares Dickey–Fuller unit root test is significant for all series, implying that all returns and realized volatility series are stationary.

**Empirical methodology**

As previously stated, we investigate the transmission mechanism in a time-varying manner using the methodology outlined a TVP-VAR model and DY spillover index of Diebold and Yilmaz (2009, 2012). To capture the dynamics of connection, the suggested TVP-VAR model eliminates the necessity for the researcher to fix a length-mile sample window. The method takes advantage of the benefits of Bayesian shrinkage for estimating high-dimensional systems without requiring computationally intensive simulation methods. The resulting dynamic connectedness index and directional connectedness measures would be immune to the persistence seen in rolling window estimation. This methodology overcomes the shortcomings of the generalized VAR approach.

Let the $n \times 1$ dimensional vector of variables be defined as $Y_t = (OIL_t, CE_t, S&P500_t, BTC_t)^T$ with $n = 4$. Then, the TVP-VAR model of order $p$ can be written as follows:

$$Y_t = \Phi_0 Z_{t-1} + \epsilon_t, \quad \epsilon_t \sim N(0, \Sigma_t)$$

(1)

vec($\Phi_t$) = vec($\Phi_0$) + $\eta_t, \quad \eta_t \sim T(0, \Omega_t)$

(2)

where $Z_{t-1} = (Y_{t-1}, Y_{t-2}, \ldots, Y_{t-p})^T$ is an $np \times 1$ vector, $\Phi_t = (\Phi_{1t}, \Phi_{2t}, \ldots, \Phi_{pt})^T$ is an $n \times np$ coefficient matrix with $n \times n$ coefficient sub-matrices $\Phi_{ij}, i = 1, 2, \ldots, p$. $\epsilon_t$ and $\eta_t$ are $n \times 1$ and $np \times 1$, respectively, normally distributes error vectors with time-varying variance–covariance matrices $\Sigma_t$ and $\Omega_t$, which are $n \times n$ and $np \times np$, respectively. Using the Wold representation theorem the vector moving average (VMA) form of the TVP-VAR model in Eqs. (1)–(2) can be written as:

$$y_t = \sum_{i=1}^{p} \Phi_{ij} y_{t-i} + \epsilon_t = \sum_{j=1}^{\infty} \Psi_{ij} \epsilon_{t-j}$$

(3)

where $\Psi_{ij}$ are linear functions of $\{\Phi_{ij}, \Phi_{2j}, \ldots, \Phi_{pj}\}$. The fundament of time-varying coefficients of vector moving average (VMA) model can be used to obtain generalized impulse response functions (GIRF) and generalized forecast error variance decompositions (GEFD) as defined by Koop et al. (1996) and Pesaran and Shin (1998). The GEFD defined by Diebold and Yilmaz (2012), which can be understood as the variance of variable $i$ explained by variable $j$, $\varphi_{ij}(H)$, at forecasting step $H$, and its normalized version, $\phi_{ij}(H)$, can be calculated as:

$$\varphi_{ij}(H) = \sum_{l=1}^{H} \psi_{ijl} \epsilon_{l} \sim \sum_{j=1}^{\infty} \phi_{ij}(H)$$

(4)

where $\epsilon_{i}$ is a zero vector with unity on the $i$ position, $\sum_{j=1}^{\infty} \phi_{ij}(H) = 1$, and $\sum_{i,j=1}^{n} \phi_{ij}(H) = 1$.

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

$$c_i(H) = \frac{\sum_{j=1,i\neq j}^{n} \phi_{ij}(H)}{\sum_{j=1}^{n} \phi_{ij}(H)} \times 100$$

(5)
Intuitively, it can be defined as the average spillover from all other markets to a given asset, ignoring the market’s effect on itself due to lags. Therefore, firstly, we are concerned with the spillovers of variable $i$ to all others $j$, which indicate the total directional connectedness to others:

$$c_{i\rightarrow j}(H) = \frac{\sum_{j=1,j\neq i}^{n} \varphi_{ij}(H)}{n} \times 100$$

(6)

Secondly, we calculate total directional connectedness from others:

$$c_{i\leftarrow j}(H) = \frac{\sum_{j=1,j\neq i}^{n} \varphi_{ji}(H)}{n} \times 100$$

(7)

In addition, net directional connectedness can be calculated by subtracting Eq. (6) from Eq. (8):

$$c_{i,j}(H) = c_{i\rightarrow j}(H) - c_{i\leftarrow j}(H)$$

(8)

Finally, by computing net pairwise directional connectedness (NPDC) as below, we may infer bidirectional linkages and demonstrate that variable $i$ affects variable $j$ or vice versa.

$$NPDC_{ij}(H) = \left[ \varphi_{ji}(H) - \varphi_{ij}(H) \right] \times 100$$

(9)

The Bayesian information criterion (BIC) is used to select the order of the TVP-VAR, which gives $p = 8$ for both the returns and volatility.

**Empirical results**

### Averaged dynamic connectedness

Table 2 presents the average full sample return and volatility spillover indices, as well as their decomposition as receivers and transmitters among oil, clean energy, stocks, and Bitcoin. The values in Table 2 represent the average of the spillover values obtained from the estimated TVP-VAR model over the sample period from November 11, 2013 to September 30, 2021. Total connectedness index (TCI) values are close to each other with 25.13% and 23.96% for return and volatility, respectively, which means around 25% of returns is spillover effect from other markets on average, also around 24% for realized volatility is spillover volatility from other assets on average.

The results show that oil and Bitcoin are net receivers with $-4.31\%$ and $-0.08\%$ for returns, respectively and stocks (clean energy and conventional) are net transmitters. In contrast to the return results, oil and Bitcoin are net transmitters with $2.07\%$ and $2.15\%$ in realized volatility estimations. 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 2 Panel (a), the most significant contributor is clean energy stocks with $41.60\%$, followed by conventional stocks ($40.26\%$), oil ($12.96\%$), and Bitcoin ($5.72\%$).

The net spillover for S&P500 is 30.44% to CE, and 7.08% and 2.75% for oil and Bitcoin, respectively. Additionally, clean energy contributes 2.2% for Bitcoin, 8.69%, and 30.70% for oil and S&P500, respectively. Overall spillover between oil and Bitcoin is the lowest magnitude for both return and realized volatility, which are 0.85% and 1.87%, respectively, implying 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 transmission of shocks from other assets to Bitcoin is very low.

Concerning the results of realized volatility in Table 2, TCI is $23.96\%$, and it is quite the same as the TCI for returns. In addition, the volatility spillovers from S&P 500 index are $23.96\%$, $8.79\%$, and $1.77\%$ for clean energy, oil, and Bitcoin, respectively. Moreover, the lowest volatility spillover is from CE to BTC by $1.75\%$ and the highest is from S&P500 to CE with $24.25\%$. The findings for volatility spillover from Bitcoin to other markets have about the same intensity (about 3%), although it is more significant than the case for return spillover. The bidirectional

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**Table 2 Average dynamic connectedness**

**a) Return spillover**

|                | 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|         |
| NET spillovers| 1.83   | 2.56 | -4.31| -0.08|          |

**b) Volatility spillover**

|                | 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|         |
| NET spillovers| -2.13  | -2.09| 2.07 | 2.15 |          |

The underlying variance decompositions are produced using the TVP-VAR model with a 10-day-ahead forecast window in return and volatility spillovers. The numbers reported in the table are the average of the spillover values obtained from the estimated TVP-VAR model over the sample period from November 11, 2013 to September 30, 2021.
volatility spillover from oil to other markets is higher than return spillover.

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

**Dynamic total connectedness**

In comparison to the average TCI, we observe that the total connectedness index, given in Fig. 3, across the sample period based on the TVP-VAR model varies between 16 and 55% for return and between 11 and 49% for realized volatility. The overall images indicate that the coronavirus pandemic will cause similar prominent peaks in early 2020. The World Health Organization (WHO) declared a global health emergency in January 2020, and in March, COVID-19 was declared a pandemic, which corresponds to the peak level in Fig. 3 for both return and volatility spillovers.

The realized volatility results exhibit more pronounced peaks and troughs. Six significant occurrences stand out in particular. The first peak corresponds to the oil crash, during which oil fell to 44 dollars per barrel from a high of 107 dollars per barrel in June 2014, while the second peak corresponds to the August 2015 stock market selloff. The third peak is connected to Syria's civil war. The fourth peak occurs in the USA following the election of a new president. The next two prominent peaks, in January 2018 and January 2020, respectively, correspond to the great crypto crash and the start of the COVID-19 pandemic.

**Rolling VAR results**

The rolling window VAR estimates of total connectedness are shown in Fig. 4. The two indices behave similarly across the entire sample. Despite this, the TVP-VAR estimates have distinct features from the RW-VAR. To begin with, jumps in the total connectedness index calculated using the TVP-VAR method are more frequent and significant than those calculated using the RW-VAR method. This is true for all

![Fig. 3 Total return and volatility spillover indices from the TVP-VAR](image)

![Fig. 4 The RW-VAR based total return and volatility spillover indices](image)
significant global economic events since 2014, such as the 2014 energy crisis, the 2018 crypto meltdown, and the 2020 coronavirus pandemic. As another illustration, the difference in behavior between the two indices during the global financial crisis is also significant, with the RW-VAR-based total connectedness index exhibiting greater smoothness. The TVP-VAR index accurately captures all significant events leading up to the global financial crisis, whereas the RW-VAR index can capture only the effect of the 2020 coronavirus pandemic.

Additionally, the magnitude of the local peaks varies significantly between the two estimates. The result persuades us to pay closer attention to the details of TVP-VAR-based connectedness analysis. Perhaps more importantly, the TVP-VAR index more accurately reflects market conditions than the rolling window. The TVP-VAR index drops more quickly when financial markets return to their normal state after big market changes.

**Net total directional connectedness**

The net total directional connectedness is calculated using the formula in Eq. (8). As illustrated in Fig. 5(a), conventional and clean energy stocks are net transmitters for the majority of the sample period, whereas oil is a net receiver for the majority of the period. Until the early 2020s, Bitcoin was a net transmitter, but the spillover effect was negligible. After 2020, it becomes a net receiver, with a similar small spillover index magnitude, confirming our findings in Table 2. As illustrated in panel (b) of Fig. 5, the S&P 500 is a net risk transmitter. Following 2018, clean energy was largely a net volatility receiver. The findings confirm that Bitcoin and oil are net transmitters during the majority of the sample periods. In general, this finding corroborates the findings in Table 2. It implies that stock markets, including clean energy and conventional stocks, transmit price shocks to Bitcoin and oil and receive volatility shocks from Bitcoin and oil.

**Net pairwise directional connectedness**

We analyze the net pairwise directional connectedness in order to more clearly distinguish the propagation processes of return and realized volatilities across the four assets we study. We can determine the net transmitters and receivers between pairs of markets using the NPDC. Figure 6 shows the NPDC estimates, with Panel (a) depicting return spillovers and Panel (b) depicting volatility spillovers.

We are particularly interested in the net pairwise spillover with Bitcoin because it appears to be the most disconnected from other markets. The six distinct combinations of pairwise net return spillovers for the four variables are depicted in Panel (a) of Fig. 6. Bitcoin acts as a shock absorber for oil, receiving shocks from the conventional stock market. From early 2014, Bitcoin contributed to clean energy shocks, but following the coronavirus pandemic, it became a receiver of clean energy shocks in returns. According to Panel (b) of Fig. 6, Bitcoin continues to be the primary source of volatility for clean energy, following the same trend as the traditional stock market. In comparison to clean energy and conventional stock markets, oil became a net receiver of volatility during all major crises, including the oil crash of
2015, the great crypto crash of 2018, and the COVID-19 pandemic. However, oil is a net transmitter of volatility during periods devoid of major crises. Additionally, prior to the COVID-19 pandemic, clean energy was a contributor to the S&P500’s volatility.

**Network structure**

The network plot in Fig. 7 depicts the relationship between the S&P500, CE, OIL, and BTC, using the net average pairwise spillover values from Table 2. The direction of the arrows indicates the direction of spillover flow. Edges (arrows) are weighted using average net pairwise directional spillover estimates. The nodes in red (green) indicate the network receiver (transmitter). The average net total spillover determines the size of the nodes. Additionally, we use a 25% threshold to highlight significant spillovers and conceal insignificant ones. The 25% thresholding effectively eliminates all net directional pairwise spillovers less than the 0.75-th quantile. Figure 7 corroborates our findings in Table 2, as it demonstrates oil as a significant net return shock receiver, while Bitcoin’s net return spillover is quite small in Panel (a) of Fig. 7. Additionally, clean energy is the sole net transmitter between these four markets, transmitting return shocks to all other markets. Oil and Bitcoin are net transmitters of return shocks in Panel (b) of Fig. 7, whereas clean energy and the S&P 500 are net receivers. Additionally, the S&P 500 is the sole net receiver of risk from these four markets.

Considering the thresholding network diagrams in Panels (c) and (d) of Fig. 7 for return and volatility spillovers, respectively, Bitcoin is disconnected from all other markets in terms of both return and volatility spillovers. The oil market is the sole return receiver, while it is the sole transmitter of risk to clean energy and the S&P 500.

**Discussion**

Our results support Ji et al. (2019), as we obtain evidence that shows low connectedness between Bitcoin and oil. In addition, bidirectional spillover was found between oil and Bitcoin, which supports Okorie and Lin (2020). By contrast, to Jareño et al. (2021) and Bouri et al. (2018), we find that oil shocks have a significant linkage with Bitcoin volatility. Moreover, we support Baur et al. (2015), Bouri et al. (2017), and Ji et al. (2018a, b) suggestions to use Bitcoin as a diversifier and hedge against any uncertainty. We use the low connectedness of Bitcoin to other assets to support our recommendation. By contrast to Naeem et al. (2020), during booming US oil production, which caused oil prices to crash in 2014–2016, we do not find significant connectedness among oil and clean energy stocks.
Furthermore, we find that oil price and stock market connectedness are time-varying, and they are not pure transmitters of shocks to the clean energy market, which contrasts with Elsayed et al. (2020). The rise in the clean energy index and the oil price meltdown during the COVID-19 pandemic crisis confirm Foglia and Angelini (2020), demonstrating that the dynamic volatility of oil prices and the renewable market intensified. This result can confirm our results in terms of dynamic volatility during the COVID-19 pandemic crisis.

**Conclusion and policy recommendation**

The TVP-VAR-based spillover index-based connectedness approach is used to determine the dynamic linkage in return and realized volatility between the Bitcoin price, the S&P 500 index, the Wilder Hill clean energy index, and the WTI crude oil price. We use the TVP-VAR approach to overcome the shortcomings of the static VAR models. We use daily data from November 11, 2013 to September 30, 2021. In terms of return connectedness, clean energy and conventional stocks are net transmitters, so it can be argued that stock prices can be well thought out as an exogenous source of shocks. However, the total net return spillover is around 25%. In contrast to the return spillover results, oil and Bitcoin markets are net transmitters of volatility.

Our findings suggest that stock markets, such as clean energy and conventional stocks, transmit return shocks to Bitcoin and oil prices during our study period. On the other hand, they receive volatility shocks from Bitcoin and oil prices. Furthermore, the realized volatility results show that large shocks caused by events such as the COVID-19 pandemic and cryptocurrency crashes have a massive impact on connectedness during this period.

Our study provides evidence to support the existence of time-varying connectedness between Bitcoin, oil, clean energy, and the stock market. Our findings indicate that the total connectedness of these markets can be divided into three major periods: (i) the period from 2014 to 2017, (ii) the period from 2018 to 2020, and (iii) the period after 2020. The rapid growth of cryptocurrencies marks the first stage. During this period, positive expectations regarding cryptocurrencies lead to increased connectivity regarding return...
and volatility. From 2018 to 2020, the second period is marked by the Bitcoin meltdown and a significant amount of negative publicity for cryptocurrencies, such as cryptocurrency hacking. The third period, which begins in early 2020, corresponds to the COVID-19 pandemic, which caused the financial-economic crisis and encouraged investors to invest in safe and liquid assets.

This paper extends the empirical findings on information transmission among cryptocurrencies and energy markets. In summary, the study demonstrates that the realized volatility connectedness of Bitcoin and financial markets is greater than their connectedness in terms of returns. While our findings have practical consequences for investors in terms of hedging and diversification strategies, they also have ramifications for environmentally concerned policymakers. Specifically, the results suggest that fossil fuel and clean energy stocks are weakly related to Bitcoin during non-crisis periods. Hence, investors might opt to hedge their Bitcoin portfolio with either fossil fuel or clean energy investments.

Furthermore, a policy encouraging green financial markets may encourage Bitcoin investors to use green assets as their primary diversification strategy. However, it should be noted that such a program might not be desirable to environmentally aware investors. As a result, the development of technology that lowers the carbon footprint of the Bitcoin mining process may make cryptocurrencies more appealing to environmentally sensitive investors.

Bitcoin has the potential to be a hedging tool against any type of uncertainty, be it political, economic, or natural. The exploration of the primary reasons for this phenomenon is left to future research. Nevertheless, we believe our results are noteworthy and may be valuable to researchers and Bitcoin market actors in evaluating the impact of Bitcoin on the energy and financial markets. As a limitation of this paper, it would be useful to expand it by focusing on various methodologies. For example, the QVAR model can explore the consequences of shocks that are larger than the average shock. We will leave that to future studies. Our study is also limited in terms of country-specific experiences. Further research may look at how each country is different because of different economic factors.

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Data availability The data are available at www.investing.com and DataStream.

Declarations

Ethics approval and consent to participate All authors have given their consent to participate in the manuscript.

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