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A clean, green haven?—Examining the relationship between clean energy, clean and dirty cryptocurrencies

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ABSTRACT

Is clean energy a safe haven for cryptocurrencies, or vice versa? In this paper, we investigate the hedge and safe haven property of a wide range of clean energy indices against two distinct types of cryptocurrencies based on their energy consumption levels, termed “dirty” and “clean”. Statistical evidence shows that clean energy is not a direct hedge for either of types. However, it serves as at least a weak safe haven for both in extreme bearish markets. Moreover, clean energy is more likely to be a safe haven for dirty cryptocurrencies than clean cryptocurrencies during increased uncertainty. We further study the spillover patterns among clean energy, cryptocurrency, stock, and gold markets. Weak connectedness is found between clean energy and cryptocurrencies which implies the potential use of clean energy as a hedge and diversification tool for cryptocurrencies in the future.

1. Introduction

Cryptocurrencies have been developing rapidly and become sought-after assets. However, the energy footprint of conventional energy-intensive cryptocurrencies (hereinafter referred to as “dirty” cryptocurrencies) that use “Proof of Work” (PoW) consensus has caused significant ecological damage and has resulted in heightened public concerns (Corbet and Yarovaya, 2020). In a recent study of Mora et al. (2018), the authors projected that the carbon emissions from the continuous adoption of Bitcoin, the most representative dirty cryptocurrency, might itself lift global warming beyond two degrees Celsius within thirty years. The estimated annual energy usage of Bitcoin now has increased to 169.98 TWh, not just comparable but even higher than the gross power consumption of Poland.[1] Due to its computationally expensive PoW mechanism, a single transaction of Bitcoin is estimated to consume approximately 1834.02 kWh electricity which is equivalent to the amount of energy used by an American family for more than 62 days. Researchers have been emphasising the urgency of reducing cryptocurrency mining activities and using non PoW cryptocurrencies (Schinckus, 2021). In recent years, an increasing number of eco-friendly cryptocurrencies (hereinafter: “clean” cryptocurrencies) have been launched to compete in the market, which is more valued and appreciated in today’s context of moving towards greener industry. Some of the new players have already become leading cryptocurrencies by market capitalisation such as Cardano, Solana, etc.

At the same time we have also seen a strong growth track in clean energy sectors. Revenue of clear energy companies is just under $700b, with an annual growth rate of 6.8%.[2] There have been created a wide range of clean energy related equity indices to capture the movements of publicly quoted clean energy related companies, and much research has emerged showing their usefulness in acting as portfolio constituents against regular stock and bond indices (see as examples Rezec and Scholtens (2017), Ahmad and Rais (2018) and Kuang (2021))

The extant literature on the relationship between cryptocurrencies and other assets has often considered traditional energy assets due to the tremendous energy use involved in most cryptocurrency mining and

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[1] Retrieved from https://digiconomist.net/bitcoin-energy-consumption on Oct 5, 2021.

[2] https://www.businesswire.com/news/home/20210902005385/en/Global-Renewable-Energy-Industry-Guide-2021-Value-and-Volume-2016-2020-and-Forecast-to-2025---ResearchAndMarkets.com.

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transactions. Jiang et al. (2022) analyse the role of Bitcoin, gold, equity, foreign exchange and energy (crude oil/natural gas) have played in the global volatility connectedness network. They argue that the overall volatility transmission in the financial system is possibly driven by external investor attention between different markets. Moreover, they find that Bitcoin, gold, foreign exchange and natural gas are volatility transmitters, while crude oil and the stock market are receivers. Ji et al. (2019b) test the information interdependence between leading cryptocurrencies and several commodities and they pointed out that the cryptocurrencies are unexpectedly weakly connected, but still integrated to energy markets such as natural gas, unleaded gas, heating oil, and crude oil using both static and dynamic entropy-based spillover measures. Zeng et al. (2020) show that the financial linkage between Bitcoin and traditional assets such as stock, oil, and gold is weak, but has been increasing. Rehman and Kang (2021) document the existence of lead–lag relationships between Bitcoin and crude oil and natural gas, while it is not the case for coal, which is quite interesting as we know that China is the largest Bitcoin miner where power generation relies extensively on coal. Akyildirim et al. (2021) further investigate the dynamic correlation and extreme dependence between Bitcoin and Chinese coal markets. They show that dynamic correlations between Bitcoin and coal indices increases when extreme mining events occur in China and such incidents are likely to induce Bitcoin volatilities. Okorie (2021) and Corbet et al. (2021) discover significant correlation and volatility spillovers between leading cryptocurrencies and electricity markets. Okorie and Lin (2020) find both bi-directional and uni-directional volatility spillovers between the crude oil market and cryptocurrencies. They further claim that crude oil is a good hedge tool for risks of holding various cryptocurrencies. While Umar et al. (2021) show that cryptocurrency market is less connected with global technology sectors. Le et al. (2021b) further investigate whether the spillover patterns between financial technology stocks and Bitcoin, gold, global stock, crude oil, and foreign exchange are changed by Covid-19 outbreak. Results suggest that the pandemic has shaped and strengthened the volatility spillovers across markets and only gold and U.S. dollar remains as safe havens, while other assets such as Bitcoin, oil, financial technology stocks being large volatility spillover receivers are not. Maghyereh and Abdoh (2020), Bouri et al. (2018), and Uzonwanne (2021) have examined the direction of spillovers between Bitcoin and other markets. Wang et al. (2021) measure the time and frequency connectedness among Bitcoin and other assets including stock, gold oil, etc, but from a hedge perspective.

Relatively little literature has focused attention on the linkage between cryptocurrency and green markets, even after the latter market has witnessed a major rise in recent years, especially for clean energy actions which are sustainable alternatives to traditional carbon-intensive energy such as electricity, oil, and coal. Le et al. (2021a) consider the time and frequency domain connectedness between cryptocurrencies, green bond, and a variety of other assets, but their focal point is on financial technology and not clean energy stocks.

There are few papers which can be regarded as closely related to our research. For instance, Symitsi and Chalvatzis (2018) examine the spillovers among, Bitcoin, fossil and clean energy, and technology indices. There are significant return spillovers from energy and technology markets to Bitcoin, while volatility spillovers are found from Bitcoin to energy markets in the long run and from technology market to Bitcoin in the short run. While Corbet et al. (2021) show that there is no significant linkage between the volatility of Bitcoin price and largest green ETFs markets, Naeem and Karim (2021) further use a time-varying optimal copula approach to examine the tail dependence between Bitcoin and green investments. They find no tail dependence between clean energy and Bitcoin, but they suggest that clean energy is a potential diversification tool for Bitcoin as the hedge ratio and hedge effectiveness are with clean energy in the portfolio. A similar comment is provided by Pham et al. (2021) who propose that green investments could offer diversification benefits to cryptocurrency since only weak connectedness between cryptocurrencies such as Bitcoin and Ethereum and green assets is found during non-crisis periods. However, these papers actually opened up a question — whether clean energy is a direct hedge or even a safe haven for Bitcoin or Ethereum, or more broadly, for cryptocurrencies. If we find that particular types of clean energy stocks can act as safe havens or hedges against particular types of cryptocurrency, or vice versa, it has implications for investors. For example, it may be practical to protect against drawdowns in cryptocurrencies using clean energy stocks or vice versa. But the form of currency matters. If we find that only dirty cryptocurrencies are a useful hedge or safe haven against clean energy that suggests that the economic incentive to invest in clean energy will be counter to the ecological argument. Moreover, although there has been quite a lot of work done on the interconnection of cryptocurrency with other financial assets, the debate on whether Bitcoin or cryptocurrency market is isolated from other assets (markets) has not come to an end.[3]

To answer the above questions we first test the potential role for clean energy as a hedge or safe haven for two distinct types of cryptocurrencies based on their characteristics of eco-efficiency[4] and vice versa, and then the spillovers across these two, along with general stock and gold markets. The hedge and safe haven property are examined using a dynamic conditional correlation Generalised Autoregressive Conditional Heteroskedasticity (DCC-GARCH) model. The DCC-GARCH model and its variants have been extensively employed in safe haven analysis. For instance, Ratner and Chiu (2013) find that credit default swaps are useful hedge and safe haven tools for different sector stocks of U.S. market using the standard DCC-GARCH model. Yousaf et al. (2022) use this model to investigate the hedge and safe haven property of gold and green investments for conventional stock market. Wang et al. (2020) use the this model to investigate the difference between gold-backed and USD-backed stablecoins' ability of being hedges and safe havens against traditional cryptocurrencies. Akhtaruzzaman et al. (2021) study the evolution of the role gold has played as a safe haven asset in the first two phases of COVID-19 crisis using the DCC-GARCH model. Urquhart and Zhang (2019) discover the intraday hedge and safe haven ability of Bitcoin against major currencies using several variants and specifications of DCC-GARCH model. More practice of DCC-GARCH application in safe haven analysis can be seen in studies of Bouri et al. (2017b), Bouri et al. (2017a), Wang et al. (2019) and Peng (2020), etc. Next, the spillover effects are measured using the Diebold and Yilmaz (2012) and Diebold and Yılmaz (2014) (DY) connectedness framework in line with some previously mentioned (e.g., Umar et al. (2021) and Zeng et al. (2020), etc.), and many other papers in the area of connectedness analysis. For example, Yi et al. (2018) follow the DY approach to investigate the volatility connectedness among three tiers of eight cryptocurrencies, and they found that Bitcoin is not dominating as expected. Ji et al. (2019a) employ this framework to analyse the connectedness and inter-dependency among six large cryptocurrencies. Aharon et al. (2021) measure the spillover effects between Bitcoin, five major currencies, and the US yield curve elements using the DY approach. Jalan et al. (2021) employ the DY in measuring the spillover between Bitcoin, gold, and gold-pegged stablecoins. They find that gold market had more pronounced impact on the volatility of these stablecoins than the Bitcoin during the studied period.

Our study contributes to the literature from at least four aspects. First, we provide statistical evidence that clean energy is not a direct hedge for either dirty or clean cryptocurrencies currently.

Second, our study is among the first to empirically examine the safe haven property of a wide range of clean energy indices during dirty

[3] See Ji et al. (2018) and Corbet et al. (2020) as examples.

[4] Corbet et al. (2021) suggest that cryptocurrencies have varying carbon footprints and power usage levels, possibly affecting how they interact with energy and utility businesses.

and clean cryptocurrency market turmoils and its reverse. We find that, in general, clean energy stocks serve as at least weak safe havens in times of extreme falling cryptocurrency markets. In times of increased volatility, clean energy is more likely to serve as a safe haven for dirty cryptocurrencies than for clean cryptocurrencies.

Third, we measure the dynamic connectedness between different clean energy subsectors and cryptocurrencies, which has not been done in previous literature. Findings reveal that none of the clean energy subsectors, nor general stock, or the gold market is strongly associated with cryptocurrency markets, which extends the understanding of the research on the interconnection of cryptocurrencies with other markets.

Fourth, our findings also provide references and implications for regulators and policy makers as well as cryptocurrency founders in designing the framework of further financial integration and promoting greener industry, and ultimately the society.

The remainder of this paper is organised as follows. Section 2 describes the data, followed by Section 3 which details the methodology used in the analysis. Section 4 presents the empirical findings and Section 5 checks the robustness of previous results. Lastly, Section 6 concludes and addresses the implications of our study.

2. Data

We collected daily closing price data for five major dirty cryptocurrencies including Bitcoin (BTC), Ethereum (ETH), Bitcoin Cash (BCH), Ethereum Classic (ETC) and Litcoin (LTC), as well as five clean cryptocurrencies, Cardano (ADA), Ripple (XRP), IOTA (MIOTA), Stellar (XLM), and Nano (NANO) from CoinMarketCap,[5] spanning from January 1, 2018 to September 17, 2021.[6] The dirty cryptocurrencies are all built on PoW algorithms for consensus which results in massive energy usage regarding mining and transactions, while clean cryptocurrencies are built on different varieties of energy-efficient consensus algorithms, including Proof-of-Stake (PoS), Ripple Protocol, Stellar Protocol, and some other alternatives. We further created two value-weighted indices of the dirty and clean cryptocurrencies, respectively named as DCRYPT and CCRYPT to track the overall performance of the two distinct cryptocurrency groups. Next, clean energy indices sourced from Bloomberg were used to represent the performance of the clean energy industry. We not only used the S&P Global Clean Energy Index (SPGTCED) and WilderHill Clean Energy Index (ECO) which tracks the overall performance of global or U.S. clean energy sectors, but also selected several indices from NASDAQ OMX Green Economy Index Family to track the performance of individual clean energy generation subsectors, partly following the literature of Pham (2019).[7] Specifically, we used the NASDAQ OMX Bio/Clean Fuels Index (GRNBIO), Fuel Cell Index (GRNFUEL), Renewable Energy Index (GRNREG), Geothermal Index (GRNGEO), Solar Energy Index (GRNSOLAR), and Winde Energy Index (GRNWIND). The description of each clean energy index is provided in Table 1. To account for the general stock market performance, we collected the data for the S&P 500 Index (SP500) from Bloomberg. Finally, we collected the London P.M. gold fixing price (GOLD) from Federal Reserve Economic Data.[8] Note that all data were sourced in U.S. dollars and transformed to their first-differenced natural logarithms before use. Table 2 summaries the statistics for the log returns in percentage.[9] All return series are stationary and are not normal distributed based on Augmented Dickey–Fuller (ADF) test and Jarque–Bera (JB) test, respectively.

3. Methodology

3.1. Safe haven analysis

We adopt the estimation framework introduced by Baur and Lucey (2010) and Baur and McDermott (2010) to examine the hedge and safe haven property of clean energy indices against dirty and clean cryptocurrencies. Similar to Akhtaruzzaman et al. (2021), Peng (2020), Ratner and Chiu (2013), and some others mentioned earlier, we start by using a DCC–GARCH model proposed by Engle (2002) to estimate the correlation of underlying asset pairs.

The estimation comprises two steps. The first is to estimate a GARCH(1,1) model. Let r_t be the $N \times 1$ vector of pairs of return series r_{1t} and r_{2t}, given the information set I_{t-1}:

$$\begin{aligned} r_t &= \mu_t + \epsilon_t, \\ h_t &= \alpha_0 + \alpha_1 \epsilon_{t-1}^2 + \beta h_{t-1}, \end{aligned} \tag{1}$$

where ϵ is the vector of residuals.

Secondly, we estimate the DCC parameter. Let H_t be the conditional covariance matrix of r_t. We have assumed r_t to be normally distributed with a zero mean and we write H_t as the following:

$$\begin{aligned} H_t &= D_t R_t D_t, \\ D_t &= diag\ [h_{1t}^{1/2},\ h_{2t}^{1/2}], \\ R_t &= diag[Q_t]^{-1/2}\ Qt\ diag[Q_t]^{-1/2}, \end{aligned} \tag{2}$$

where R_t denotes the matrix of time-varying conditional correlations, Q_t is the positive definite matrix of $q_{12,t}$, and h_t is the conditional standard deviations (SDs). Then we can get the estimated DCC model as:

$$Q_t = (1 - a - b)\bar{Q} + a u_{t-1} u_{t-1}^T + b Q_{t-1}, \tag{3}$$

[5] https://www.coinmarketcap.com.

[6] Our selection takes into account the market capitalisation, data availability of closing price and market capitalisation, and recent online media attention. We chose BCH and ETC in addition to BTC, ETH, and LTC as these two cryptos have been the largest PoW players following LTC for years, both are listed in the top 6 by market cap. Although DOGE is the third largest PoW crypto, we did not consider it as: 1. it was originally designed as a meme coin without other uses; 2. Its energy consumption is arbitrary due to its relatively complicated mining mechanism; 3. It has been highly influenced/boosted by Musk's social media comments. The selection of clean cryptocurrencies was not as straightforward as choosing dirty cryptocurrencies. The first issue is the data availability. The data of closing price and market cap should be available from January 1, 2018, so some other top players such as Solana, Polkadot, Avalanche, etc, were not considered as they came to the market much later. BNB was not considered as it shares a completely different nature as a derivative of the Binance Exchange, historically built on Ethereum blockchain technology, and began to support staking in 2020. MIOTA and NANO are chosen as they have been the most frequently discussed and compared to the dirty cryptos and even other clean players regarding energy consumption in more recent period (e.g., see https://www.trgdatacenters.com/most-environment-friendly-cryptocurrencies/, https://www.leafscore.com/blog/the-9-most-sustainable-cryptocurrencies-for-2021/ (retrieved in September of 2021), and https://www.thetimes.co.uk/money-mentor/article/eco-friendly-cryptocurrencies/). Although they may have become smaller players (compared to other cryptos we use) in recent months, historically, MIOTA ranked as 10th largest, and NANO ranked as the 20th among all as of January 7, 2018 (e.g., see the historical snapshot of CoinMarketCap data at https://coinmarketcap.com/historical/20180107/). Additionally, NANO is, to the best of our knowledge, one of the very few and earliest cryptos that explicitly address the "eco-friendly" characteristic, which can be seen from its description on CoinMarketCap website and from their official website's title *Nano | Eco-friendly & feeless digital currency*, which makes it a ideal representative of clean cryptos to attract potential environmentally conscious investors.

[7] We focus on clean energy generation subsectors in this paper.

[8] https://fred.stlouisfed.org/series/GOLDPMGBD228NLBM.

[9] The number of observations used in spillover analysis is less than that in safe haven analysis as we included gold in the spillover analysis which has slightly fewer trading days than the stock markets.

Table 1
Description of clean energy indices

Index name	Description
S&P Global Clean Energy Index	SPGTCED tracks the performance of world top 100 companies in clean energy sectors from both developed and emerging markets.
WilderHill Clean Energy Index	ECO is the first index that tracks the performance of top clean energy companies traded on the NASDAQ.
NASDAQ OMX Bio/Clean Fuels Index	GRNBIO tracks the performance of companies operating in plant-based fuel generation sector.
NASDAQ OMX Renewable Energy Index	GRNREG tracks the performance of companies operating in renewable energy generation sectors, such as solar, wind, geothermal, and fuel cells.
NASDAQ OMX Geothermal Index	GRNGEO tracks the performance of companies operating in geothermal power generation sector.
NASDAQ OMX Fuel Cell Index	GRNFUEL tracks the performance of companies operating in fuel cell energy sector.
NASDAQ OMX Solar Index	GRNSOLAR tracks the performance of companies operating in solar energy generation sector.
NASDAQ OMX Wind Index	GRNWIND tracks the performance of companies operating in wind energy generation sector

Table 2
Descriptive statistics of returns (%).

	Mean	Min	Max	Std. Dev	Skewness	Kurtosis	ADF	JB
SPGTCED	0.089	−12.498	11.035	1.697	−0.888	10.900	−7.257***	4949.7***
ECO	0.119	−16.239	13.399	2.415	−0.657	6.733	−7.230***	1911.1***
GRNBIO	0.051	−18.193	13.394	2.272	−1.380	13.061	−6.645***	7230.9***
GRNFUEL	0.177	−18.028	21.617	3.829	0.180	3.735	−20.283***	572.7***
GRNREG	0.071	−15.256	8.930	1.319	−1.632	25.452	−7.535***	26 707***
GRNGEO	0.015	−13.390	18.255	2.186	0.686	11.250	−9.351***	5212.6***
GRNSOLAR	0.106	−19.334	12.049	2.548	−0.704	6.551	−8.259***	1823.7***
GRNWIND	0.074	−10.982	7.720	1.584	−0.276	4.651	−16.126***	891.8***
BTC	0.128	−46.473	20.305	4.750	−1.156	11.468	−13.594***	5554.2***
ETH	0.153	−55.071	35.365	6.258	−0.796	8.834	−20.648***	3271.1***
ETC	0.052	−50.779	35.865	7.143	−0.441	7.293	−7.421***	2191.5***
BCH	−0.141	−56.140	42.082	7.447	−0.350	8.936	−20.230***	3262.0***
LTC	−0.025	−44.901	29.062	6.224	−0.668	7.122	−21.313***	2132.5***
ADA	0.121	−50.371	32.209	7.238	0.002	4.197	−20.127***	716.3***
XRP	−0.083	−55.040	62.668	7.405	0.238	12.606	−30.085***	6457.8***
XLM	−0.042	−41.004	55.932	7.283	0.667	9.026	−22.001***	3379.6***
MIOTA	−0.085	−54.333	33.224	7.478	−0.528	6.744	−20.483***	1892.5***
NANO	−0.176	−61.455	54.654	9.113	0.028	8.112	−14.095***	2672.2***
DCRYPT	0.136	−47.692	19.470	4.917	−1.266	11.057	−13.579***	5222.2***
CCRYPT	0.027	−41.826	55.388	6.780	0.036	9.146	−14.665***	3396.4***
SP500	0.053	−12.765	8.968	1.361	−1.117	18.298	−9.018***	13 248.0***
GOLD	0.031	−5.265	5.133	0.913	−0.453	5.478	−12.866***	1203.9***

Note:
***Indicates the significance level of 1%.

where a and b are non-negative scalars satisfying $a + b < 1$, and $\bar{Q}$ is the unconditional variance matrix of standardised residuals u_t. We can thereby obtain the dynamic conditional correlations series $\rho_{12,t}$ as:

$$\rho_{12,t} = q_{12,t} / \sqrt{q_{11,t}\ q_{22,t}}. \tag{4}$$

With the dynamic conditional correlations between cryptocurrencies and clean energy indices, we now can proceed to examine the safe haven property of clean energy against cryptocurrencies. Following the work of Ratner and Chiu (2013) and Peng (2020), the dynamic conditional correlation DCC_t are regressed on dummy variables representing the extreme movements of assets as follows:

$$DCC_{ij,t} = c_0 + c_1 D(r_{crypto_i} q_{10}) + c_2 D(r_{crypto_i} q_5) + c_3 D(r_{crypto_i} q_1), \tag{5}$$

where $D(\ldots)$ are dummy variables that capture extreme negative returns of a cryptocurrency at the 10%, 5%, and 1% quantiles of the distribution. According to the definition of safe haven in Baur and Lucey (2010), clean energy is a weak hedge for an individual cryptocurrency if c_0 is insignificantly different from zero, or a strong hedge if c_0 is negative. Clean energy serves as a weak (strong) safe haven for an individual cryptocurrency under certain market condition if any of c_1, c_2 or c_3 are non-positive (significantly negative).

Alternatively, a similar approach to Eq. (5) is to regress DCC_t on the lagged extreme conditional volatility of dirty or clean cryptocurrency index which is proxied for market uncertainty, motivated by Baur and McDermott (2010):

$$DCC_{ij,t} = c_0 + c_1 D(v_{crypto} q_{90,t-1}) + c_2 D(v_{crypto} q_{95,t-1}) + c_3 D(v_{crypto} q_{99,t-1}), \tag{6}$$

where the dummy variables c_1, c_2 and c_3 here are equal to one if the conditional volatility at $t-1$ exceeds the 90%, 95% and 99% quantiles, respectively. This allows us to examine the safe haven property of clean energy against cryptocurrencies during increased market uncertainty.

To investigate the other way around that whether cryptocurrencies are safe havens for clean energy stocks in times of extreme negative markets and uncertainty, we simply replace with clean energy data on the right hand side for Eqs. (5) and (6), respectively.

3.2. Spillover measures

We use the DY connectedness framework (Diebold and Yilmaz, 2012; Diebold and Yılmaz, 2014) to estimate the spillover effects between clean energy indices and cryptocurrency indices. The DY model is basically a generalised vector autoregressive (VAR) model which can be used to trace the dynamic spillover relationship between two time series in a rolling window basis.

We begin with a VAR model with an infinite order of P:

$$y_t = \sum_{i=1}^{P} \varphi_i y_{t-i} + \varepsilon_t, \tag{7}$$

where y_t is the vector of endogenous variables, φ_i is the matrix of parameters, and ε_t represents the vector of $i.i.d.$ residuals.

In addition, we write the moving average representation of the model defined in Eq. (7) as:

$$y_t = \sum_{i=0}^{\infty} A_i \varepsilon_{t-i}, \tag{8}$$

Table 3
DCCs between clean energy indices and cryptocurrencies.

	SPGTCED	ECO	GRNBIO	GRNFUEL	GRNREG	GRNGEO	GRNSOLAR	GRNWIND
BTC	0.1572	0.1186	0.1370	0.0990	0.1491	0.0874	0.1088	0.1188
ETC	0.1301	0.1079	0.0852	0.0709	0.1260	0.0722	0.0956	0.0883
BCH	0.1338	0.1028	0.0908	0.0791	0.1250	0.0764	0.0799	0.0868
LTC	0.1464	0.1309	0.1206	0.0979	0.1561	0.0646	0.1115	0.1194
ETH	0.1493	0.1309	0.1244	0.1103	0.1425	0.0672	0.1007	0.1234
ADA	0.1605	0.1399	0.1354	0.1064	0.1588	0.1121	0.1331	0.0817
MIOTA	0.1530	0.1432	0.1456	0.1093	0.1557	0.1226	0.1396	0.0925
XRP	0.1348	0.1519	0.1195	0.1334	0.1271	0.0595	0.1043	0.0688
XLM	0.1743	0.1620	0.1607	0.1112	0.1713	0.0988	0.1385	0.0964
NANO	0.1601	0.1642	0.0998	0.1166	0.1526	0.0716	0.1353	0.0973

where the coefficient of the $N \times N$ matrix A_i is recursively determined as $A_i = \varphi_1 A_{i-1} + \varphi_2 A_{i-2} + \cdots + \varphi_{k-1} A_{i-k+1} + \varphi_k A_{i-k}$, but noted that A_i equals to zero if i is a negative number. A_0 is an identity matrix.

Under the framework of generalised VAR model, $\phi_{ij}(H)$, the H-step ahead generalised forecast error variance will be first decomposed and then normalised by its row sum as the following:

$$\phi_{ij}(H) = \frac{\sigma_{jj}^{-1} \sum_{h=0}^{H-1} \left(e_i' A_h \Sigma e_j\right)^2}{\sum_{h=0}^{H-1} \left(e_i' A_h \Sigma A_h' e_i\right)}, \qquad \tilde{\phi}_{ij}(H) = \frac{\phi_{ij}(H)}{\sum_{j=1}^{N} \phi_{ij}(H)} \tag{9}$$

where the σ_{jj} denotes the estimated SD of the error term for variable j, Σ is the variance matrix for the error-term vector ε, and e_i is the selection vector with one as the ith element and zero otherwise.

Ultimately, the total spillover (TS), directional spillover received by asset i from j ($DS_{i\leftarrow j}$), directional spillover transmitted to j by i ($DS_{i\to j}$), and net spillover (NS) indices are calculated as the following:

$$TS(H) = \frac{\sum_{i,j=1,i\neq j}^{N} \tilde{\phi}_{ij}(H)}{\sum_{i,j=1}^{N} \tilde{\phi}_{ij}(H)} \times 100 = \frac{\sum_{i,j=1,i\neq j}^{N} \tilde{\phi}_{ij}(H)}{N} \times 100 \tag{10}$$

$$DS_{i\leftarrow j}(H) = \frac{\sum_{j=1,j\neq i}^{N} \tilde{\phi}_{ij}(H)}{\sum_{i,j=1}^{N} \tilde{\phi}_{ij}(H)} \times 100 = \frac{\sum_{j=1,j\neq i}^{N} \tilde{\phi}_{ij}(H)}{N} \times 100 \tag{11}$$

$$DS_{i\to j}(H) = \frac{\sum_{j=1,j\neq i}^{N} \tilde{\phi}_{ji}(N)}{\sum_{i,j=1}^{N} \tilde{\phi}_{ji}(H)} \times 100 = \frac{\sum_{j=1,j\neq i}^{N} \tilde{\phi}_{ji}(H)}{N} \times 100 \tag{12}$$

$$NS_i(H) = DS_{i\to j}(H) - DS_{i\leftarrow j}(H) \tag{13}$$

4. Results

4.1. Safe haven analysis

4.1.1. Dynamic conditional correlations

Table 3 lists the average DCC coefficients between clean energy indices and the two groups of cryptocurrencies. All mean DCC coefficients are universally positive. The time-varing DCCs between clean energy indices and cryptocurrencies are in the Appendix A. From Figs. A.1 to A.8, it can be observed that large variations in correlations appeared around the April of 2020 for most pairs, except for GRNFUEL versus NANO and GRNGEO versus ETC. The dynamic correlations between GRNFUEL and both ETC and NANO and that between GRNGEO and both ETC and IMOTA are lower, but more stable than the other pairs. Complemented by Table 3, we see that the correlations between clean energy indices and cryptocurrencies are positive in most of the time, regardless of cryptocurrency types, which implies that the clean energy indices might not have direct hedge potentials for both types of cryptocurrency during the periods under study and in the near future. Moreover, clean energy stocks react heterogeneously to cryptocurrencies and there is no differentiated patterns between clean energy stocks and the two cryptocurrency groups.

4.1.2. Return analysis

Table 4 summarises the results of the hedge and safe haven property of clean energy indices in extreme bearish cryptocurrency market conditions. All the hedge ratios (θ_0) in Table 4 are significantly positive, which confirms that none of the clean energy indices can be a direct hedge for either types of cryptocurrencies during the studied period. The θ_1 for most of the panels are negative and some of which are significant, which indicates that clean energy indices can be weak or even strong safe havens for cryptocurrencies in the 10% quantile during the period, with very few exceptions. In terms of θ_2 and θ_3, the results are more spotty. It suggests that clean energy can also be a weak safe haven for cryptocurrency in 5% and 1% quantiles, but it depends very much on which clean energy and cryptocurrency are used.

Reversing the relationship in Table 5, we see that the results for θs are not uniformed. Cryptocurrency, regardless of types, seems to be a weak safe haven for GRNSOLAR in the 10% quantile as all θ_1 for GRNSOLAR are insignificantly negative in all panels. Most of the cryptocurrencies are weak havens for GRNGEO at 10% except for BTC which is a strong safe haven, and XRP, MIOTA, and NANO which are not safe havens for GRNGEO in the 10% quantile at all. For θ_2 and θ_3, we can only see few of cryptocurrencies are safe havens for clean energy stocks, such as ETC which acts as safe havens for most clean energy subsectors in various quantiles. Clearly, the results are even more spotty than the reverse, and we cannot clearly say that cryptocurrencies are general safe havens for clean energy stocks and we cannot distinguish the difference between types.

Overall, we find that clean energy can be generally viewed as a safe haven for the extreme returns of either dirty or clean cryptocurrencies in the 10% quantiles; clean energy can be a safe haven for them in the 5% and 1% quantiles as well, but it really depends on the selection of underlying assets. Most of the cryptocurrencies are not evident as general safe havens for clean energy stocks. Given the ecological footprint of dirty cryptocurrencies that is perhaps a comforting finding. The portfolio suggestion that arises from this is that investors with significant exposure to (in particular, from an ecological perspective, dirty) cryptocurrencies can choose clean energy stocks for safe haven benefits and environmental responsibility.

4.1.3. Uncertainty analysis

Table 6 summarise the results of the hedge and safe haven property of clean energy indices for cryptocurrencies in periods of increased crypto market uncertainty. All hedge coefficients (θ_0) in Table 6 are significantly positive, which confirms that clean energy indices cannot be a direct hedge for either types of cryptocurrencies during the times of increased market uncertainty. Although the results of θ_1 coefficients are spotty, most of them are positive, which indicates that clean energy indices are not safe havens for either types of cryptocurrency during high market uncertainty (90% threshold). For θ_2, most of them for dirty cryptocurrencies are negative and some of which are significant, which suggests that most of the clean energy indices are weak or strong safe havens for dirty cryptocurrencies on the 95% threshold of volatility. Exceptions are GRNFUEL which is not a safe haven for BTC and ETH, GRNREG which is not a safe haven for LTC, GRNGEO which is not a

Table 4
Results of hedge and safe haven analysis of clean energy indices for daily cryptocurrency extreme returns.

	Hedge (θ_0)	10% quantile (θ_1)	5% quantile (θ_2)	1% quantile (θ_3)
Panel A :SPGTCED				
BTC	0.1574***	*−0.0052*	0.0080	*−0.0098*
ETC	0.1299***	*−0.0034*	0.0065	0.0147
BCH	0.1339***	*−0.0031*	0.0040	0.0017
LTC	0.1461***	*−0.0002*	0.0053	0.0043
ETH	0.1495***	*−0.0098*	0.0119	0.0143
ADA	0.1610***	*−0.0032*	*−0.0064*	0.0080
MIOTA	0.1534***	***−0.0486*****	0.0184**	0.0105
XRP	0.1368***	*−0.0163*	*−0.0052*	*−0.0047*
XLM	0.1744***	0.0002	*−0.0027*	0.0003
NANO	0.1604***	***−0.0132*****	0.0157**	0.0189
Panel B: ECO				
BTC	0.1194***	*−0.0164*	0.0208	*−0.0210*
ETC	0.1076***	*−0.0017*	0.0043	0.0196
BCH	0.1035***	*−0.0009*	*−0.0137*	0.0031
LTC	0.1323***	0.0007	*−0.0067*	*−0.0055*
ETH	0.1317***	*−0.0055*	*−0.0066*	0.0090
ADA	0.1408***	*−0.0028*	*−0.0136*	0.0027
MIOTA	0.1444***	*−0.0196*	0.0137	*−0.0045*
XRP	0.1529***	*−0.0168*	0.0097	0.0234
XLM	0.1625***	*−0.0053*	*−0.0007*	0.0081
NANO	0.1652***	***−0.0155****	0.0086	0.0085
Panel C: GRNBIO				
BTC	0.1372***	*−0.0107*	0.0205	*−0.0114*
ETC	0.0863***	*−0.0183*	0.0123	0.0042
BCH	0.0921***	*−0.0155*	*−0.0042*	0.0363
LTC	0.1203***	0.0011	0.0012	0.0113
ETH	0.1250***	*−0.0128*	0.0064	0.0387
ADA	0.1357***	*−0.0066*	0.0009	0.0307
MIOTA	0.1471***	***−0.0397******	0.0475**	0.0017
XRP	0.1205***	*−0.0211*	0.0127	0.0409
XLM	0.1605***	*−0.0122*	0.0361	*−0.0354*
NANO	0.1008***	***−0.0265*****	0.0282*	0.0229
Panel D: GRNFUEL				
BTC	0.0991***	*−0.0088*	0.0056	0.0296
ETC	0.0727***	***−0.0254*****	0.0220	*−0.0400*
BCH	0.0788***	*−0.0037*	0.0099	0.0065
LTC	0.0972***	0.0025	0.0108	*−0.0090*
ETH	0.1105***	*−0.0027*	*−0.0010*	0.0101
ADA	0.1073***	*−0.0038*	*−0.0094*	*−0.0027*
MIOTA	0.1096***	***−0.0218*****	0.0381***	0.0011
XRP	0.1337***	*−0.0055*	0.0111	*−0.0251*
XLM	0.1121***	*−0.0052*	*−0.0095*	0.0105
NANO	0.1167***	*−0.0020*	0.0025	*−0.0004*
Panel E: GRNREG				
BTC	0.1501***	*−0.0220*	0.0251	*−0.0030*
ETC	0.1266***	*−0.0120*	0.0049	0.0374
BCH	0.1272***	*−0.0277*	0.0074	0.0218
LTC	0.1570***	*−0.0069*	*−0.0029*	*−0.0024*
ETH	0.1445***	***−0.0327****	0.0138	0.0569
ADA	0.1604***	*−0.0118*	*−0.0109*	0.0154
MIOTA	0.1570***	***−0.0306*****	0.0320	0.0090
XRP	0.1299***	***−0.0265*****	*−0.0024*	*−0.0004*
XLM	0.1719***	*−0.0067*	*−0.0041*	0.0181
NANO	0.1543***	***−0.0293******	0.0182	0.0301
Panel F: GRNGEO				
BTC	0.0875***	*−0.0041*	0.0040	0.0096
ETC	0.0722***	*−0.0000*	0.0000	0.0000
BCH	0.0764***	*−0.0015*	*−0.0008*	0.0180**
LTC	0.0644***	*−0.0011*	0.0060	0.0049
ETH	0.0673***	*−0.0052*	*−0.0011*	0.0466***
ADA	0.1119***	0.0009	0.0032	0.0077
MIOTA	0.1225***	*−0.0022*	0.0050**	0.0044
XRP	0.0595***	*−0.0015*	0.0014	0.0092
XLM	0.0983***	0.0056	*−0.0026*	*−0.0015*
NANO	0.0720***	***−0.0116******	0.0138***	0.0149*

(*continued on next page*)

Table 4 (*continued*).

Panel G: GRNSOLAR				
BTC	0.1095***	*−0.0114*	0.0115	*−0.0173*
ETC	0.0981***	***−0.0319******	0.0143	*−0.0052*
BCH	0.0819***	*−0.0161*	*−0.0146*	0.0345
LTC	0.1119***	*−0.0011*	*−0.0043*	*−0.0122*
ETH	0.1017***	*−0.0108*	*−0.0025*	0.0217
ADA	0.1335***	0.0006	*−0.0118*	0.0133
MIOTA	0.1409***	***−0.0260******	0.0239*	0.0007
XRP	0.1064***	***−0.0326****	0.0160	0.0337
XLM	0.1385***	*−0.0070*	0.0129	0.0028
NANO	0.1369***	***−0.0239*****	0.0125	0.0134
Panel I: GRNWIND				
BTC	0.1196***	*−0.0139*	0.0082	0.0206
ETC	0.0883***	*−0.0009*	*−0.0088*	0.0501**
BCH	0.0871***	*−0.0042*	0.0022	0.0027
LTC	0.1193***	*−0.0030*	0.0090	*−0.0046*
ETH	0.1236***	***−0.0091****	0.0067	0.0315***
ADA	0.0828***	*−0.0087*	*−0.0062*	0.0126
MIOTA	0.0932***	***−0.0183*****	0.0216**	0.0028
XRP	0.0694***	*−0.0063*	0.0051	*−0.0172*
XLM	0.0971***	*−0.0054*	*−0.0065*	0.0162
NANO	0.0981***	***−0.0147*****	0.0119	0.0066

Notes:
1. Eq. (5) is used. Table shows the relationship between each clean energy index (each panel) as a safe haven and various cryptocurrencies.
2. Clean energy is a weak hedge for an individual cryptocurrency if θ_0 is insignificantly different from zero, or a strong hedge if θ_0 is negative. Clean energy serves as a weak (strong) safe haven for an individual cryptocurrency under certain market condition if any of θ_1, θ_2 or θ_3 are non-positive (significantly negative).
*Denote the rejections of the null hypothesis at the significance level of 10%.
**Denote the rejections of the null hypothesis at the significance level of 5%.
***Denote the rejections of the null hypothesis at the significance level of 1%.

Table 5
Results of hedge and safe haven analysis of cryptocurrencies for daily clean energy extreme returns.

	Hedge (θ_0)	10% quantile (θ_1)	5% quantile (θ_2)	1% quantile (θ_3)
Panel A: BTC				
SPGTCED	0.1532***	0.0224**	0.0306***	0.0142
ECO	0.1145***	0.0234*	0.0175	0.0865**
GRNBIO	0.1327***	*−0.0016*	0.0649***	0.1138***
GRNFUEL	0.0961***	0.0190*	0.0046	0.0460*
GRNGEO	0.0872***	***−0.0098****	0.0213*	0.0076
GRNREG	0.1414***	0.0485***	0.0406	0.0777*
GRNSOLAR	0.1062***	*−0.0095*	0.0053*	0.0778*
GRNWIND	0.1170***	*−0.0013*	0.0291**	0.0424*
Panel B: ETC				
SPGTCED	0.1290***	0.0090*	*−0.0003*	0.0180
ECO	0.1082***	***−0.0196*****	0.0210*	0.0549***
GRNBIO	0.0807***	0.0073	0.0345	0.1872***
GRNFUEL	0.0702***	0.0137	*−0.0093*	*−0.0237*
GRNGEO	0.0722***	*−0.0000*	0.0000	0.0000
GRNREG	0.1245***	0.0107	*−0.0079*	0.0798***
GRNSOLAR	0.0948***	*−0.0098*	0.0214	0.0653
GRNWIND	0.0873***	0.00533	0.0089	*−0.0045*
Panel C: BCH				
SPGTCED	0.1318***	0.0112**	0.0173**	0.0070
ECO	0.0991***	0.0236**	0.0134	0.0590*
GRNBIO	0.0853***	0.0036	0.0695**	0.1533***
GRNFUEL	0.0762***	0.0266**	0.0009	0.0188
GRNGEO	0.0725***	0.0032	0.0161***	0.0011
GRNREG	0.1186***	0.0426**	0.0265	0.0796**
GRNSOLAR	0.0770***	0.0000	0.0433*	0.0696*
GRNWIND	0.0861***	0.0024	0.0070	0.0146
Panel D: LTC				
SPGTCED	0.1454***	0.0026	0.0073	0.0296***
ECO	0.1304***	0.0061	0.0057	0.0584***
GRNBIO	0.1171***	0.0027	0.0299*	0.1666***
GRNFUEL	0.0974***	0.0071	*−0.0131*	0.0421**
GRNGEO	0.0644***	*−0.0032*	0.0087	0.0125
GRNREG	0.1538***	0.0114	0.0109	0.0625***
GRNSOLAR	0.1105***	*−0.0088*	0.0269**	0.0480**
GRNWIND	0.1185***	*−0.0012*	0.0145**	0.0146

(*continued on next page*)

Table 5 (*continued*).

Panel E: ETH				
SPGTCED	0.1468***	0.0092	0.0255**	0.0251
ECO	0.1282***	0.0168***	−0.0007	0.1026***
GRNBIO	0.1205***	0.0074	0.0385*	0.1194***
GRNFUEL	0.1091***	0.0133*	*−0.0021*	*−0.0067*
GRNGEO	0.0669***	*−0.0077*	0.0208***	0.0019
GRNREG	0.1363***	0.0307*	0.4150	0.1029**
GRNSOLAR	0.0984***	*−0.0020*	0.0319*	0.0879**
GRNWIND	0.1226***	*0.0003*	0.0095*	0.0245***
Panel F: ADA				
SPGTCED	0.1594***	*−0.0012*	0.0160*	0.0365**
ECO	0.1381***	0.0106	*−0.0020*	0.0835***
GRNBIO	0.1322***	0.0042	0.0255	0.1411***
GRNFUEL	0.1057***	0.0140*	*−0.0154*	0.0107
GRNGEO	0.1120***	*−0.0081*	0.0173**	0.0035
GRNREG	0.1561***	0.0058	0.0275	0.0677***
GRNSOLAR	0.1320***	*−0.0041*	0.0176	0.0631***
GRNWIND	0.0798***	0.0022	0.0227*	0.0506**
Panel G: MIOTA				
SPGTCED	0.1510***	0.0094	0.0179**	0.0146
ECO	0.1398***	0.0243**	0.0046	0.0682**
GRNBIO	0.1412***	0.0012	0.0572***	0.1318***
GRNFUEL	0.1068***	0.0232**	0.0010	0.0192
GRNGEO	0.1219***	0.0022	0.0086***	*−0.0001*
GRNREG	0.1510***	0.0291**	0.0242	0.0527*
GRNSOLAR	0.1386***	*−0.0060*	0.0226*	0.0443**
GRNWIND	0.0906***	0.0046	0.0187*	0.0472***
Panel H: XRP				
SPGTCED	0.1325***	*−0.0077*	0.0508***	0.0544*
ECO	0.1465***	0.0303*	0.0219	0.1210***
GRNBIO	0.1155***	0.0085	0.0342*	0.1330***
GRNFUEL	0.1313***	0.0280*	*−0.0258*	0.0665*
GRNGEO	0.0589***	0.0022	0.0071	0.0021***
GRNREG	0.1235***	0.0093	0.0354*	0.0870***
GRNSOLAR	0.1012***	*−0.0034*	0.0485*	0.0963**
GRNWIND	0.0678***	*−0.0005*	0.0160**	0.0225*
Panel I: XLM				
SPGTCED	0.1728***	0.0020	0.0207***	0.0221**
ECO	0.1580***	0.0144	0.0386**	0.0650**
GRNBIO	0.1559***	0.0111	0.0375*	0.0172***
GRNFUEL	0.1085***	0.0270***	*−0.0007*	0.0053
GRNGEO	0.0988***	*−0.0044*	0.0072	0.0065
GRNREG	0.1661***	0.0292**	0.0307*	0.0697***
GRNSOLAR	0.1358***	*−0.0024*	0.0449***	0.0678**
GRNWIND	0.0950***	0.00723	0.0096	0.0260**
Panel J: NANO				
SPGTCED	0.1588***	0.0063	0.0076	0.0286**
ECO	0.1613***	0.0152*	0.0176	0.0479**
GRNBIO	0.0973***	0.0015	0.0191	0.1367***
GRNFUEL	0.1161***	0.0040***	0.0006	*−0.0027*
GRNGEO	0.0713***	0.0005	0.0049	0.0009
GRNREG	0.1477***	0.0135	0.0512***	0.0907***
GRNSOLAR	0.1334***	*−0.0038*	0.0337**	0.0578**
GRNWIND	0.0960***	*−0.0020*	0.0293***	0.0066

Notes:
1. Modified Eq. (5) is used. Table shows the relationship between each cryptocurrency index (each panel) as a safe haven and various clean energy indices.
2. A cryptocurrency is a weak hedge for clean energy subsector index if θ_0 is insignificantly different from zero, or a strong hedge if θ_0 is negative. A cryptocurrency serves as a weak (strong) safe haven for a clean energy subsector index under certain market condition if any of θ_1, θ_2 or θ_3 are non-positive (significantly negative).
*Denote the rejections of the null hypothesis at the significance level of 10%.
**Denote the rejections of the null hypothesis at the significance level of 5%.
***Denote the rejections of the null hypothesis at the significance level of 1%.

safe haven for ETC, and GRNWIND which is not a safe haven for ETH. Finally, regarding θ_3, we can see that coefficients for most of the panels are positive, except for some of which in Panel E and F, which indicates that more than half of the clean energy indices are not safe havens for either dirty or clean cryptocurrencies during extreme uncertainty (99% threshold). Exceptions are GRNREG which is a weak safe haven for NANO on the 99 99% threshold; and GRNGEO which is a weak safe haven for clean cryptocurrencies on the 99% threshold.

Table 7 presents the results of the hedge and safe haven property of dirty and clean cryptocurrencies in periods of increased clean energy market uncertainty. We find that none of the cryptocurrencies is a safe haven on the 90% threshold. Interestingly, we notice that some of the cryptocurrencies are strong safe havens for GRNFUEL on the 95% threshold of volatility, including ETC, BCH, ETH, ADA, XLM. ETC is also a weak haven for ECO and GRNWIND. LTC is a weak safe haven for GRNGEO and NANO is for GRNWIND on the 99% threshold. BTC, MIOTA, and XRP are not safe havens for clean energy at all. Similar to the previous analysis on returns, these spotty and inconsistent results suggest that cryptocurrencies in regardless types are not a appropriate safe haven choice for clean energy stocks.

Table 6
Results of hedge and safe haven analysis of clean energy indices in periods of extreme dirty and clean cryptocurrency volatility proxied for market uncertainty.

	Hedge (θ_0)	90% threshold (θ_1)	95% threshold (θ_2)	99% threshold (θ_3)
Panel A: SPGTCED				
BTC	0.1553***	0.0191*	*−0.0184*	0.0898***
ETC	0.1285***	0.0197	***−0.0286******	0.0976***
BCH	0.1450***	0.0097*	***−0.0138****	0.0775***
LTC	0.1477***	0.0168***	***−0.0233******	0.0846***
ETH	0.1472***	0.0136*	*−0.0134*	0.1340***
ADA	0.1599***	−0.0050	0.0181**	0.0172
MIOTA	0.1508***	0.0151**	0.0107	0.0139
XRP	0.1337***	−0.0109	0.0356*	0.0370
XLM	0.1734***	0.0010	0.0137**	0.0138
NANO	0.1580***	−0.0001	0.0359***	0.0214*
Panel B: ECO				
BTC	0.1162***	0.0147	*−0.0242*	0.2111***
ETC	0.1055***	0.0277***	***−0.0356******	0.1386***
BCH	0.1019***	0.0102	***−0.0383*****	0.1694***
LTC	0.1308***	0.0065	*−0.0136*	0.1138***
ETH	0.1301***	*−0.0000*	*−0.0260*	0.2012***
ADA	0.1382***	*−0.0033*	0.0289**	0.0542**
MIOTA	0.1383***	0.0260**	0.0312*	0.0630**
XRP	0.1457***	0.0174	0.0664**	0.1112***
XLM	0.1576***	0.0168	0.0399**	0.0731**
NANO	0.1607***	0.0103	0.0357***	0.0584***
Panel C: GRNBIO				
BTC	0.1336***	0.0251	*−0.0262*	0.2142***
ETC	0.0790***	0.0435***	*−0.0151*	0.2459***
BCH	0.0875***	0.0234	*−0.0345*	0.2558***
LTC	0.1158***	0.0282**	*−0.0048*	0.2173***
ETH	0.1209***	0.0229	*−0.0162*	0.1997***
ADA	0.1329	0.0056	0.0282*	0.0461*
MIOTA	0.1401***	0.0350**	0.0273	0.0579*
XRP	0.1155***	0.0074	0.0452**	0.0883***
XLM	0.1558***	0.0074	0.0702***	0.0646*
NANO	0.0962***	0.0033	0.0517***	0.0655**
Panel D: GRNFUEL				
BTC	0.0947***	0.0111	0.0172	0.2087***
ETC	0.0701***	*−0.0079*	*−0.0072*	0.1828***
BCH	0.0768***	0.0059	*−0.0072*	0.1959***
LTC	0.0965***	0.0045	*−0.0135*	0.1549***
ETH	0.1087***	*−0.0070*	0.0050	0.1346***
ADA	0.1065***	***−0.0191*****	0.0265**	0.0471**
MIOTA	0.1041***	0.0274***	0.0284**	0.0967***
XRP	0.1272***	0.0142	0.0740***	0.1045***
XLM	0.1096***	*−0.0020*	0.0251*	0.0585***
NANO	0.1159***	0.0029**	0.0050***	0.0092***
Panel E: GRNREG				
BTC	0.1441***	0.0347*	*−0.0169*	0.2361***
ETC	0.1238***	0.0120	***−0.0215****	0.2001***
BCH	0.1224***	0.0108	*−0.0186*	0.2355***
LTC	0.1536***	0.0076	0.0041	0.1499***
ETH	0.1385***	0.0159	*−0.0102*	0.2786***
ADA	0.1577***	*−0.0056*	0.0290*	0.0205
MIOTA	0.1532***	0.0178	0.0117	0.0110
XRP	0.1274***	*−0.0224*	0.0317	0.0287
XLM	0.1689***	0.0101	0.0245	0.0061
NANO	0.1494***	0.0062	0.0507***	*−0.0007*
Panel F: GRNGEO				
BTC	0.0867***	0.0033	*−0.0126*	0.0955***
ETC	0.0722***	0.0000	0.0000	0.0000***
BCH	0.0754***	0.0026	*−0.0011*	0.0750***
LTC	0.0643***	0.0030	***−0.0100****	0.0518***
ETH	0.0664***	0.0025	*−0.0108*	0.1088***
ADA	0.1100***	0.0202***	0.0036	*−0.0095*
MIOTA	0.1218***	0.0077***	*−0.0001*	*−0.0020*
XRP	0.0589***	0.0051	0.0034	*−0.0108*
XLM	0.0977***	0.0105***	0.0032	*−0.0154*
NANO	0.0708***	*−0.0021*	0.0258***	***−0.0207******

(*continued on next page*)

Table 6 (*continued*).

Panel G: GRNSOLAR				
BTC	0.1063***	0.0185	*−0.0380*	0.2462***
ETC	0.0943***	0.0061	***−0.0296*****	0.2133***
BCH	0.0798***	0.0045	*−0.0522*	0.2300***
LTC	0.1097***	0.0097	*−0.0139*	0.1446***
ETH	0.0996***	0.0023	*−0.0316*	0.2345***
ADA	0.1304***	0.0103	0.0269**	0.0316*
MIOTA	0.1370***	0.0134	0.0160	0.0360
XRP	0.1003***	0.0038	0.0566**	0.0799*
XLM	0.1334***	0.0224*	0.0477***	0.0457
NANO	0.1327***	0.0076	0.0400***	0.0426*
Panel I: GRNWIND				
BTC	0.1164***	0.0031	*−0.0075*	0.2458***
ETC	0.0862***	0.0094	*−0.0146*	0.1841***
BCH	0.0859***	0.0007	*−0.0049*	0.1095***
LTC	0.1176***	0.0087*	*−0.0062*	0.1220***
ETH	0.1213***	0.0073**	0.0009	0.1295***
ADA	0.0808***	*−0.0048*	0.0211	0.0266
MIOTA	0.0909***	0.0064	0.0157	0.0096
XRP	0.0685***	*−0.0019*	0.0063	0.0207*
XLM	0.0961***	0.0008	0.0044	0.0090
NANO	0.0955***	0.0011	0.0339***	0.0010

Notes:
1. Eq. (6) is used; Table shows the relationship between each clean energy index (each panel) as a safe haven and various cryptocurrencies under extreme uncertainty.
2. Clean energy is a weak hedge for an individual cryptocurrency under extreme uncertainty if θ_0 is insignificantly different from zero, or a strong hedge if θ_0 is negative. Clean energy serves as a weak (strong) safe haven for an individual cryptocurrency under certain level of uncertainty if any of θ_1, θ_2 or θ_3 are non-positive (significantly negative).
*Denote the rejections of the null hypothesis at the significance level of 10%.
**Denote the rejections of the null hypothesis at the significance level of 5%.
***Denote the rejections of the null hypothesis at the significance level of 1%.

Table 7
Results of hedge and safe haven analysis of cryptocurrencies in periods of extreme clean energy market uncertainty.

	Hedge (θ_0)	90% threshold (θ_1)	95% threshold (θ_2)	99% threshold (θ_3)
Panel A: BTC				
SPGTCED	0.1477***	0.0924***	0.0006	0.0170
ECO	0.1035***	0.1312***	0.0239	0.0757**
GRNBIO	0.1186***	0.1436***	0.0694***	0.0546
GRNFUEL	0.0900***	0.0653***	0.0194	0.1249***
GRNGEO	0.0842***	0.0228***	0.0124	0.0235*
GRNREG	0.1289***	0.1706***	0.0371	0.1266***
GRNSOLAR	0.0933***	0.0986***	0.0938***	0.0857**
GRNWIND	0.1129***	0.0256***	0.0595***	0.0369*
Panel B: ETC				
SPGTCED	0.1281***	0.0118**	0.0106	0.0258**
ECO	0.1045***	0.0302***	0.0102	*−0.0126*
GRNBIO	0.0663***	0.1311***	0.0880***	0.1266***
GRNFUEL	0.0668***	0.0502***	***−0.0358*****	0.0876***
GRNGEO	0.0722***	0.0000	0.0000***	0.0000***
GRNREG	0.1206***	0.0303***	0.0034	0.1364***
GRNSOLAR	0.0873***	0.0326***	0.0756***	0.1196***
GRNWIND	0.0856***	0.0119	0.0353***	*−0.0309*
Panel C: BCH				
ECO	0.0901***	0.1179***	0.0094	0.0429
GRNBIO	0.0680***	0.1873***	0.0631***	0.0808*
GRNFUEL	0.0719***	0.0813***	***−0.0374*****	0.0873***
GRNGEO	0.0740***	0.0112***	0.0208***	0.0223***
GRNREG	0.1085***	0.1224***	0.0590***	0.1295***
GRNSOLAR	0.0647***	0.1100***	0.0709***	0.0620
GRNWIND	0.0848***	0.0053	0.0271***	0.0048
Panel D: LTC				
SPGTCED	0.1438***	0.0126***	0.0186***	0.0326***
ECO	0.1239***	0.0665***	0.0160	0.0578***
GRNBIO	0.1059***	0.0898***	0.0830***	0.1421***
GRNFUEL	0.0943***	0.0229***	0.0064	0.0985***
GRNGEO	0.0623***	0.0160***	0.0140**	*−0.0013*
GRNREG	0.1475***	0.0499***	0.0459***	0.1297***
GRNSOLAR	0.1036***	0.0326***	0.0748***	0.0856***
GRNWIND	0.1169***	0.0128***	0.0235***	0.0005

(*continued on next page*)

Table 7 (*continued*).

Panel E: ETH				
SPGTCED	0.1423***	0.0490***	0.0230**	0.0883***
ECO	0.1186***	0.1004***	0.0241	0.0926***
GRNBIO	0.1075***	0.1365***	0.0487***	0.0814**
GRNFUEL	0.1068***	0.0401***	***−0.0254*****	0.0728***
GRNGEO	0.0649***	0.0103*	0.0187**	0.0332***
GRNREG	0.1243***	0.1167***	0.0920***	0.1748***
GRNSOLAR	0.0885***	0.059***	0.1125***	0.1064***
GRNWIND	0.1209***	0.0135***	0.0105*	0.0540***
Panel F: ADA				
SPGTCED	0.1559***	0.0258***	0.0191**	0.1012***
ECO	0.1313***	0.0638***	0.0249**	0.0899***
GRNBIO	0.1218***	0.0893***	0.0657***	0.1242***
GRNFUEL	0.1042***	0.0278***	***−0.0230****	0.0567***
GRNGEO	0.1096***	0.0056	0.0356***	0.0106
GRNREG	0.1491***	0.0440***	0.0749***	0.1471***
GRNSOLAR	0.1256***	0.0201**	0.0871***	0.1051***
GRNWIND	0.0737***	0.0337***	0.0646***	0.1311***
Panel G: MIOTA				
SPGTCED	0.1478***	0.0350***	0.0179**	0.0759***
ECO	0.1318***	0.1001***	0.0126	0.0678**
GRNBIO	0.1272***	0.1468***	0.0570***	0.0760**
GRNFUEL	0.1034***	0.0437***	0.0087	0.1089***
GRNGEO	0.1214***	0.0055***	0.0099***	0.0087**
GRNREG	0.1432***	0.0777***	0.0663***	0.1323***
GRNSOLAR	0.1315***	0.0448***	0.0580***	0.0646***
GRNWIND	0.0853***	0.0287***	0.0664***	0.0944***
Panel H: XRP				
SPGTCED	0.1245***	0.0806***	0.0120	0.1588***
ECO	0.1361***	0.1317***	0.0288	0.1156***
GRNBIO	0.1030***	0.1279***	0.0534***	0.0924***
GRNFUEL	0.1250***	0.0457***	0.0374*	0.1884***
GRNGEO	0.0580***	0.0069**	0.0129***	0.0144**
GRNREG	0.1143***	0.0701***	0.0808***	0.1669***
GRNSOLAR	0.0898***	0.0761***	0.1108***	0.1315***
GRNWIND	0.0654***	0.0160***	0.0310***	0.0255**
Panel I: XLM				
SPGTCED	0.1691***	0.0405***	0.0141***	0.0444***
ECO	0.1481***	0.1237***	0.021	0.0508**
GRNBIO	0.1431***	0.1190***	0.0854***	0.1323***
GRNFUEL	0.1054***	0.0699***	***−0.0288*****	0.0305
GRNGEO	0.0969***	0.0086**	0.0169***	0.0102
GRNREG	0.1567***	0.1151***	0.0388**	0.1029***
GRNSOLAR	0.1261***	0.0696***	0.0866***	0.1051***
GRNWIND	0.0915***	0.0269***	0.0331***	0.0561***
Panel J: NANO				
SPGTCED	0.1574***	0.0112**	0.0237***	0.0349***
ECO	0.1549***	0.0850***	0.0051	0.0502***
GRNBIO	0.0867***	0.0925***	0.0532***	0.1141***
GRNFUEL	0.1154***	0.0100***	0.0014	0.0090***
GRNGEO	0.0710***	*−0.0041*	0.0179***	0.0124
GRNREG	0.1381***	0.1014***	0.0520***	0.1627***
GRNSOLAR	0.1255***	0.0564***	0.0658***	0.0738***
GRNWIND	0.0939***	0.0148*	0.0447***	*−0.0256*

Notes:
1. Modified Eq. (6) is used; Table shows the relationship between each cryptocurrency index (each panel) as a safe haven and various clean energy indices under extreme uncertainty.
2. A cryptocurrency is a weak hedge for a clean energy subsector index under extreme uncertainty if θ_0 is insignificantly different from zero, or a strong hedge if θ_0 is negative. A cryptocurrency serves as a weak (strong) safe haven for a clean energy subsector index under certain level of uncertainty if any of θ_1, θ_2 or θ_3 are non-positive (significantly negative).
*Denote the rejections of the null hypothesis at the significance level of 10%.
**Denote the rejections of the null hypothesis at the significance level of 5%.
***Denote the rejections of the null hypothesis at the significance level of 1%.

Overall, we conclude that clean energy is more likely to be a safe haven for dirty cryptocurrencies than clean cryptocurrencies in the periods of increased market uncertainty, depending on the choice of underlying assets while the reverse is not the case, cryptocurrencies not showing consistent safe haven properties for clean energy stocks.

4.2. Spillover effects

4.2.1. Return spillovers

We use an optimal lag length of 1 selected by the Akaike Information Criterion (AIC) for the VAR model to calculate the TS, DS,

Table 8
Average dynamic total return connectedness.

	GOLD	SP500	SPGTCED	ECO	GRNBIO	GRNFUEL	GRNGEO	GRNREG	GRNSOLAR	GRNWIND	DCRYPT	CCRYPT	FROM OTHERS
GOLD	71.35	2.73	3.14	2.67	3.25	1.63	1.49	3.78	2.39	3.08	3	1.49	28.65
SP500	1.14	25.51	10.41	13.21	8.32	5.15	5.06	11.53	12.25	3.83	1.96	1.66	74.49
SPGTCED	1.06	9.58	21.83	15.00	7.11	6.51	4.79	13.06	11.14	7.43	1.27	1.23	78.17
ECO	0.81	12.16	14.56	21.61	7.97	8.84	4.74	9.72	13.84	3.31	1.17	1.28	78.39
GRNBIO	1.62	10.53	10.34	11.7	33.97	4.96	4.03	7.17	8.63	3.29	2.06	1.7	66.03
GRNFUEL	0.88	7.92	10.44	14.52	5.51	37.41	2.47	7.32	7.58	3.55	1.18	1.23	62.59
GRNGEO	1.5	8.02	9.24	8.52	5.55	3.03	43.25	8.22	6.05	3.3	1.84	1.48	56.75
GRNREG	1.41	10.64	13.7	10.29	5.24	4.91	4.48	23.11	11.72	11.54	1.68	1.29	76.89
GRNSOLAR	1.01	12.51	12.29	15.34	6.7	4.98	4.02	12.65	24.26	3.27	1.58	1.4	75.74
GRNWIND	1.48	6.18	13.04	6.07	3.71	3.82	2.73	18.63	4.92	37.33	1.2	0.88	62.67
DCRYPT	2.03	2.93	2.49	1.98	2.78	1.5	1.66	3.27	2.39	1.44	49.99	27.53	50.01
CCRYPT	1.19	2.73	2.33	2.57	2.78	2.01	1.25	2.55	2.32	0.9	28.02	51.36	48.64
TO OTHERS	14.14	85.92	101.96	101.86	58.92	47.33	36.72	97.9	83.22	44.93	44.96	41.16	759.03
Inc. OWN	85.49	111.42	123.79	123.47	92.89	84.75	79.97	121.01	107.47	82.26	94.95	92.53	TOTAL
NET	−14.51	11.42	23.79	23.47	−7.11	−15.25	−20.03	21.01	7.47	−17.74	−5.05	−7.47	63.25

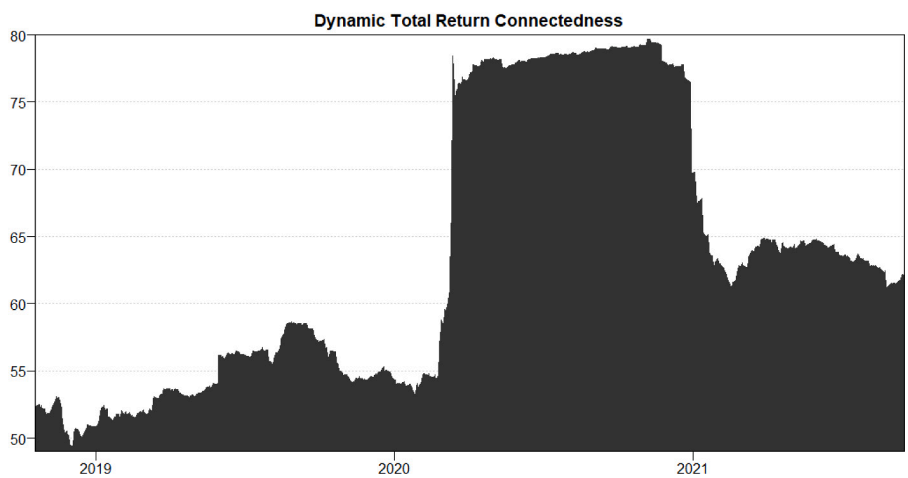

Fig. 1. Dynamic total return connectedness.

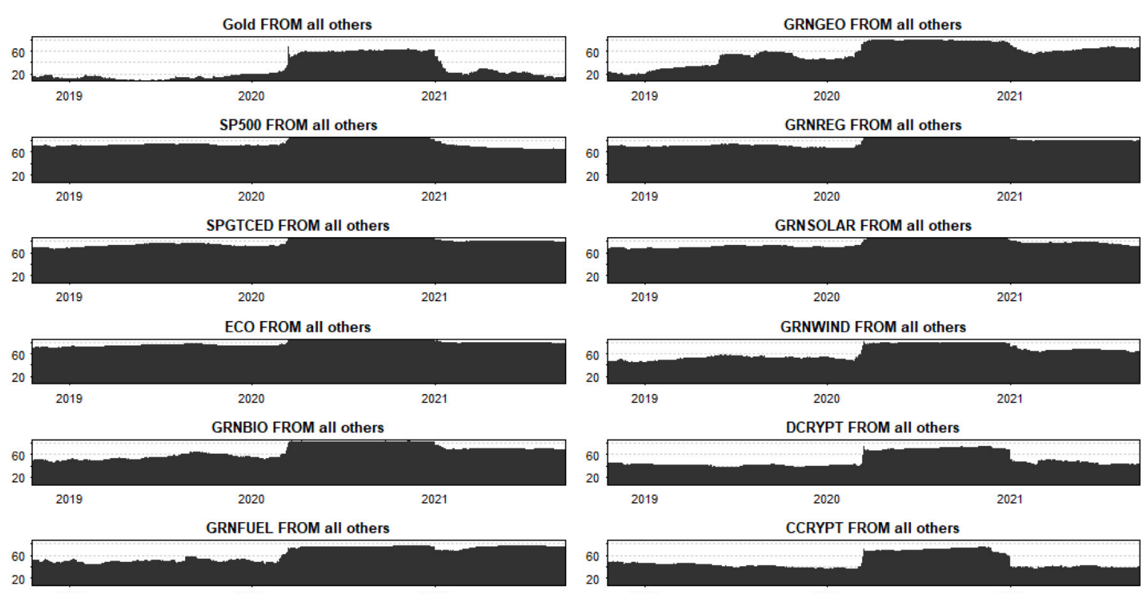

Fig. 2. Dynamic directional return connectedness FROM others.

NS for the return series. Following Saeed et al. (2021), Aharon et al. (2021), Zeng et al. (2020) and Diebold and Yilmaz (2012), and many other studies, we set a 200-day rolling window size and a 10-day ahead forecast horizon.

As shown in Table 8, the average dynamic total return connectedness from January 2018 to September 2021 is 63.25%, which is about medium-high level. From Fig. 1, we can observe that there was a notable increase in total connectedness of around 25% in the April of 2020, which can be explained by the increased correlations between

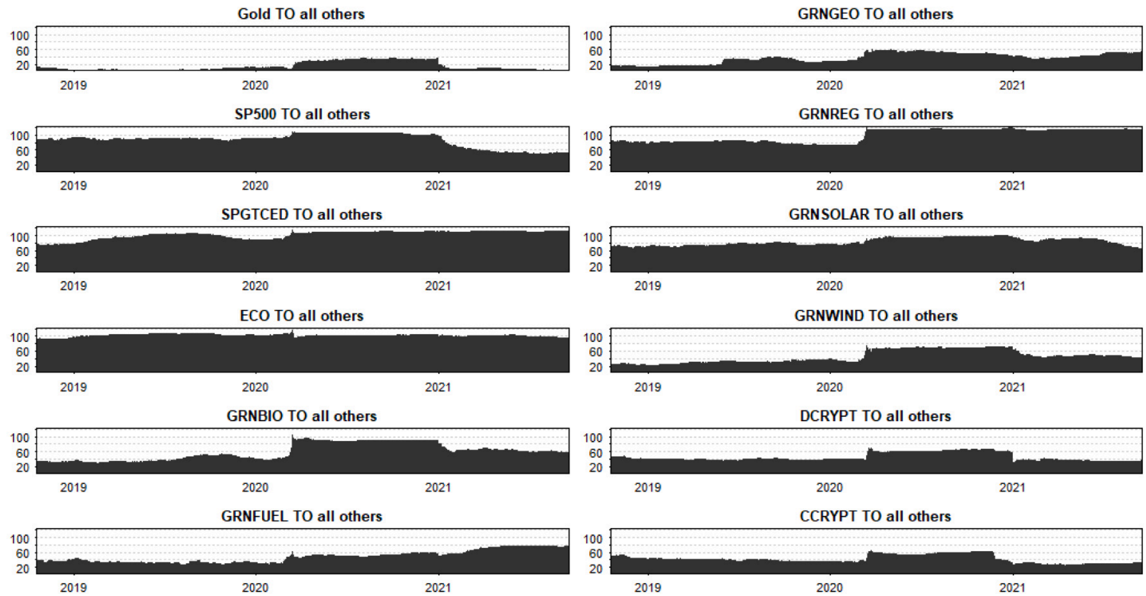

Fig. 3. Dynamic directional return connectedness TO others.

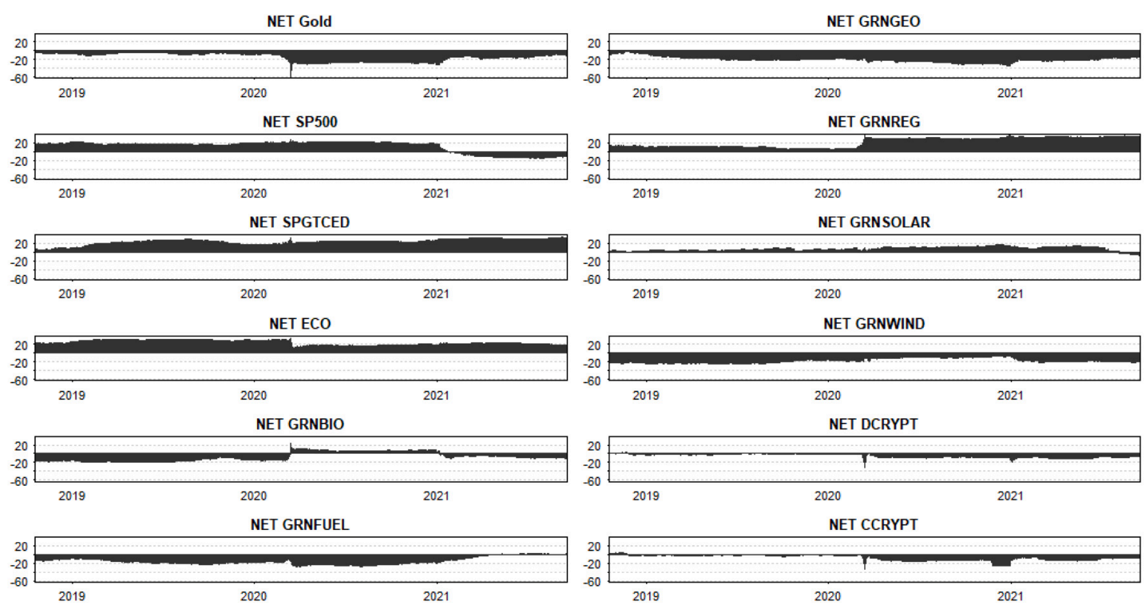

Fig. 4. Total net return connectedness.

assets at that time from DCCs plots (Appendix A). However, if we dig into the total connectedness table, we can see that the average total spillovers between either of the cryptocurrency markets and clean energy markets are relatively low during the period, despite the fact that SPGTCED and ECO are the two largest spillover transmitters (101.96% and 101.86%). The FROM connectedness between clean energy indices and cryptocurrency indices is much lower than that between clean energy and general stock markets (SP&500), and are at the same level of that between clean energy and gold. The TO connectedness shows that cryptocurrency market transmits more information to gold than to clean energy markets on average. Gold market is the most isolated as it is the smallest spillover receiver (28.65%)/transmitter (14.14%), followed by the dirty cryptocurrency (50.01%/37.9%) and clean cryptocurrency (48.64%/41.16%).

Fig. 2 depicts the dynamic directional return spillovers received by one market from other markets over time. Clearly, S&P500 and most of the clean energy markets heavily are affected by other markets as they continue receiving the highest spillover effects during the whole period. Clean energy markets are greater spillover receivers than cryptocurrency markets, while gold is the smallest receiver at both the beginning and the end. All market received much more spillovers from other markets in 2020 than in other periods.

Fig. 3 presents the dynamic directional return spillovers of one market transmitted to other markets. General clean energy indices such as SPGTCED and ECO have higher spillover effects to others than most of the other subsector indices. S&P500 had relatively high spillover effects to others until the early 2021. Dirty cryptocurrency market convey slightly higher spillover effects to others than clean cryptocurrency and gold markets. Gold, similar to previous results, has the least spillover effect to others at all time.

If look at the net spillovers (Fig. 4), we can easily tell that both of the gold, dirty and clean cryptocurrency markets are spillover receivers during the whole sample period. General market (s&p500) has received much more spillovers from other markets since 2021. More

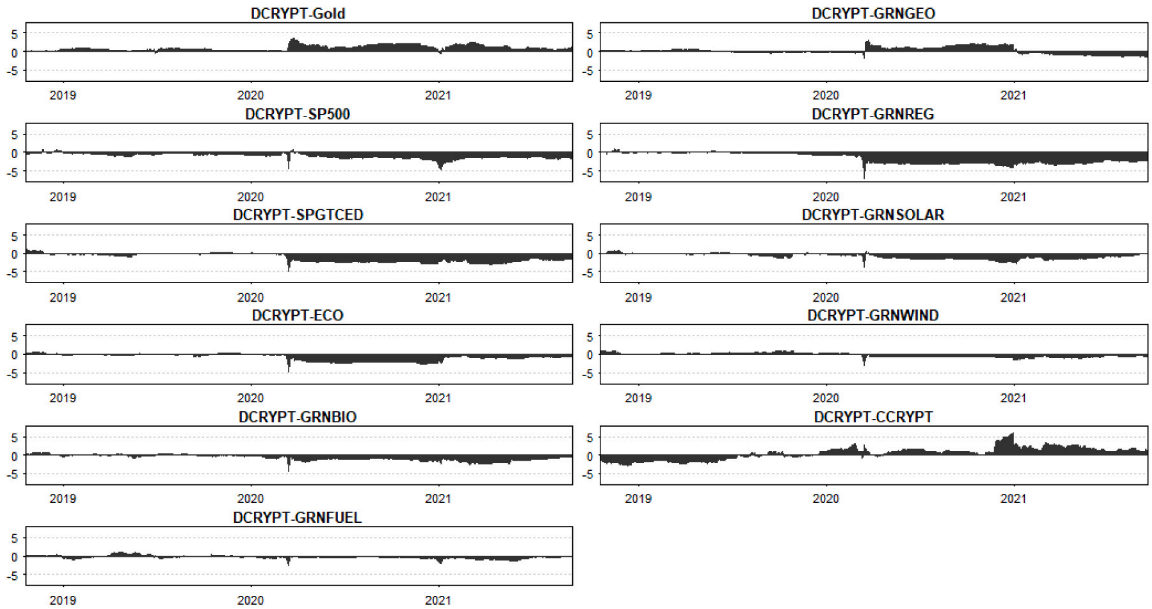

Fig. 5. Net pairwise directional return connectedness for DCRYPT.

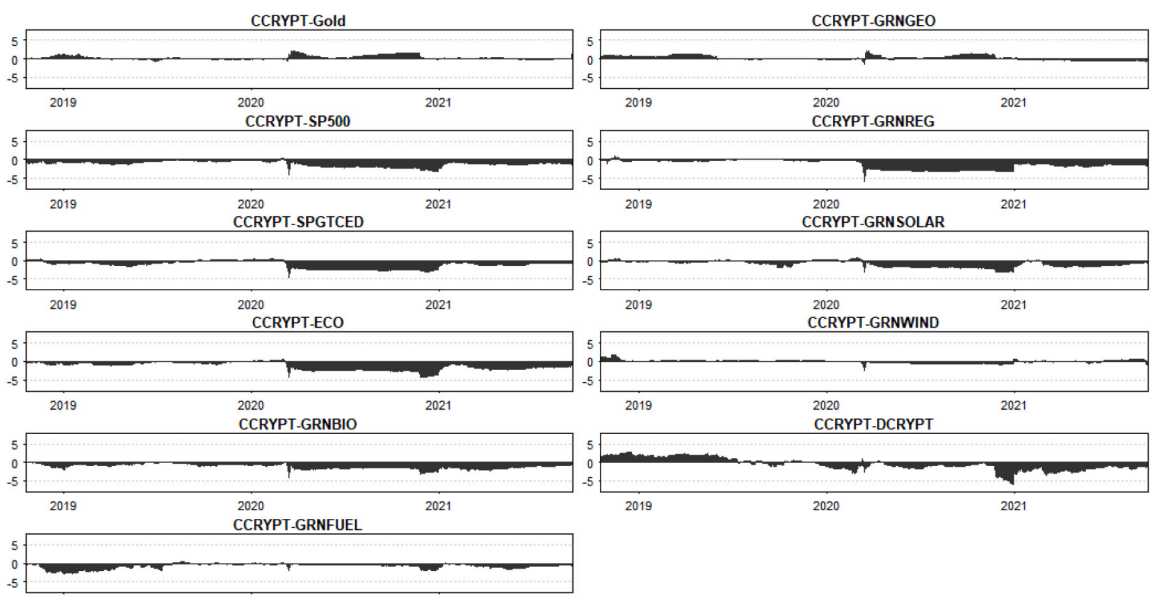

Fig. 6. Net pairwise directional return connectedness for CCRYPT.

interestingly, the role of clean energy indices play in terms of spillovers varied from sectors to sectors. Half of the clean energy indices are spillover transmitter in the whole period, including SPGTCED, ECO, GRNREG, and GRNSOLAR, while GRNFUEL, GRNGEO, and GRNWIND are spillover receivers. GRNBIO switched from receivers to transmitters in the April of 2020 and then switched back from 2021 onward.

Figs. 5 and 6 are the net pairwise directional return connectedness for dirty and clean cryptocurrency indices, respectively. The net spillovers from dirty cryptocurrency to clean cryptocurrency was negative at the beginning, and turned positive from the mid of 2019, which means that dirty cryptocurrency has regained the market dominance from clean cryptocurrency. Generally, both CCRYPT and DCRYPT are spillover receivers of the general stock market and most of the clean energy markets. Both DCRYPT and CCRYPT are transmitters for gold.

4.2.2. Volatility spillovers

The volatility series are estimated using standard GARCH(1,1) model (Appendix B). We choose an optimal lag order of 4 based on the AIC and same other settings to calculate the TS, DS, and NS for the volatility series. As recorded in Table 9, the average dynamic total connectedness of volatilities from January 2018 to September 2021 is 64.12%, which is slightly higher than that of returns. Fig. 7 presents the time-varing dynamic total volatility spillovers among different markets. It can observed that there was a even sharper increase in total connectedness between volatilities than returns in the April of 2020 when the correlations between markets increased at the same time (Appendix A). If we zoom in total spillovers table, we can see that the average total spillovers between either of the cryptocurrency market and clean energy markets are still relatively low during the period, but are higher than the that observed in return connectedness.

Table 9
Average dynamic total volatility connectedness.

	Gold	SP500	SPGTCED	ECO	GRNBIO	GRNFUEL	GRNGEO	GRNREG	GRNSOLAR	GRNWIND	DCRYPT	CCRYPT	FROM OTHERS
GOLD	56.98	4.58	5.88	4.1	4.21	1.88	2.48	5.62	3.68	4.02	2.93	3.63	43.02
SP500	2.82	30.78	10.56	10.2	8.83	4.5	4.54	11.87	6.55	5	2.15	2.21	69.22
SPGTCED	2.5	9.36	23.9	12.67	8.49	4.24	7.12	12.75	8.34	5.85	2.63	2.16	76.1
ECO	2.94	12.51	15.23	21.57	9.53	5.24	5.56	10.13	8.2	4.68	2.36	2.05	78.43
GRNBIO	2.35	10.34	10.29	7.8	32.52	2.5	7.12	8.71	4.94	6.76	3.31	3.34	67.48
GRNFUEL	1.64	7.97	8.99	10.79	4.49	45.92	5.72	4.61	3.31	2.92	2.15	1.5	54.08
GRNGEO	3.94	6.52	10.55	7.21	7.41	2.33	39.23	6.85	5.86	4.3	2.85	2.95	60.77
GRNREG	2.11	11.81	14.14	8.41	6.94	4.82	4.71	24.6	9.5	8.06	2.68	2.22	75.4
GRNSOLAR	2.44	10.76	12.38	11.77	7.77	3.06	3.84	13.7	25.29	4.26	2.8	1.93	74.71
GRNWIND	2.05	4.09	11.15	5.94	5.07	4.38	6.38	14.63	5.4	34.64	3.62	2.64	65.36
DCRYPT	1.99	3.17	4.68	3.66	5.46	1.7	2.29	4.86	4.15	5.52	45.87	16.65	54.13
CCRYPT	1.31	3.05	4.99	4.13	4.89	3.31	2.85	5	3.03	2.84	15.35	49.26	50.74
TO others	26.09	84.17	108.84	86.69	73.09	37.97	52.62	98.72	62.97	54.2	42.8	41.28	769.43
Inc. own	83.07	114.96	132.73	108.25	105.62	83.88	91.85	123.33	88.26	88.85	88.67	90.54	TOTAL
NET	−16.93	14.96	32.73	8.25	5.62	−16.12	−8.15	23.33	−11.74	−11.15	−11.33	−9.46	64.12

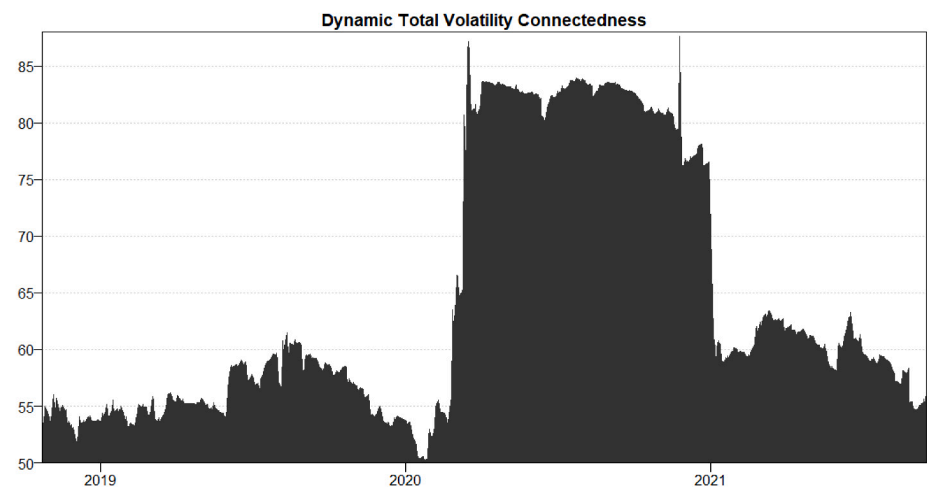

Fig. 7. Dynamic total volatility connectedness.

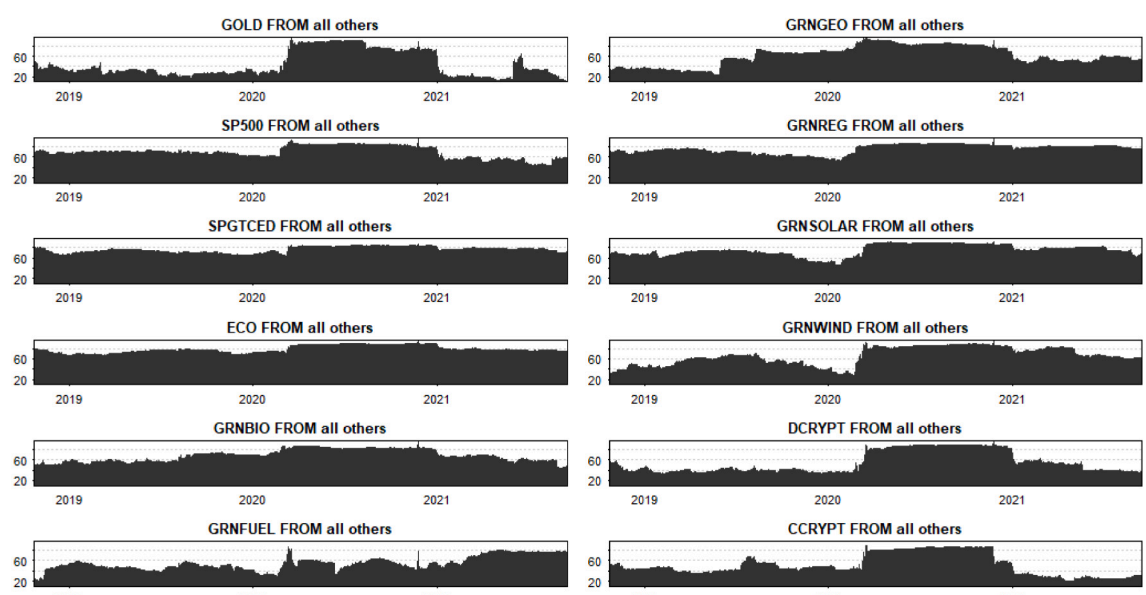

Fig. 8. Dynamic directional volatility connectedness FROM others.

SPGTCED and ECO are the largest transmitters, followed by GRNREG and S&P500. Half of the clean energy markets are larger receivers than the general stock market. The cryptocurrency and the gold market generally are involved the least in the volatility transmission. The level of FROM and TO connectedness between clean energy indices and cryptocurrency indices are slightly higher than that of return connectedness, but are still slightly lower than that between clean energy and gold on average. Gold market remains as the most isolated

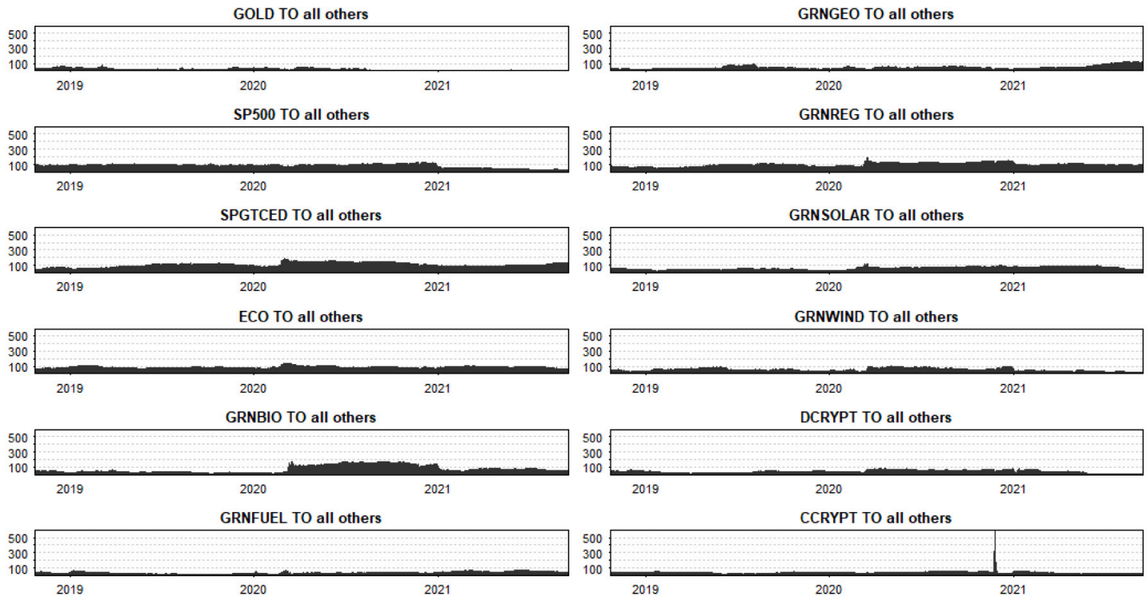

Fig. 9. Dynamic directional volatility connectedness TO others.

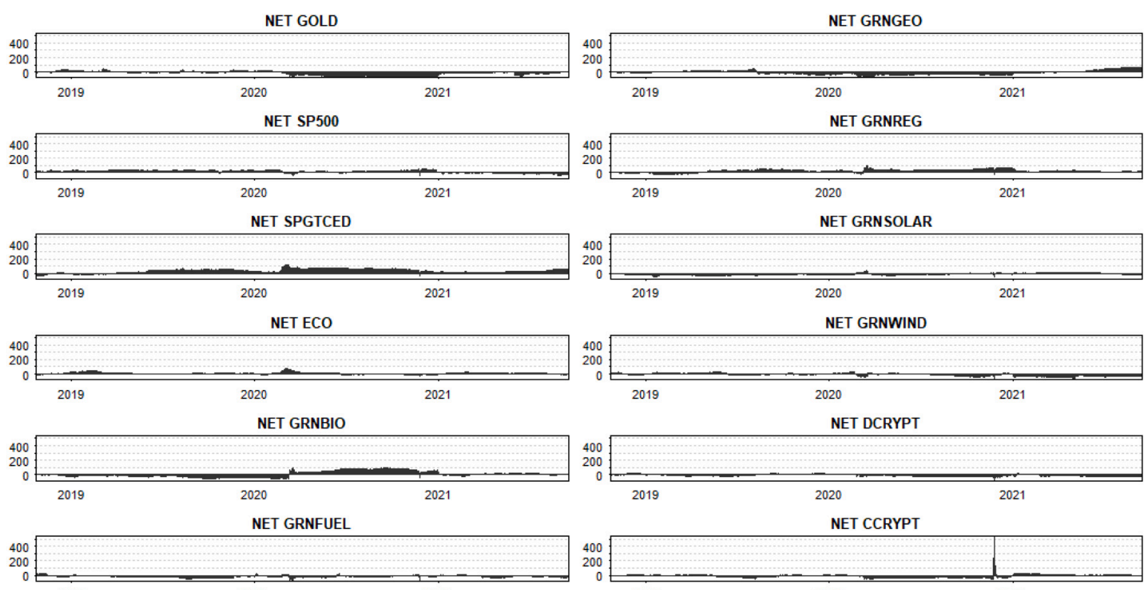

Fig. 10. Total net volatility connectedness.

market as it is the smallest spillover receiver (43.02%) and transmitter (26.09%) again.

Fig. 8 depicts the dynamic directional volatility spillovers received by one market from other markets over time. This time, the two major clean energy indices SPGTCED and ECO are the largest receivers. Most of the other clean energy subsectors share similar pattern, but not for the case in GRNFUEL which is more volatile. Clean cryptocurrency received more spillovers than dirty cryptocurrency before the mid of 2020, but has received much less afterwards. All market received much more spillovers from other markets in 2020 than in other periods.

Fig. 9 presents the dynamic directional volatility spillovers of one market transmitted to other markets. S&P500 and some of the clean energy indices have relatively higher spillover effects to others than from the others. Dirty cryptocurrency conveys slightly higher spillover effects to others than clean cryptocurrency and gold on average. Gold, similar to previous result, has the least spillover effects to others at all time. One important feature is that the clean cryptocurrency once had a extremely large spillover effect to other markets near the end of year 2020.

The plots of net volatility spillovers show quite a different picture to those of returns (Fig. 10). Gold is no longer a all time receiver as it was a transmitter before 2020 April. S&P500 and major clean energy indices such as SPGTCED and ECO still can be considered as transmitters during the whole sample period. Other clean energy subsectors vary from type to type. They have been switching between receiver and transmitter at different time. Dirty cryptocurrency generally can be classified as a receiver after 2020 April. Clean cryptocurrency is a receiver at most of the time, but it transmitted very large spillovers once in December of 2020.

Figs. 11 and 12 are the net pairwise directional volatility connectedness for dirty and clean cryptocurrency indices, respectively. Surprisingly, the net spillover from dirty to clean cryptocurrency was positive, but has become negative following a extreme negative shock

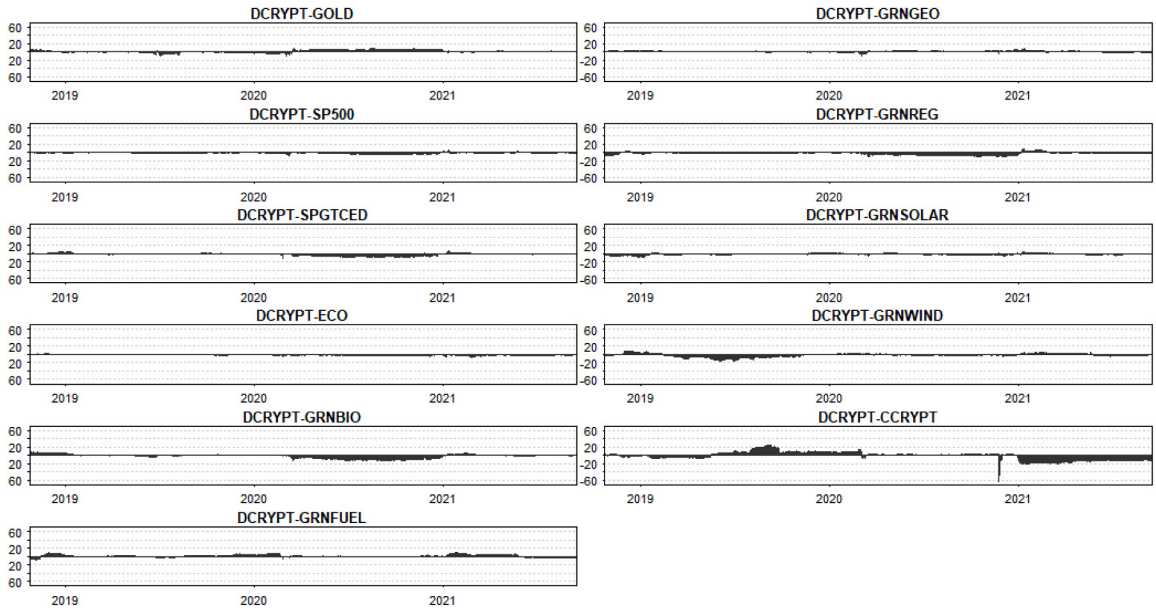

Fig. 11. Net pairwise directional volatility connectedness for DCRYPT.

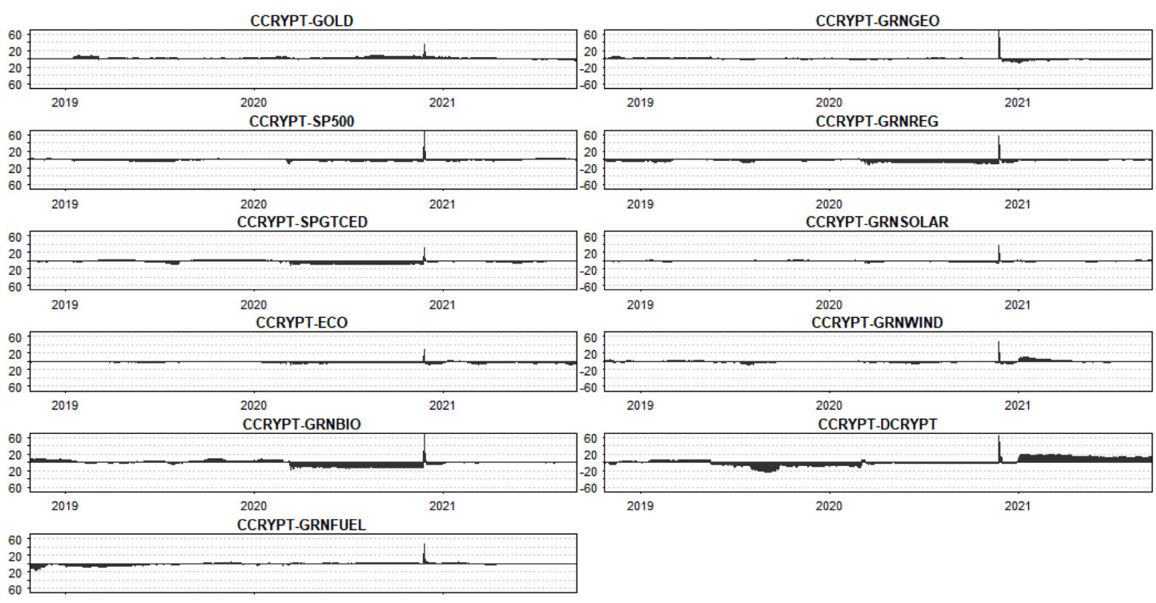

Fig. 12. Net pairwise directional volatility connectedness for CCRYPT.

at the end of 2020. This tells us that when clean cryptocurrency is experiencing high volatility, the dirty cryptocurrency market get affected. In addition, the net volatility spillover from dirty cryptocurrency to gold has become quite negative from 2020 April to December, which suggests that investments have been somehow transferred from dirty cryptocurrency to gold market when the former is experiencing high uncertainty. Another interesting pattern is that clean cryptocurrency had a extreme volatility spillover effect to all other market near the end of 2020, which has decayed rapidly. Similar to previous findings, the net spillovers between cryptocurrencies and clean energy are different and there is no unified pattern among them.

Overall, the return and volatility connectedness between clean energy and general market or between clean energy subsectors are more pronounced than that between clean energy and cryptocurrencies, which suggests that investor in the market have not really linked the clean energy and cryptocurrencies together regardless of whether the cryptocurrency is dirty or clean.

5. Robustness check

We further consider using a time-varying parameter VAR model (TVP-VAR) proposed by Antonakakis et al. (2020) to examine the robustness of previous results of spillover analysis sections. The TVP-VAR approach is claimed to have advantages over the DY (rolling window VAR) approach such that it does not require a rolling window size to be biasedly assigned and it avoids loosing observations as it introduces a time-varing variance–covariance matrix by adopting the Kalman filter in estimation with forgetting factors assigned (Antonakakis et al., 2020).

The TVP-VAR model with p lags is defined as the following:

$$\begin{aligned} y_t &= \Phi_t z_{t-1} + \epsilon_t & \epsilon_t \mid I_{t-1} \sim N\left(0, \Sigma_t\right), \\ vec\left(\Phi_t\right) &= vec\left(\Phi_{t-1}\right) + e_t & e_t \mid I_{t-1} \sim N\left(0, E_t\right), \end{aligned} \tag{14}$$

where y_t represents $m \times 1$ vector of endogenous variables, while z_{t-1} represents $pm \times 1$ vector of lagged y_t from $t-p$ to $t-1$. ϵ_t and e_t are

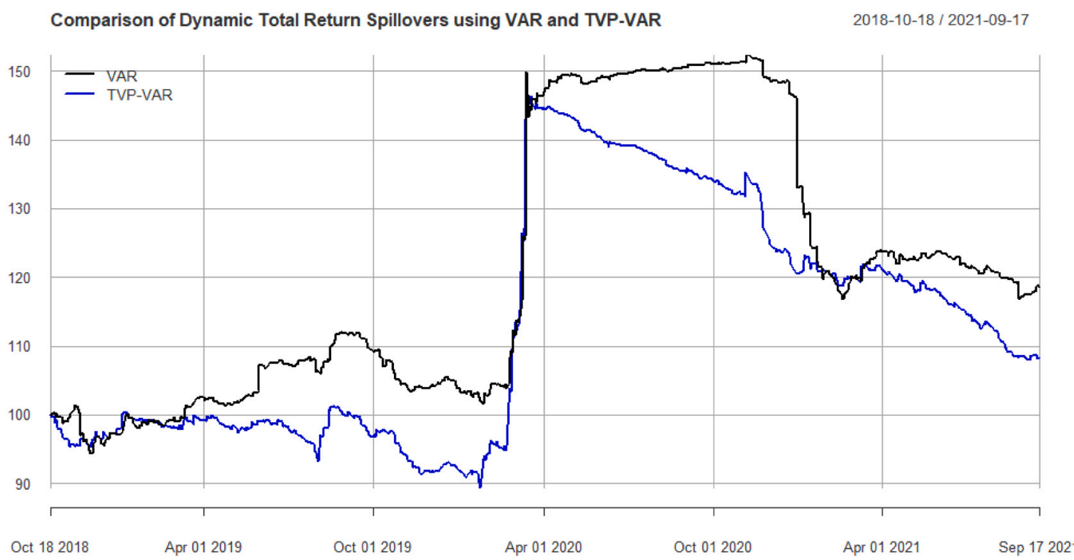

Fig. 13. Dynamic total return spillovers using VAR and TVP-VAR.

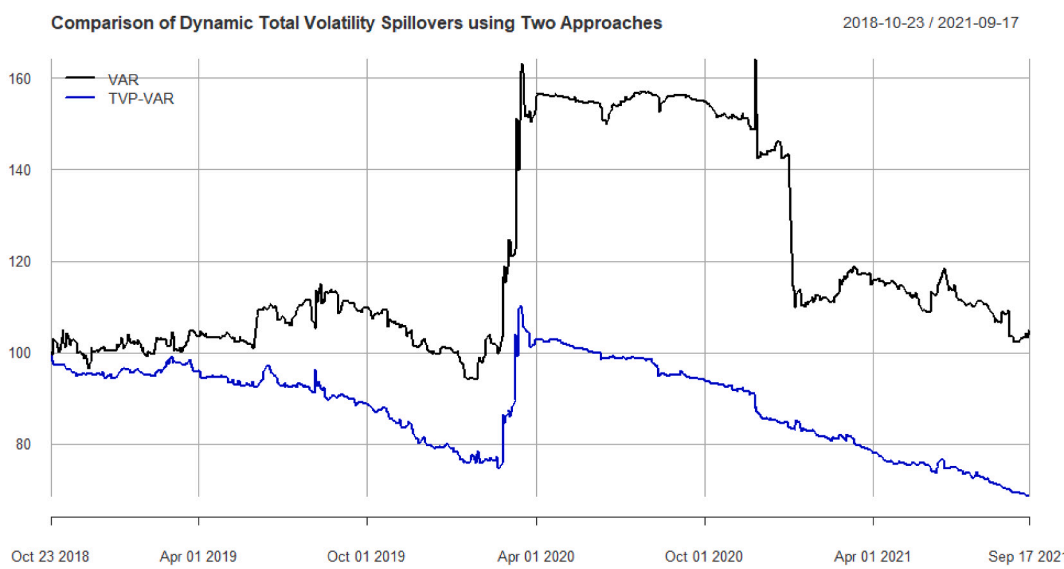

Fig. 14. Dynamic total volatility spillovers using VAR and TVP-VAR.

vectors of error terms. I_{t-1} denotes all known information until $t-1$. Σ_t and E_t are time-varying variance–covariance matrices.

Following Antonakakis et al. (2020), we initiate the Kalman filter using the Minnesota prior, followed by using the benchmark decay factors of (0.99, 0.99) in the estimation step to calculate the time-varing coefficients and variance–covariance matrices. Finally, the time-varing coefficients and the time-varing variance–covariance matrices are introduced to the step of generalised forecast error variance decomposition in the DY approach so that we can calculate the spillover indices TS, $DS_{i\leftarrow j}$, $DS_{i\rightarrow j}$, and NS.

Tables C.1 and D.1 list the average dynamic total return and volatility connectedness, respectively. Figs. C.1 to C.6 are plots of dynamic return connectedness results, while Figs. D.1 to D.6 are plots of dynamic volatility connectedness results.

By using the TVP-VAR model, we avoid the loss of the first 200 observations, and we show that there was a decaying return connectedness from 2018 to 2019 and same for the volatility connectedness but from 2018 to 2020, which were probably due to the collapse in crypto market started in the January of 2018. The major differences between the results of using the DY and TVP-VAR models happens in the period from 2020 April till the year end. To better illustrate the difference, we drop the first 200 results of total connectedness obtained using the TVP-VAR model, and scale both results obtained by DY and TVP-VAR models to 100 at the start. Figs. 13 and 14 compare the dynamic total return and volatility connectedness using VAR and TVP-VAR approaches, respectively. Both show a drastic increase in the total spillovers approaching the April of 2020. However, while using the VAR approach the high level of spillovers lasted for nearly a year before collapsing at the beginning of 2021, the spillover calculated using the TVP-VAR model has been decaying after the peak. This is not surprising as the DY approach is more sensitive to outliers than the TVP-VAR method as the latter is smoothed by a Kalman filter. Overall, both approaches provided qualitatively similar information and our findings remain robust.

6. Conclusions

Previous studies such as Naeem and Karim (2021) and Pham et al. (2021) suggest that green investments such as clean energy could be used as diversification or hedge tool for cryptocurrency investors.

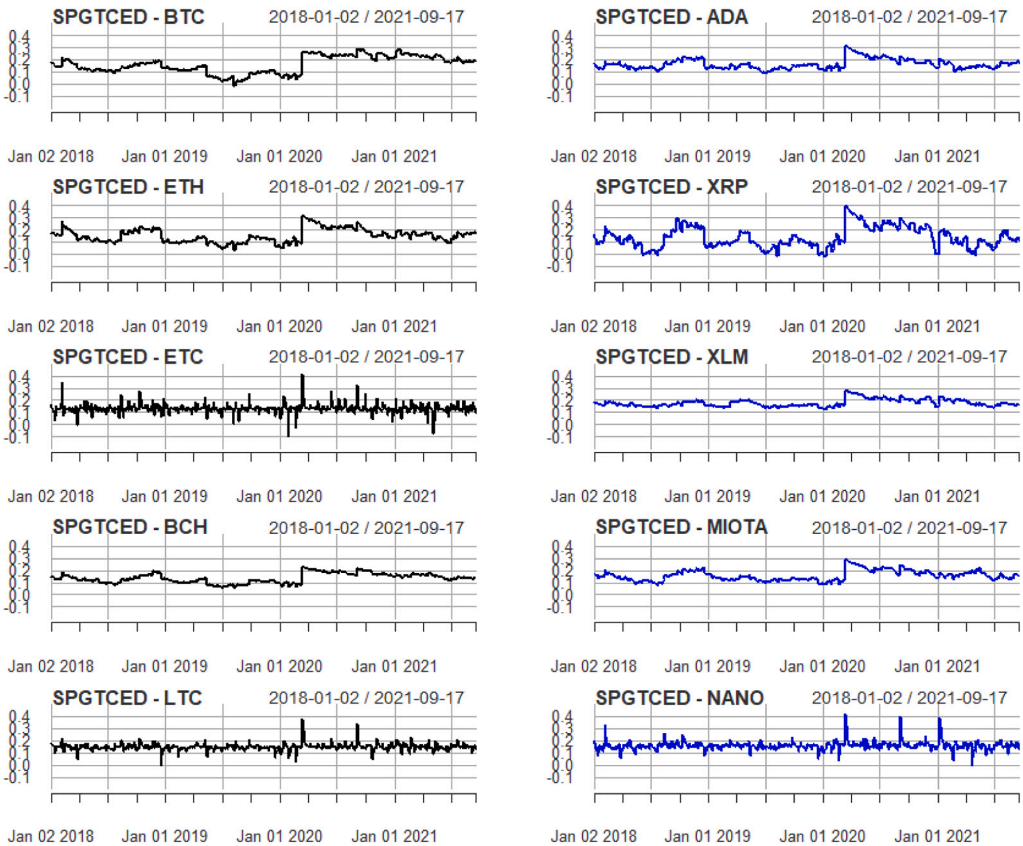

Fig. A.1. DCCs between SPGTCED and cryptocurrencies.

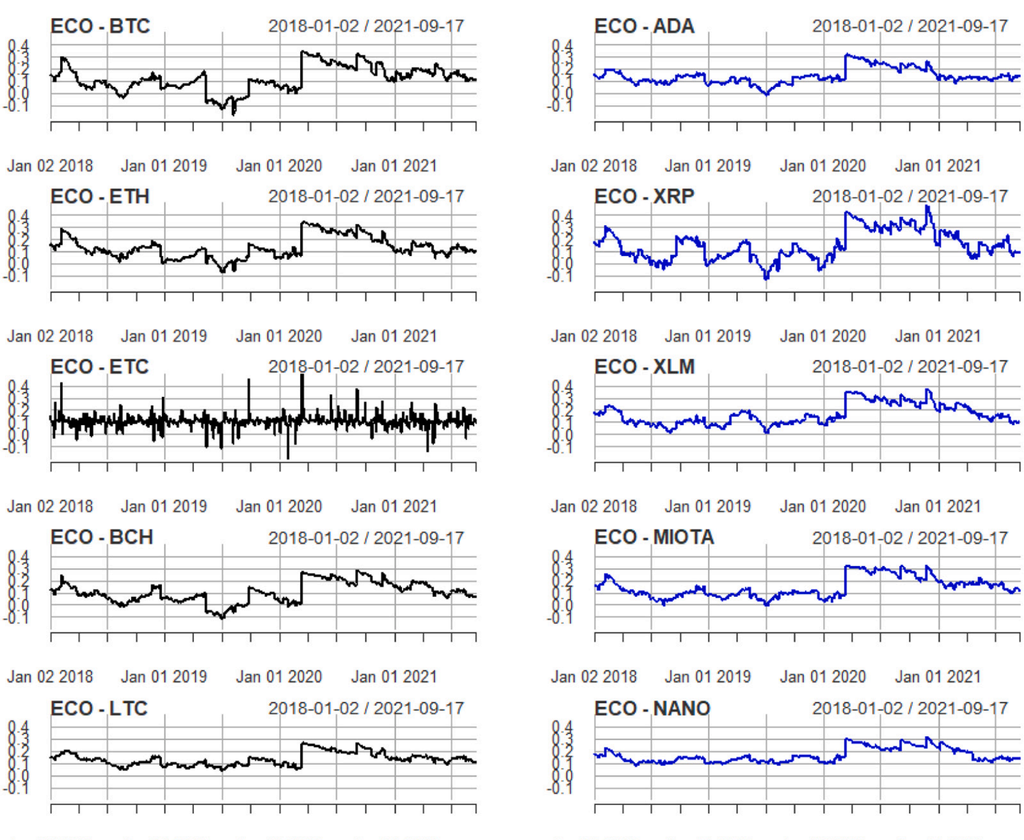

Fig. A.2. DCCs between ECO and cryptocurrencies.

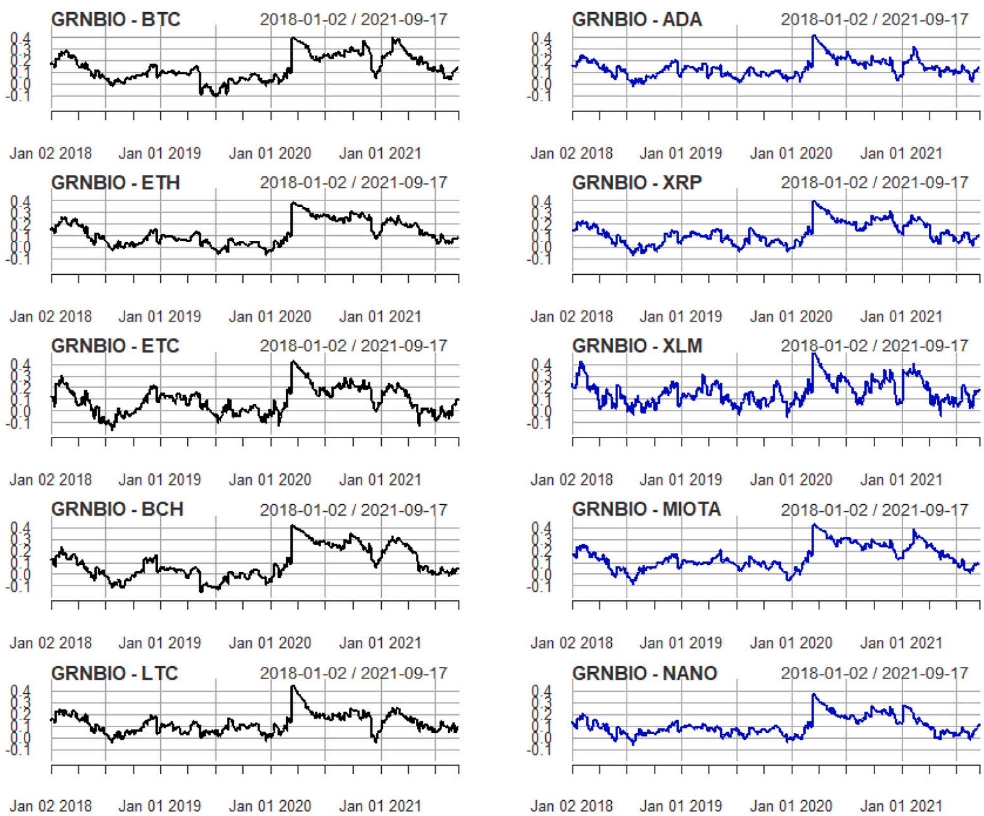

Fig. A.3. DCCs between GRNBIO and cryptocurrencies.

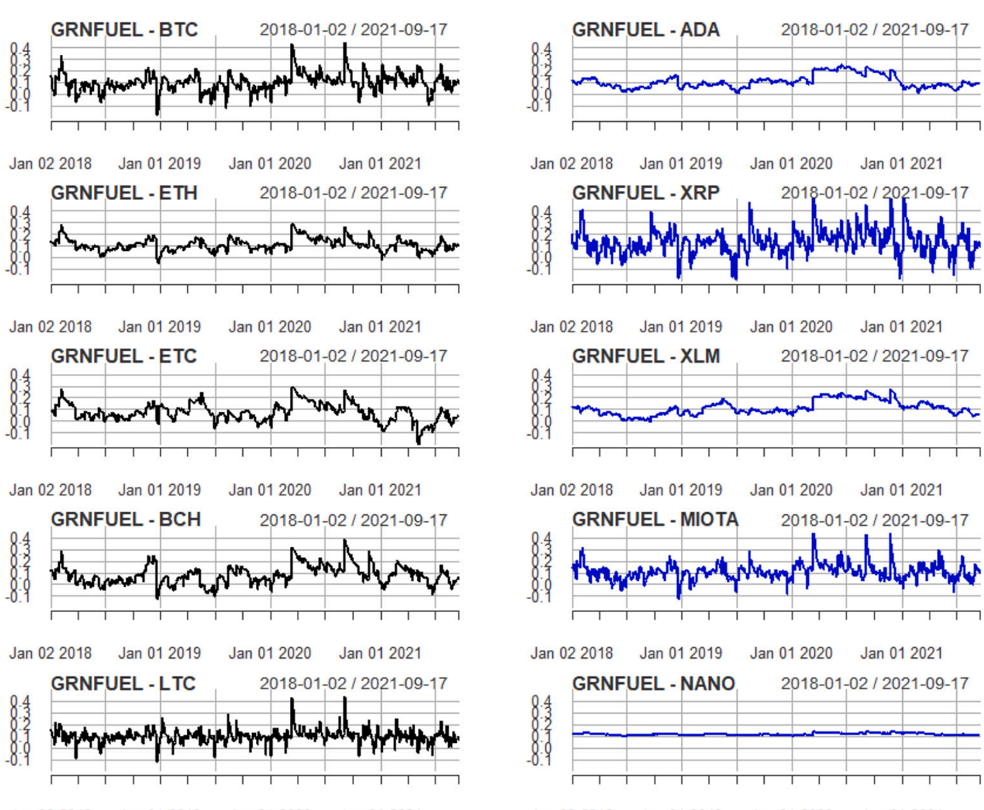

Fig. A.4. DCCs between GRNFUEL and cryptocurrencies.

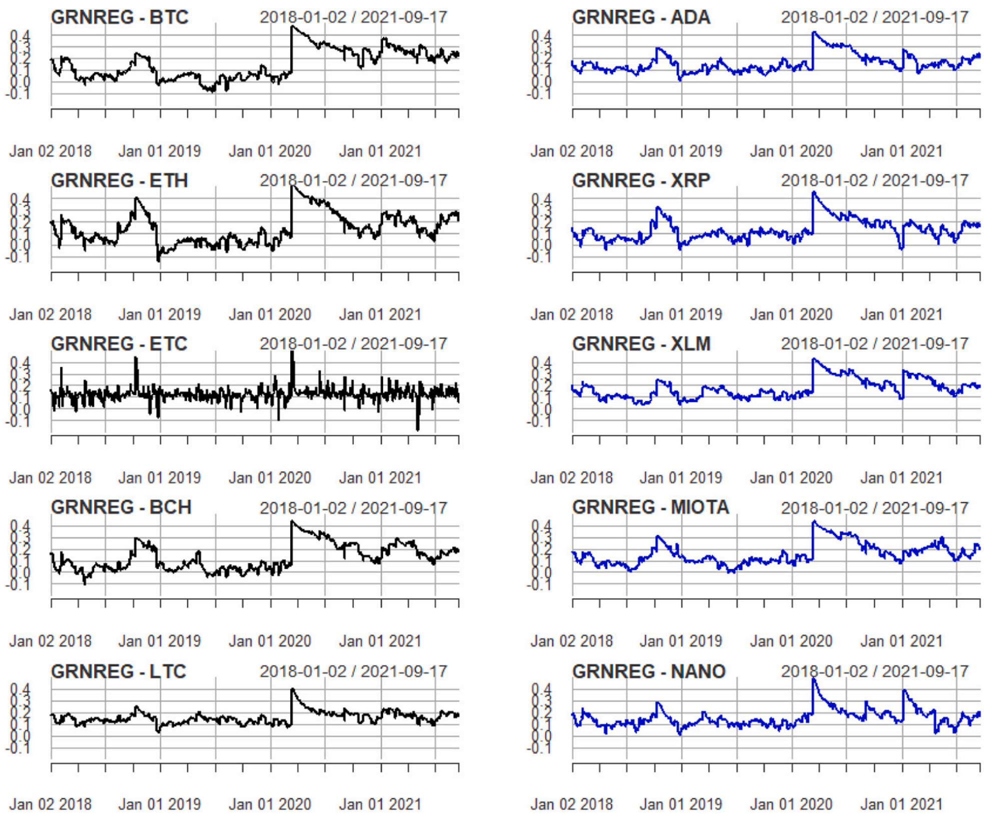

Fig. A.5. DCCs between GRNREG and cryptocurrencies.

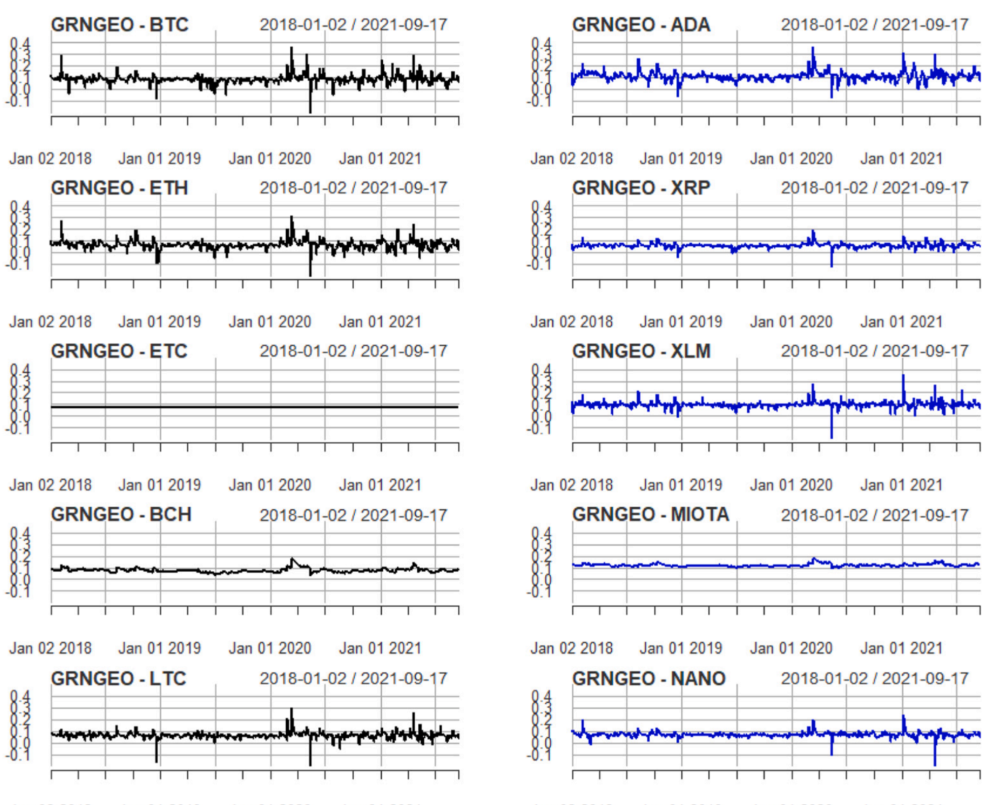

Fig. A.6. DCCs between GRNGEO and cryptocurrencies.

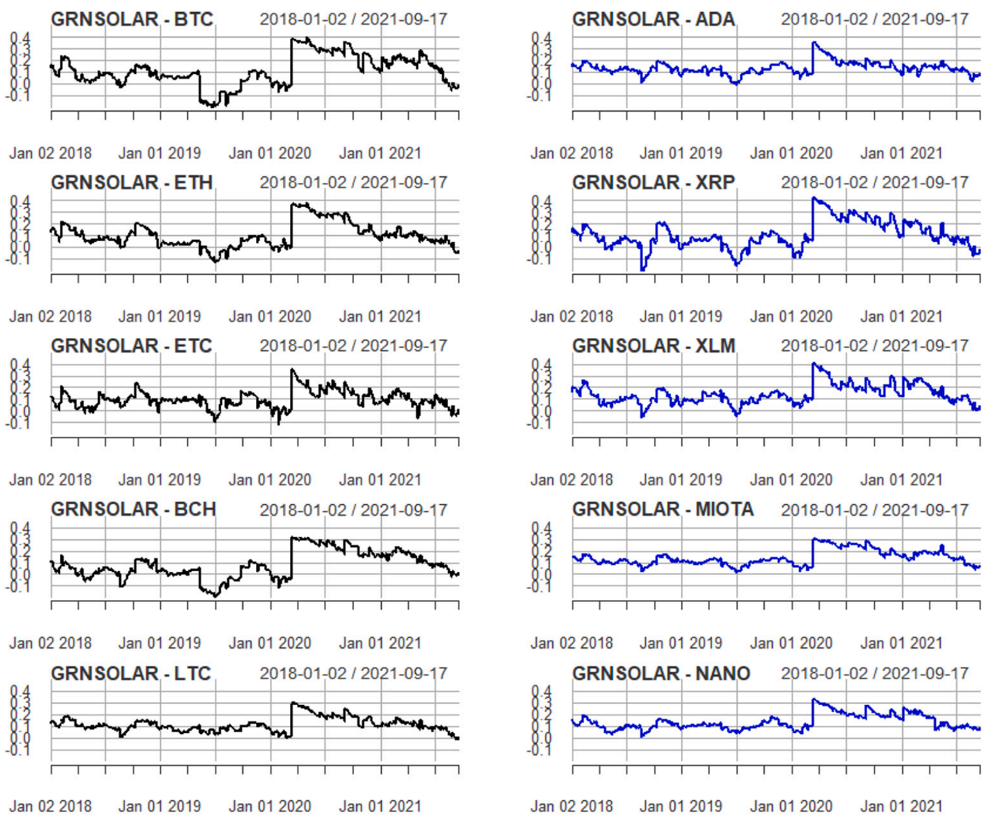

Fig. A.7. DCCs between GRNSOLAR and cryptocurrencies.

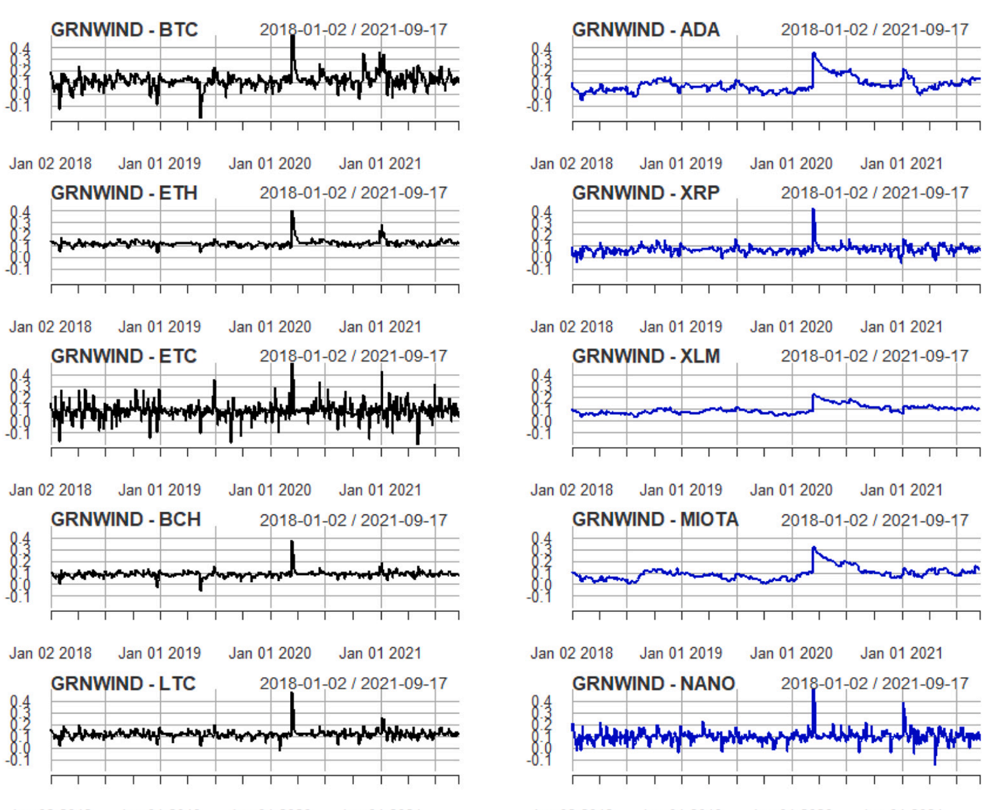

Fig. A.8. DCCs between GRNWIND and cryptocurrencies.

However, in this paper, we show that the time-varing dynamic conditional correlations between clean energy indices and cryptocurrencies is positive the majority of the time, regardless of cryptocurrency types, which implies that clean energy indices might not be a direct hedge for either dirty and clean cryptocurrencies.

Furthermore, we test the hedge and safe haven property of clean energy indices in spells of extreme falling crypto markets and extreme crypto market uncertainty and the reverse based on the framework proposed by Baur and Lucey (2010) and Baur and McDermott (2010). We confirm our previous finding that clean energy stocks have not yet become an effective direct hedge for cryptocurrencies. However, we find compelling evidence that clean energy *can* can be viewed as a safe haven for both dirty or clean cryptocurrencies at the 10% quantiles of negative returns, in general; it can be a safe haven in the 5% and 1% quantiles as well, depending on the selection of underlying assets. In addition, clean energy is more likely to be a safe haven for dirty cryptocurrencies than for clean cryptocurrencies in periods of extreme market volatility, subject to the selection of underlying assets as well. In contrast, cryptocurrency asset is not a universal safe haven for clean energy stocks. We believe that retail investors or institutional managers who have used or are seeking to use clean energy stocks to hedge cryptocurrencies would find this study beneficial for their

Table B.1
Estimation results of GARCH(1,1) model.

	μ	ω	α	β	Log-Likelihood
SPGTCED	0.0008**	0.0000***	0.1537***	0.8447***	2731.232
ECO	0.0008	0.0000***	0.0946***	0.9001***	2343.399
GRNBIO	0.0007	0.0000***	0.1364***	0.8268***	2380.133
GRNFUEL	0.0008	0.0000**	0.0647***	0.9309***	1861.709
GRNREG	0.0007**	0.0000**	0.1562***	0.8391***	3005.217
GRNGEO	0.0006	0.0000***	0.3488***	0.6854***	2368.953
GRNSOLAR	0.0010	0.0000***	0.1018***	0.8599***	2215.170
GRNWIND	0.0010**	0.0000*	0.0972***	0.8646***	2617.024
DCRYPT	0.0015	0.0003***	0.1343***	0.7439***	1505.958
CCRYPT	−0.0024	0.0004***	0.1942***	0.7526***	1230.797
SP500	0.0011***	0.0000***	0.2907***	0.6967***	3027.870
Gold	0.0001	0.0000**	0.0631***	0.9271***	3136.461

Note:
1. Volatility clustering are captured as the coefficients α and β for all series are significantly positive and their sum are closed to one.
*Indicate the significance level of 10%.
**Indicate the significance level of 5%.
***Indicate the significance level of 1%.

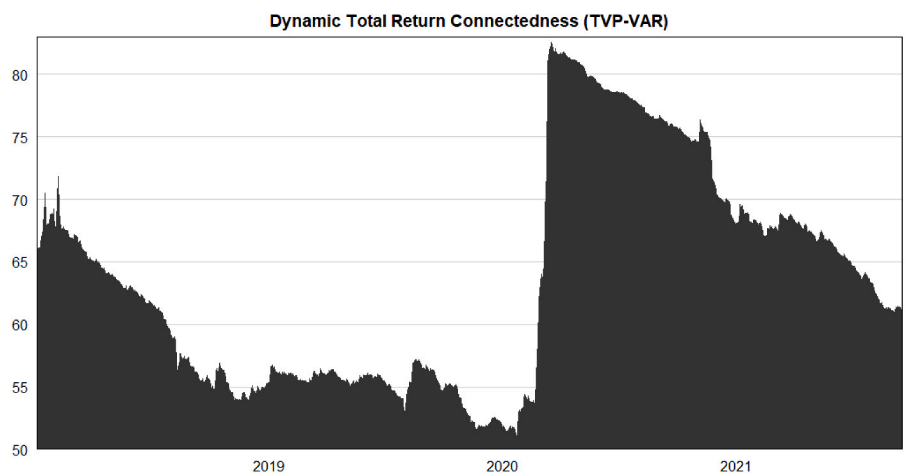

Fig. C.1. Dynamic total return connectedness (TVP-VAR).

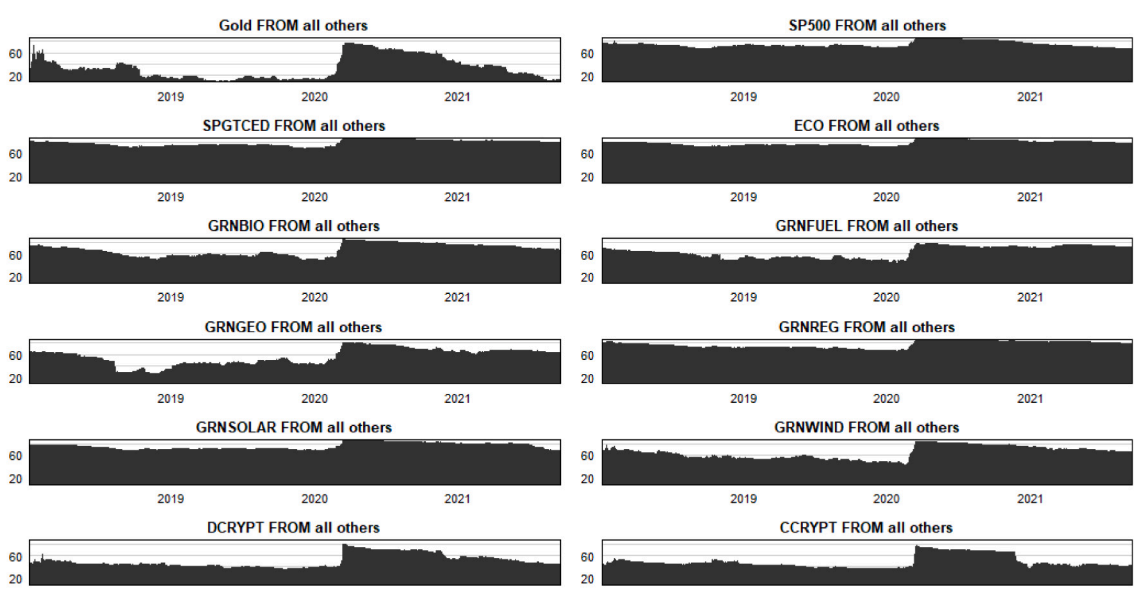

Fig. C.2. Dynamic directional return connectedness FROM others (TVP-VAR).

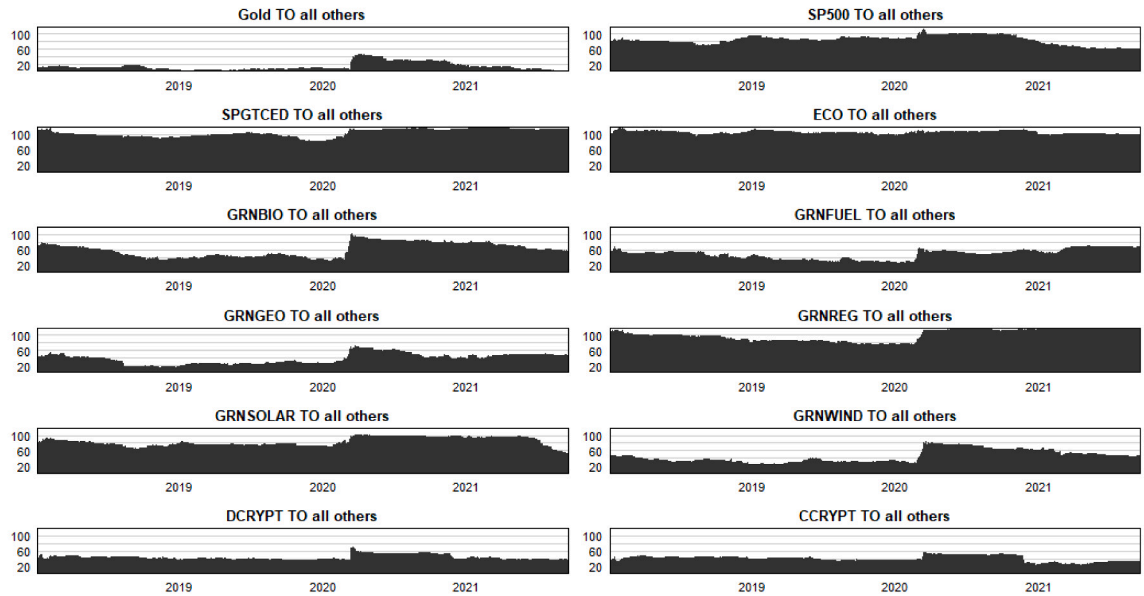

Fig. C.3. Dynamic directional return connectedness TO others (TVP-VAR).

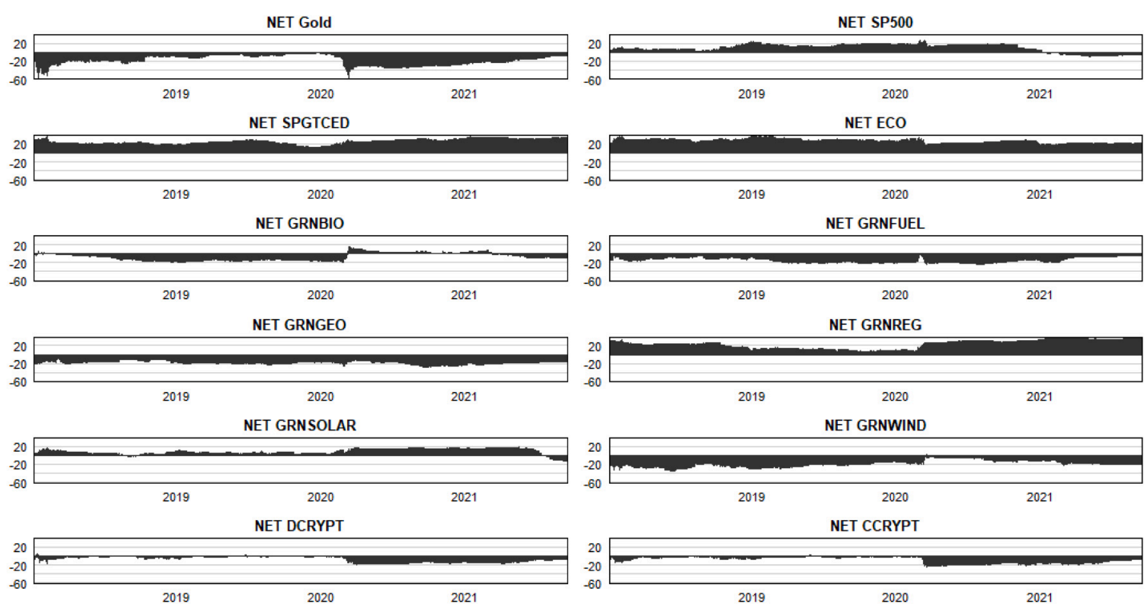

Fig. C.4. Total net return connectedness (TVP-VAR).

investments and portfolio constructions. As we see more investors, especially from institutions, are pouring their money into the crypto market, investing in clean energy stocks seems to be a valuable decision. While cryptocurrencies have a significant negative ecological impact this can be perhaps mitigated by investors in these assets also choosing clean energy assets, which supports companies undergoing sustainable actions as well as the market growth, while also receiving the safe haven benefits for encountering cryptocurrency extreme risks in return. In other words, portfolio stability and ecological protection are not necessarily incompatible.

Finally, we adopt a widely used spillover measure by Diebold and Yilmaz (2012) to calculate the spillover indices across selected markets. Overall, we find that the return and volatility connectedness between clean energy and cryptocurrencies is much lower than that between clean energy and the general equity market or between clean energy subsectors, which suggests that clean energy markets are more associated with the general market, while cryptocurrencies are more isolated and act as a separate asset class. To some extent, our results support the findings of Ji et al. (2018) which claim isolation of Bitcoin market. Clearly, investors in the financial market have not to date really connected clean energy and either types of cryptocurrencies together, and they appear to hold cryptocurrencies based on the intrinsic or expected value of cryptocurrencies and not based on their fundamental differences in transaction mechanisms or energy acquisition channels, which offers the potentials of using clean energy as a hedge for cryptocurrencies in the future. However, investors should be also aware that

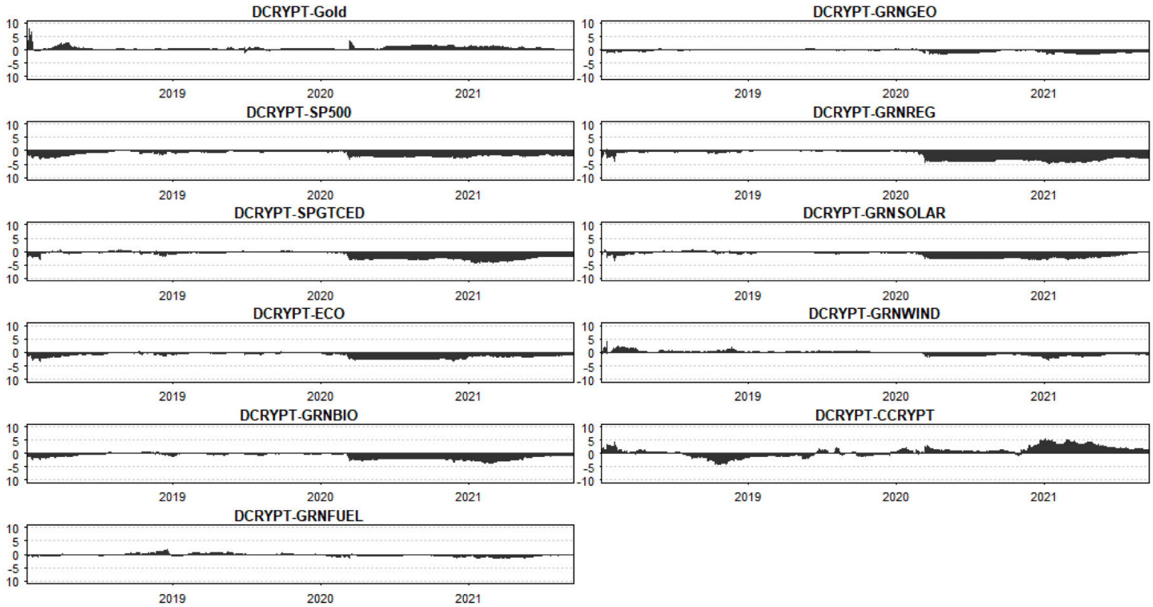

Fig. C.5. Net pairwise directional return connectedness for DCRYPT (TVP-VAR).

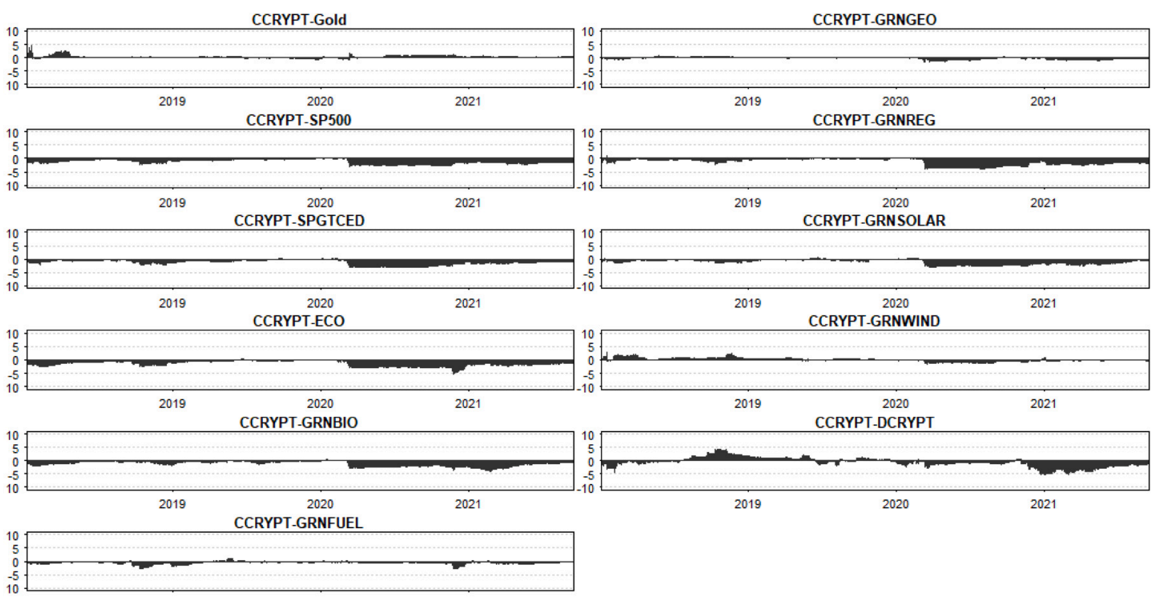

Fig. C.6. Net pairwise directional return connectedness for CCRYPT (TVP-VAR).

clean energy stocks do not homogeneously react to the movements of other markets such as cryptocurrencies in our case, while Pham (2019) discovers similar evidence in the clean energy-crude oil relationship. This suggests that investors need to consider the own characteristics of different clean energy indices/stocks and cryptocurrencies and manage their portfolio at a disaggregate level. Policy makers need to aware that single policy would not affect all clean energy markets to the same extent, instead they need to carefully research the distinctive characteristics of each sub-market before the implementation. The current weak connectedness between cryptocurrency markets and other markets also provides opportunities for further integration of these markets.

Ethereum, the second largest cryptocurrency in the market, has just announced again in the second half of 2021 its upgrade plan to Ethereum 2.0 in the near future which will abandon its current power-hungry PoW consensus and move forward with energy-efficient PoS instead. We would like to see more dirty cryptocurrencies follow the steps of Ethereum. Apparently, current policy of promoting sustainability is not appealing enough for cryptocurrency founders as investors seem to be indifferent to investing in dirty and clean cryptocurrencies, or somewhat slightly in favour of dirty cryptos. We see that clean cryptocurrencies have been conveying volatility shocks to dirty cryptos since 2021, but dirty cryptos are still dominating the crypto market being the return transmitters. Policy makers should create incentives for

Table C.1
Average dynamic total return connectedness using TVP-VAR.

	GOLD	SP500	SPGTCED	ECO	GRNBIO	GRNFUEL	GRNGEO	GRNREG	GRNSOLAR	GRNWIND	DCRYPT	CCRYPT	FROM OTHERS
Gold	67.33	2.79	4.27	3.32	3.72	1.46	1.88	4.96	3	3.57	2.39	1.31	32.67
SP500	1.16	25.69	10.17	13.18	8.64	5.09	5.14	11.64	12.67	3.74	1.56	1.32	74.31
SPGTCED	1.28	9.07	21.99	15.23	7.3	6.92	4.79	13.17	10.59	7.44	1.19	1.03	78.01
ECO	0.91	11.46	14.78	21.98	8.23	9.36	4.59	9.81	13.5	3.33	0.96	1.08	78.02
GRNBIO	1.71	10.75	10.51	12.2	33.34	5	3.77	7.89	9.01	3.12	1.46	1.24	66.66
GRNFUEL	0.7	7.24	10.92	15.35	5.59	36.99	2.75	7.26	7.53	3.4	1.12	1.17	63.01
GRNGEO	1.29	8.06	9.2	8.62	5.05	3.27	44.21	8.55	5.89	3.32	1.48	1.06	55.79
GRNREG	1.75	10.43	13.72	10.38	5.74	4.86	4.64	22.92	11.64	11.35	1.43	1.13	77.08
GRNSOLAR	1.09	12.47	11.95	15.31	7.01	5.23	3.82	12.7	24.87	3.31	1.14	1.08	75.13
GRNWIND	1.76	5.91	13.05	6.51	3.8	4.22	3.14	18.28	4.98	36.3	1.17	0.87	63.7
DCRYPT	1.74	2.76	2.49	2.02	2.45	1.42	1.88	3.03	2.23	1.36	50.21	28.43	49.79
CCRYPT	1	2.54	2.23	2.51	2.44	1.74	1.28	2.41	2.13	0.81	29.06	51.86	48.14
TO others	14.39	83.49	103.31	104.62	59.96	48.56	37.68	99.71	83.17	44.75	42.95	39.73	762.32
Inc. own	81.73	109.18	125.29	126.61	93.3	85.55	81.89	122.62	108.03	81.05	93.16	91.59	TOTAL
NET	−18.27	9.18	25.29	26.61	−6.7	−14.45	−18.11	22.62	8.03	−18.95	−6.84	−8.41	63.53

Table D.1
Average dynamic total volatility connectedness using TVP-VAR.

	GOLD	SP500	SPGTCED	ECO	GRNBIO	GRNFUEL	GRNGEO	GRNREG	GRNSOLAR	GRNWIND	DCRYPT	CCRYPT	FROM OTHERS
GOLD	35.43	4.21	9.7	10.1	6.18	5.5	2.95	9.13	6.86	6.05	1.92	1.96	64.57
SP500	3.49	25.84	10.81	9.49	11.11	4.57	3.14	13.17	9.48	5.7	2.35	0.87	74.16
SPGTCED	4.78	7.54	18.39	14.03	10.05	7.37	4.82	12.94	10.39	6.87	1.66	1.14	81.61
ECO	4.95	7.97	14.75	17.72	10.6	7.95	4.27	11.47	10.73	6.45	1.74	1.39	82.28
GRNBIO	4.38	10.38	11.74	10.95	21.48	4.53	5.08	12.2	8.78	6.08	2.75	1.66	78.52
GRNFUEL	3.96	4.32	12.98	12.32	6.51	33.73	4.72	8.5	5.33	6.1	0.7	0.84	66.27
GRNGEO	4.23	6.53	11.26	9.87	8.33	4.49	30.87	8.78	6.81	5.86	1.48	1.48	69.13
GRNREG	4.36	9.11	13.96	11.06	9.38	6.72	3.97	18.27	10.01	8.74	2.86	1.56	81.73
GRNSOLAR	4.41	9.38	13.03	12.99	9.72	5.13	3.45	13.23	18.36	6.11	2.64	1.55	81.64
GRNWIND	4.05	4.63	12.9	10.56	7.09	6.75	4.62	15.25	7.63	21.05	3.18	2.29	78.95
DCRYPT	2.51	3.65	3.74	3.56	4.73	1.47	1.07	6.77	4.05	5.2	45.79	17.46	54.21
CCRYPT	1.36	1.66	3.21	3.82	3.04	2.47	1.4	4.6	2.48	2.76	17.92	55.27	44.73
TO OTHERS	42.48	69.4	118.08	108.74	86.74	56.95	39.48	116.05	82.54	65.91	39.22	32.2	857.79
Inc. OWN	77.91	95.24	136.47	126.46	108.22	90.68	70.35	134.32	100.91	86.96	85	87.47	TOTAL
NET	−22.09	−4.76	36.47	26.46	8.22	−9.32	−29.65	34.32	0.91	−13.04	−15	−12.53	71.48

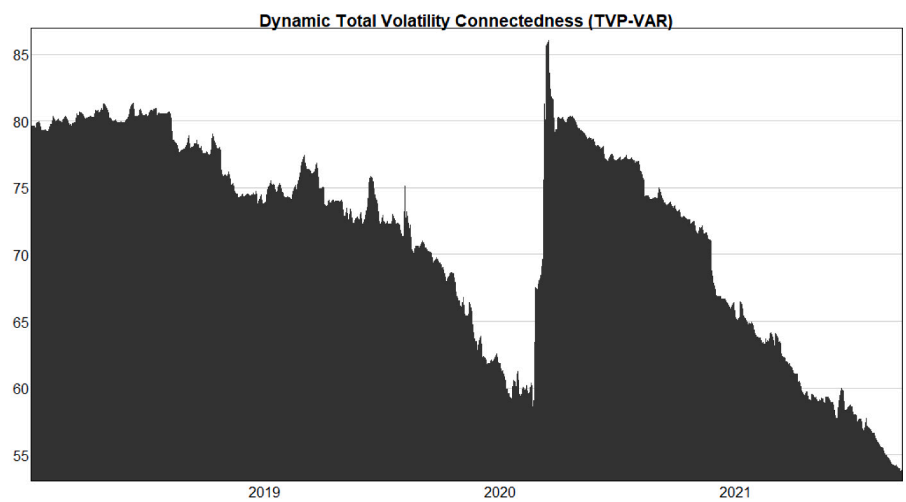

Fig. D.1. Dynamic total volatility connectedness (TVP-VAR).

the transition of dirty cryptocurrencies from PoW consensus mechanism to energy-efficient non PoW consensus, and for the investors, especially the institutional investors, to invest more in cleaner cryptocurrencies rather than the dirty ones. The development of green energy and green cryptocurrencies has brought significant environmental benefits compared to fossil energy and dirty cryptocurrencies. Restrictions and legal constraints of energy use in crypto-mining are still weak. Greater efforts should be made by the society to promote greener industry and investment, and arouse the environmental awareness of investors and founders/companies of dirty cryptocurrencies.

CRediT authorship contribution statement

Boru Ren: Data curation, Methodology, Software, Formal analysis, Visualization, Writing – original draft, Writing – review & editing. **Brian Lucey:** Conceptualization, Methodology, Writing – review & editing, Project administration, Supervision.

Acknowledgements

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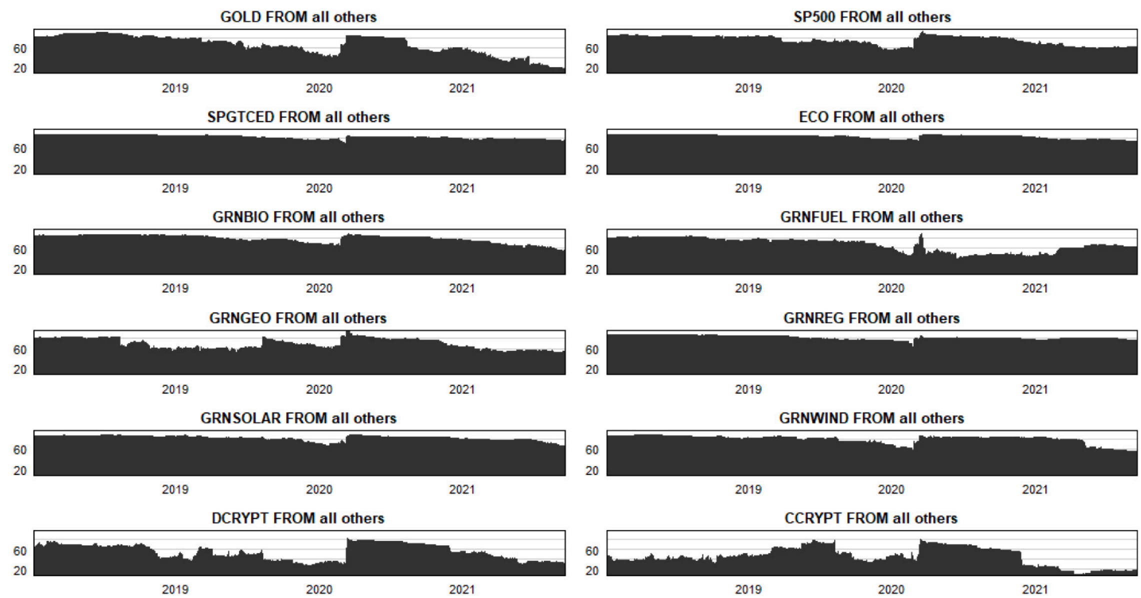

Fig. D.2. Dynamic directional volatility connectedness FROM others (TVP-VAR).

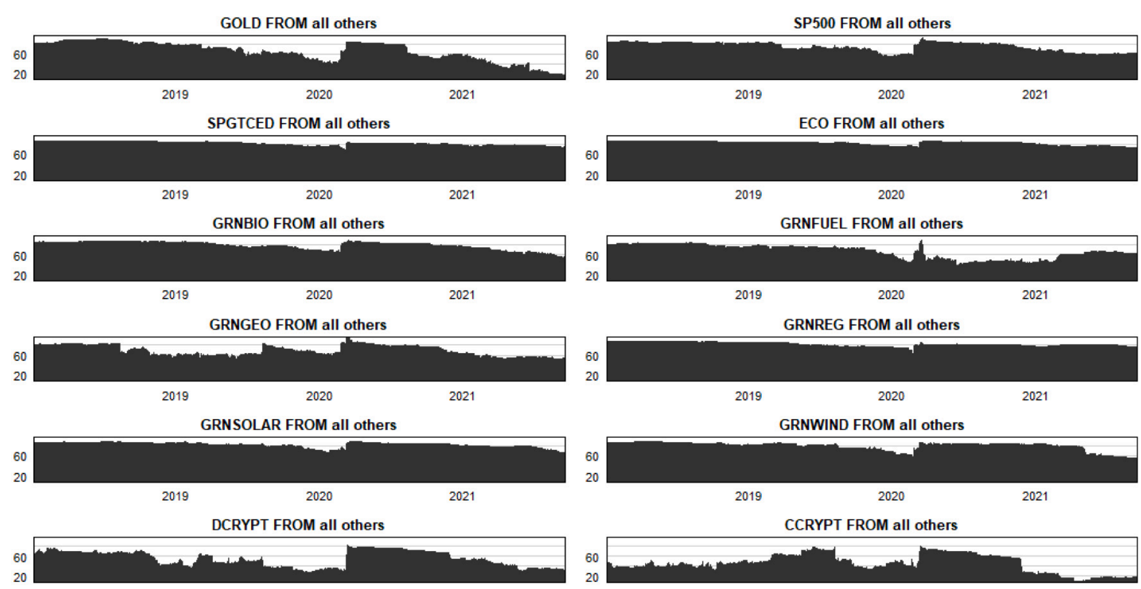

Fig. D.3. Dynamic directional volatility connectedness TO others (TVP-VAR).

Appendix A. DCCs between clean energy indices and cryptocurrencies over time

See Figs. A.1–A.8.

Appendix B. Estimation results of GARCH(1,1) model in volatility spillover analysis

See Table B.1.

Appendix C. Return spillovers analysis using TVP-VAR

See Table C.1 and Figs. C.1–C.6.

Appendix D. Volatility spillovers analysis using TVP-VAR

See Table D.1 and Figs. D.1–D.6.

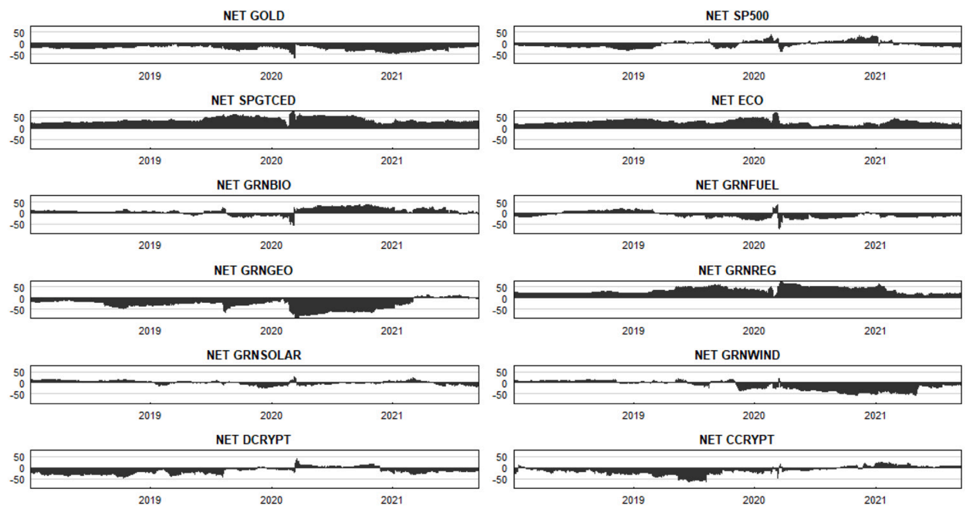

Fig. D.4. Total net volatility connectedness (TVP-VAR).

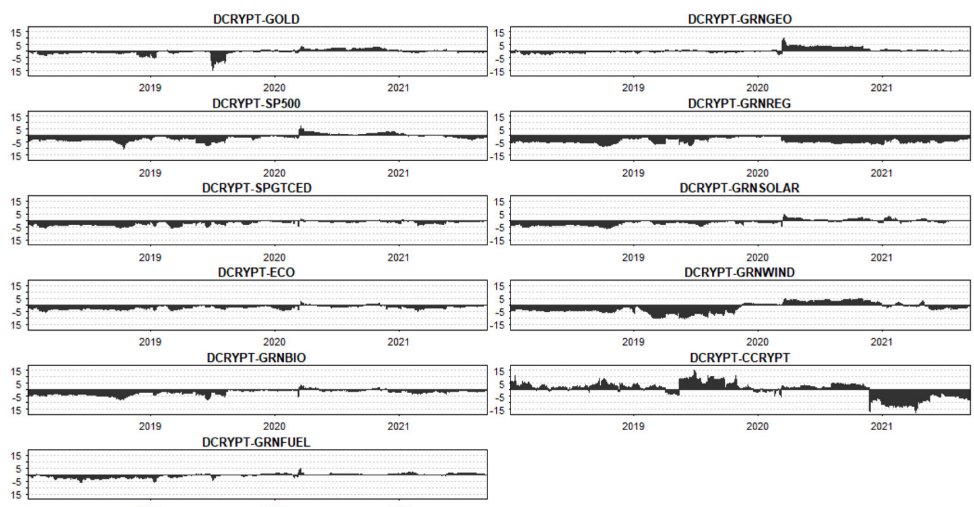

Fig. D.5. Net pairwise directional volatility connectedness for DCRYPT (TVP-VAR).

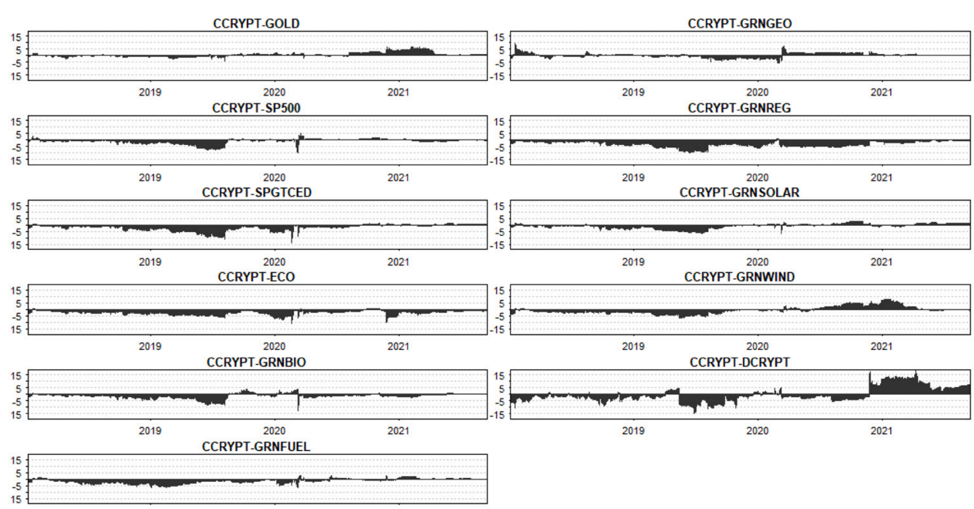

Fig. D.6. Net pairwise directional volatility connectedness for CCRYPT (TVP-VAR).

Appendix E. Supplementary data

Supplementary material related to this article can be found online at https://doi.org/10.1016/j.eneco.2022.105951.

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