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 black or 'dirty' and green or '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.

Keywords: Cryptocurrencies; Clean energy; Safe haven; Spillovers; Connectedness; DCC-GARCH
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1. Introduction

Conventional cryptocurrencies that require massive energy use (hereinafter referred to as "black" or "dirty" cryptocurrencies) have been developing rapidly and become sought-after assets. This energy footprint 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 'Proof of Work' 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 'Proof of Work' cryptocurrencies (Schinckus [2021]). To address these environmental issues and meet the expectation of greener industry, increasing number of eco-friendly cryptocurrencies (hereinafter: "green" or "clean" cryptocurrencies) are being launched to compete in the market, and some of them have already become leading cryptocurrencies by market capitalisation, such as Cardano and Ripple.

At the same time we have also seen a strong growth track in clean energy. 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 publically 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] , 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 transactions. Jiang et al. [2022] analysed the role of Bitcoin, gold, equity, foreign exchange and energy (crude oil / natural gas) played in the global volatility connectedness network. They argued that the overall volatility transmission in the financial system is possibly driven by external investor attention between different markets. Moreover, they found that Bitcoin, gold, foreign exchange and natural gas were volatility transmitters, while crude oil and the stock market were receivers. Ji et al. [2019] tested the information interdependence between leading cryptocurrencies and several commodities and they pointed out that the cryptocurrencies was unexpectedly weakly connected, but still integrated to energy markets such as natural gas, unleaded gas, heating

[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`

oil, and crude oil using both static and dynamic entropy-based spillover measures. Zeng et al. [2020] showed that the financial linkage between Bitcoin and traditional assets such as stock, oil, and gold was weak, but was increasing. Rehman and Kang [2021] documented the existence of lead-lag relationships between Bitcoin and crude oil and natural gas, while it was 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 investigated the dynamic correlation and extreme dependence between Bitcoin and Chinese coal markets. They showed that dynamic correlations between Bitcoin and coal indices increased when extreme mining events occurred in China and such incidents were likely to induce Bitcoin volatilities. Okorie [2021] and Corbet et al. [2021] discovered significant correlation and volatility spillovers between leading cryptocurrencies and electricity markets. Okorie and Lin [2020] found both bi-directional and uni-directional volatility spillovers between the crude oil market and cryptocurrencies. They further claimed that crude oil was a good hedge tool for risks of holding various cryptocurrencies. While Umar et al. [2021] showed that cryptocurrency market was less connected with global technology sectors. Le et al. [2021] further investigated whether the spillover patterns between financial technology stocks and Bitcoin, gold, global stock, crude oil, and foreign exchange were 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 remained as safe havens, while other assets such as Bitcoin, oil, financial technology stocks being large volatility spillover receivers were not. Maghyereh and Abdoh [2020], Bouri et al. [2018], and Uzonwanne [2021] examined the direction of spillovers between Bitcoin and other markets. Wang et al. [2021] measured 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. [2021] considered green bonds time and frequency domain connectedness between cryptocurrencies and a variety of assets, but their focal point was on financial technology and not clean energy stocks. If we find that particular types of cryptocurrency can act as safe havens or hedges against clean energy, or vice versa, it has implications for investors. For example, it may be practical to protect against drawdowns in clean energy stocks using cryptocurrencies. But the form of currency matters. If we find that only dirty cryptocurrencies are a useful hedge or haven against clean energy that suggests that the economic incentive to invest in clean energy will be counter to the ecological argument.

There are few papers which could be regarded as closely related to our research. For instance, Symitsi and Chalvatzis [2018] examined the spillovers among, Bitcoin, fossil and clean energy, and technology indices. There were significant return spillovers from energy and technology markets to Bitcoin, while volatility spillovers were 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] showed that there was no significant linkage between the volatility of Bitcoin price and largest green ETFs markets, Naeem and Karim [2021] further used a time-varying optimal copula approach to examine the tail dependence between Bitcoin and green investments. They found no tail dependence between clean energy and Bitcoin, but they suggested that clean energy was a potential diversification tool for Bitcoin as the hedge ratio and hedge effectiveness were with clean energy in the portfolio. A similar comment was provided by Pham et al. [2021] who proposed that green investments could offer diversification benefits to cryptocurrency since only weak connectedness between cryptocurrencies such as Bitcoin and Ethereum and green assets was 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. 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 tested 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], termed black and green, and also the spillovers across these, along with general stock and gold markets. The dirty cryptocurrencies are all built on Proof-of-Work 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, Ripple Protocol, Stellar Protocol, and some other alternatives.

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 black or green 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 and clean cryptocurrency market turmoils and its reverse. We found that, in general, clean energy serve as at least a weak safe haven 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 measured 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.

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

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

Fourth, our findings also provide references and implications for regulators and policy makers as well as cryptocurrency founders in the context of promoting greener 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 green 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] 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 subsectors, following the literature of Pham [2019]. 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). 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.[7] Note that all data are sourced in U.S. dollars and transformed to their first-differenced natural logarithms before use.[8] Table 1 summaries the statistics for the log returns in percentage.

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

[6]Our selection took into account both market capitalisation and data availability during the period.

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

[8]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: Descriptive statistics of returns (%)

	Mean	Min	Max	Std.Dev	Skewness	Kurtosis
SPGTCED	0.088	-12.498	11.035	1.697	-0.895	10.976
ECO	0.115	-16.239	13.399	2.417	-0.659	6.758
GRNBIO	0.049	-18.193	13.394	2.277	-1.379	13.014
GRNFUEL	0.177	-18.028	21.617	3.839	0.179	3.712
GRNREG	0.068	-15.256	8.930	1.319	-1.639	25.592
GRNGEO	0.015	-13.390	18.255	2.185	0.692	11.356
GRNSOLAR	0.105	-19.334	12.049	2.551	-0.703	6.558
GRNWIND	0.068	-10.982	7.720	1.581	-0.283	4.716
BTC	0.128	-46.473	20.305	4.761	-1.155	11.418
ETH	0.146	-55.071	35.365	6.273	-0.792	8.789
ETC	0.053	-50.779	35.865	7.114	-0.441	7.241
BCH	-0.146	-56.140	42.082	7.466	-0.348	8.891
LTC	-0.026	-44.901	29.062	6.238	-0.667	7.090
ADA	0.111	-50.364	32.180	7.251	0.001	4.179
XRP	-0.079	-55.040	62.668	7.426	0.236	12.521
XLM	-0.046	-41.004	55.932	7.303	0.667	8.968
MIOTA	-0.088	-54.333	33.224	7.495	-0.528	6.713
NANO	-0.182	-61.455	54.654	9.135	0.029	8.074
DCRYPT	0.136	-47.692	19.470	4.917	-1.270	11.150
CCRYPT	0.028	-41.826	55.388	6.780	0.036	9.225
SP500	0.053	-12.765	8.968	1.361	-1.117	18.298
GOLD	0.031	-5.265	5.133	0.913	-0.453	5.478

3. Methodology

3.1. Safe haven analysis

We adopted 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] and Ratner and Chiu [2013], we started by using a dynamic conditional correlation Generalized Autoregressive Conditional Heteroskedasticity (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 estimated the DCC parameter. Let H_t be the conditional covariance matrix of r_t. We had assumed r_t to be normally distributed with a zero mean and we wrote 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 could get the estimated DCC model as:

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

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 could 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 could 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 were regressed on dummy variables representing the extreme movements of assets as follows:

$$DCC_{ij,t} = c_0 + c_1 D(r_{crypto} q_{10}) + c_2 D(r_{crypto} q5) + c_3 D(r_{crypto} q1), \tag{5}$$

where $D(...)$ 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 the Equation 5 is to regress DCC_t on the lagged extreme conditional volatility of dirty or green cryptocurrency index which is proxied for market uncertainty, motivated by Baur and McDermott [2010]:

$$DCC_{ij,t} = c_0 + c_1 D(v_{crypto} q_{90,t-1}) + c_2 D(r_{crypto} q95, t-1) + c_3 D(r_{crypto} q99, t-1), \tag{6}$$

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 replaced with clean energy data on the right hand side for Equation 5 and 6, respectively.

3.2. Spillover measures

We used the Diebold and Yilmaz [2012] (DY_{2012}) connectedness approach to estimate the spillover effects between clean energy indices and cryptocurrency indices. The DY_{2012} 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 began 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 wrote the moving average representation of the model defined in Equation 7 as:

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

where the coefficient of the $N \times N$ matrix A_i is recursively determined as $A_i = \varphi_1 A_{i-1} + \varphi_2 A_{i-2} + \ldots + \varphi_{k-1} A_{i-k+1} + \varphi_k A_{i-k}$, 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 generalized forecast error variance was first decomposed and then normalised by its row sum as the following:

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

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 i^{th} 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 ($DS_{i\rightarrow j}$), and net spillover (NS) indices could be calculated as the following:

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

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

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

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

4. Results

4.1. Safe haven analysis

4.1.1. Dynamic conditional correlations

Table 2 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 Appendix A.1 to Appendix 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 were lower, but more stable than the other pairs. Complemented by Table 2, we found that the correlations between clean energy indices and cryptocurrencies were 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 reacted heterogeneously to cryptocurrencies and there is no differentiated patterns between clean energy stocks and the two cryptocurrency groups.

Table 2: DCCs between clean energy indices and cryptocurrencies

	SPGTCED	ECO	GRNBIO	GRNFUEL	GRNREG	GRNGEO	GRNSOLAR	GRNWIND
BTC	0.1584	0.1188	0.1375	0.0990	0.1479	0.0855	0.1084	0.1161
ETC	0.1313	0.1080	0.0848	0.0709	0.1252	0.0714	0.0957	0.0864
BCH	0.1346	0.1024	0.0921	0.0795	0.1252	0.0764	0.0787	0.0869
LTC	0.1483	0.1327	0.1218	0.0983	0.1554	0.0634	0.1120	0.1168
ETH	0.1509	0.1310	0.1236	0.1102	0.1414	0.0657	0.1006	0.1211
ADA	0.1616	0.1397	0.1354	0.1064	0.1571	0.1107	0.1326	0.0786
XRP	0.1354	0.1520	0.1200	0.1333	0.1271	0.0582	0.1036	0.0688
XLM	0.1757	0.1622	0.1601	0.1109	0.1711	0.0976	0.1391	0.0955
MIOTA	0.1551	0.1438	0.1459	0.1095	0.1549	0.1206	0.1398	0.0901
NANO	0.1594	0.1626	0.1000	0.1154	0.1521	0.0697	0.1336	0.0974

4.1.2. Return analysis

Table 3 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 3 are significantly positive, which confirms that none of the clean energy indices could 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 could 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 could also be a weak safe haven for cryptocurrency in 5% and 1% quantiles, but it depended very much on which clean energy and cryptocurrency were used.

Reversing the relationship in Table 4, 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 cryptocurrecies were weak havens for GRNGEO at 10% except for BTC which was a strong safe haven, and XRP, MIOTA, and NANO which were not safe havens for GRNGEO in the 10% quantile at all. For θ_2 and θ_3, we can only see few of cryptocurrencies were safe havens for clean energy stocks. Clearly, the results are even more spotty than the reverse, and we can not clearly say that cryptocurrencies are safe havens for clean energy stocks in general and we cannot distinguish the difference between types.

Overall, we find that clean energy can be generally viewed as a safe haven for the returns of either black or green 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. Cryptocurrencies are not evident as safe havens for clean energy. 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

Table 3: 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	0.1586***	*-0.0053*	0.0085	*-0.0101*
ETC	0.1312***	*-0.0034*	0.0062	0.0144
BCH	0.1347***	*-0.0030*	0.0043	0.0012
LTC	0.1480***	*-0.0030*	0.0051	0.0041
ETH	0.1511***	*-0.0097*	0.0116	0.0133
ADA	0.1621***	*-0.0027*	*-0.0075*	0.0108
XRP	0.1372***	*-0.0155*	*-0.0051*	*-0.0051*
XLM	0.1758***	0.0001	*-0.0031*	0.0005
MIOTA	0.1556***	***-0.0156******	0.0189**	0.0213
NANO	0.1597***	***-0.0133******	0.0158**	0.0190
Panel B: ECO				
BTC	0.1195***	*-0.0162*	0.0210	*-0.0210*
ETC	0.1077***	*-0.0016*	0.0041	0.0196
BCH	0.1031***	*-0.0002*	*-0.0135*	0.0028
LTC	0.1330***	0.0010	*-0.0064*	*-0.0057*
ETH	0.1317***	*-0.0049*	*-0.0072*	0.0097
ADA	0.1406***	*-0.0022*	*-0.0156*	0.0121
XRP	0.1528***	*-0.0154*	0.0093	0.0224
XLM	0.1627***	*-0.0049*	*-0.0006*	0.0076
MIOTA	0.1451***	*-0.0197*	0.0143	*-0.0051*
NANO	0.1636***	***-0.01445*****	0.0082	0.0082
Panel C: GRNBIO				
BTC	0.1376***	*-0.0103*	0.0209	*-0.0125*
ETC	0.0859***	*-0.0179*	0.0127	0.0042
BCH	0.0936***	*-0.0155*	*-0.0047*	0.0362
LTC	0.1215***	0.0011	0.0014	0.0105
ETH	0.1241***	*-0.0120*	0.0062	0.0390
ADA	0.1355***	*-0.0019*	*-0.0048*	0.0328
XRP	0.1210***	*-0.0215*	0.0134	0.0415
XLM	0.1598***	*-0.0119*	0.0362	*-0.0354*
MIOTA	0.1475***	***-0.0409*******	0.0493**	0.0015
NANO	0.1010***	***-0.0268******	0.0290*	0.0233
Panel D: GRNFUEL				

Table 3 continued from previous page

BTC	0.0993***	*-0.0088*	0.0058	0.0294
ETC	0.0726***	***-0.0245*** ***	0.0211	*-0.0381*
BCH	0.0794***	*-0.0033*	0.0083	0.0076
LTC	0.0976***	0.0025	0.0110	*-0.0090*
ETH	0.1104***	*-0.0027*	*-0.0008*	0.0107
ADA	0.1073***	*-0.0038*	*-0.0121*	0.0126
XRP	0.1336***	*-0.0055*	0.0111	*-0.0249*
XLM	0.1118***	*-0.0049*	*-0.0096*	0.0104
MIOTA	0.1098***	***-0.0223*** ***	0.0388***	0.0011
NANO	0.11545***	*-0.0017*	0.0022	*-0.0003*
Panel E: GRNREG				
BTC	0.1488***	*-0.0210*	0.0248	*-0.0025*
ETC	0.1258***	*-0.0119*	0.0045	0.0373
BCH	0.1273***	*-0.0267*	0.0074	0.0208
LTC	0.1562***	*-0.0062*	*-0.0030*	*-0.0020*
ETH	0.1434***	***-0.0323****	0.0137	0.0580
ADA	0.1586***	*-0.0097*	*-0.0119*	0.0140
MIOTA	0.1562***	***-0.0300*** ***	0.0321*	0.0088
XRP	0.1297***	***-0.0243****	*-0.0032*	*-0.0010*
XLM	0.1717***	*-0.0066*	*-0.0041*	0.0182
NANO	0.1537***	***-0.0287*****	0.0182	0.0302
Panel F: GRNGEO				
BTC	0.0856***	*-0.0040*	0.0041	0.0097
ETC	0.0714***	*-0.0000*	0.0000	0.0000
BCH	0.0764***	*-0.0017*	*-0.0005*	0.0169***
LTC	0.0632***	*-0.0010*	0.0060	0.0049
ETH	0.0658***	*-0.0058*	*-0.0011*	0.0488***
ADA	0.1104***	0.0016	0.0022	0.0030
XRP	0.0582***	*-0.0013*	0.0014	0.0090
XLM	0.0972***	0.0057	*-0.0025*	*-0.0013*
MIOTA	0.1205***	*-0.0023*	0.0054**	0.0049
NANO	0.0700***	***-0.0118*****	0.0142***	0.0155*
Panel G: GRNSOLAR				
BTC	0.1091***	*-0.0113*	0.0119	*-0.0174*
ETC	0.0982***	***-0.0318*****	0.0143	*-0.0052*
BCH	0.0806***	*-0.0149*	*-0.0142*	0.0337

Table 3 continued from previous page

LTC	0.1125***	*-0.0008*	*-0.0041*	*-0.0124*
ETH	0.1016***	*-0.0102*	*-0.0031*	0.0221
ADA	0.1329***	0.0027	*-0.0132*	0.0116
XRP	0.1056***	***-0.0309****	0.0154	0.0332
XLM	0.1391***	*-0.0065*	0.0117	0.0042
MIOTA	0.1412***	***-0.0258******	0.0241*	0.0002
NANO	0.1351***	***-0.0226*****	0.0122	0.0129
Panel I: GRNWIND				
BTC	0.1169***	*-0.0139*	0.0085	0.0225
ETC	0.0864***	*-0.0006*	*-0.0089*	0.0498**
BCH	0.0872***	*-0.0043*	0.0022	0.0026
LTC	0.1167***	*-0.0029*	0.0090	*-0.0044*
ETH	0.1214***	***-0.0096*****	0.0068	0.0325***
ADA	0.0796***	*-0.0096*	*-0.0040*	0.0116
XRP	0.0693***	*-0.0062*	0.0051	*-0.0173*
XLM	0.0962***	*-0.0054*	*-0.0065*	0.0162
MIOTA	0.0908***	***-0.0182*****	0.0224**	0.0032
NANO	0.0982***	***-0.0147****	0.0117	0.0066

Notes:

1. Equation 5 was used. Table shows the relationship between each clean energy index (each panel) and various cryptocurrencies;

2. ***, ** and * denote the rejections of the null hypothesis at the significance level of 1%, 5% and 10%, respectively.

Table 4: 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	0.1542***	0.0241**	0.0318***	0.0148
ECO	0.1144***	0.0256*	0.0170	0.0855**
GRNBIO	0.1329***	0.0004	0.0656***	0.1128***
GRNFUEL	0.0963***	0.0199*	0.0038	0.0494*
GRNGEO	0.0854***	***-0.0101****	0.0215**	0.0078
GRNREG	0.1404***	0.0481***	0.0361	0.0844*

Table 4 continued from previous page

GRNSOLAR	0.1061***	*-0.0152*	0.0598**	0.0775*
GRNWIND	0.1143***	*-0.0028*	0.0313**	0.0472**
Panel B: ETC				
SPGTCED	0.1303***	0.0080	0.0000	0.0182
ECO	0.1083***	***-0.0195****	0.0202*	0.0562***
GRNBIO	0.0801***	0.0094	0.034	0.1905***
GRNFUEL	0.0701***	0.0147	*-0.0093*	-0.0240
GRNGEO	0.0714***	*-0.0000*	0.0000	0.0000
GRNREG	0.1238***	0.0104	*-0.0084*	0.0816***
GRNSOLAR	0.0950***	*-0.0126*	0.0244	0.0650
GRNWIND	0.0855***	0.0044	0.0100	*-0.0040*
Panel C: BCH				
SPGTCED	0.1325***	0.0106*	0.01882**	0.0067
ECO	0.0986***	0.0249**	0.0133	0.0582*
GRNBIO	0.0863***	0.0066	0.0707**	0.1545***
GRNFUEL	0.0764***	0.0284**	0.0011	0.0166
GRNGEO	0.0754***	0.0021	0.0155***	0.0011
GRNREG	0.1189***	0.0431***	0.0206	0.0832**
GRNSOLAR	0.0760***	*-0.0046*	0.0483*	0.0686*
GRNWIND	0.0861***	0.0027	0.0068	0.0138
Panel D: LTC				
SPGTCED	0.14746***	0.0017	0.0076	0.02847***
ECO	0.1311***	0.0076	0.0054	0.0564***
GRNBIO	0.1180***	0.0057	0.0302*	0.1696***
GRNFUEL	0.0977***	0.0081	*-0.0142*	0.0428**
GRNGEO	0.0632***	*-0.0040*	0.0094	0.0125
GRNREG	0.1532***	0.0118	0.0056	0.06754***
GRNSOLAR	0.1112***	*-0.0114*	0.0296**	0.0460**
GRNWIND	0.1160***	*-0.0004*	0.0150**	0.0152
Panel E: ETH				
SPGTCED	0.1484***	0.0089	0.0268**	0.0236
ECO	0.1281***	0.0183	*-0.0005*	0.1023***
GRNBIO	0.1195***	0.0090	0.0384*	0.1210***
GRNFUEL	0.1089***	0.0139*	*-0.0022*	*-0.0067*
GRNGEO	0.0653***	*-0.0076*	0.0220***	0.0024
GRNREG	0.1353***	0.0344*	0.02982	0.1129**

GRNSOLAR	0.09845***	*-0.0063*	0.0372*	0.0878**
GRNWIND	0.1203***	*-0.0007*	0.0117**	0.0281***
Panel F: ADA				
SPGTCED	0.1605***	*-0.0020*	0.0173**	0.0354**
ECO	0.1378***	0.0117	*-0.0020*	0.0831***
GRNBIO	0.1320***	0.0063	0.0250	0.1419***
GRNFUEL	0.1056***	0.0147*	*-0.0154*	0.0104
GRNGEO	0.1106***	*-0.0090*	0.0188**	0.0038
GRNREG	0.1546***	0.0074	0.0199	0.07302***
GRNSOLAR	0.1315***	*-0.0059*	0.0194*	0.0621***
GRNWIND	0.0767***	0.0007	0.0244*	0.0524**
Panel G: MIOTA				
SPGTCED	0.1531***	0.008612	0.0201**	0.013279
ECO	0.1402***	0.0266**	0.0046	0.0678**
GRNBIO	0.1412***	0.0034	0.0583***	0.1349***
GRNFUEL	0.1068***	0.0244**	0.0004	0.0194
GRNGEO	0.1200***	0.0017	0.0099***	*-0.0002*
GRNREG	0.1504***	0.0316**	0.0153	0.0601*
GRNSOLAR	0.1389***	*-0.0091*	0.0264*	0.0435*
GRNWIND	0.0882***	0.0040	0.02050*	0.0495***
Panel H: XRP				
SPGTCED	0.1331***	*-0.0090*	0.0518***	0.0541*
ECO	0.1465***	0.0316*	0.021052	0.1191***
GRNBIO	0.1157***	0.0109***	0.0340*	0.1360***
GRNFUEL	0.1311***	0.0291*	*-0.0261*	0.0657*
GRNGEO	0.0577***	0.0013	0.0078	0.0020***
GRNREG	0.1237***	0.0103	0.0269	0.0929***
GRNSOLAR	0.1007***	*-0.0086*	0.0539**	0.0951**
GRNWIND	0.0677***	0.0003	0.0153**	0.0218*
Panel I: XLM				
SPGTCED	0.1740***	0.0023	0.0227***	0.0213**
ECO	0.1580***	*0.0157*	0.0391**	0.0656**
GRNBIO	0.1552***	*0.0123*	0.0369*	0.0172***
GRNFUEL	0.1081***	0.0282***	*-0.0008*	0.0053
GRNGEO	0.0976***	*-0.0045*	0.0075	0.0066
GRNREG	0.1659***	0.0300**	*0.0261*	0.0762***

Table 4 continued from previous page

GRNSOLAR	0.1365***	*-0.0074*	0.0522***	0.0640**
GRNWIND	0.0939***	0.0072	0.0104	0.0273**
Panel J: NANO				
SPGTCED	0.1581***	0.0059	0.0078	0.0289**
ECO	0.1597***	0.0153*	0.0170	0.0458**
GRNBIO	0.0972***	0.0037	0.0187	0.1401***
GRNFUEL	0.1150***	0.0040***	0.0005	*-0.0023*
GRNGEO	0.0694***	0.0002	0.0056	0.0009
GRNREG	0.1474***	0.0147	0.0433***	0.0947***
GRNSOLAR	0.1318***	*-0.0070*	0.0366***	0.0570**
GRNWIND	0.0960***	*-0.0017*	0.0290***	0.0064

Notes:

1. Modified Equation 5 was used. Table shows the relationship between each cryptocurrency index (each panel) and various clean energy indices;

2. ***, ** and * denote the rejections of the null hypothesis at the significance level of 1%, 5% and 10%, respectively.

4.1.3. Uncertainty analysis

Table 5 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 5 are significantly positive, which confirms that clean energy indices can not 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 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 green 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 green cryptocurrencies on the 99% threshold.

Table 6 presents the results of the hedge and safe haven property of dirty and clean cryptocurrencies in periods of increased clean energy market uncertainty. We found that none of the cryptocurrencies was a safe haven on the 90% threshold. Interestingly, we noticed that some of the cryptocurrencies were strong safe havens for GRNFUEL on the 95% threshold of volatility, including ETC, BCH, ETH, ADA, XLM. ETC was also a weak haven for ECO and GRNWIND. LTC was a a weak safe haven for GRNGEO and NANO was for GRNWIND on the 99% threshold. BTC, MIOTA, and XRP were 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.

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.

Table 5: 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**

Table 5 continued from previous page

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***

Table 5 continued from previous page

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******
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. Equation 6 was used;

2. ***, ** and * denote the rejections of the null hypothesis at the significance level of 1%, 5% and 10%, respectively.

Table 6: 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	0.1484***	0.0971***	0.0006	0.0152
ECO	0.1034***	0.1329***	0.0239	0.0748**
GRNBIO	0.1179***	0.1574***	0.0629***	0.0489
GRNFUEL	0.0901***	0.0663***	0.0184	0.1254***
GRNGEO	0.0824***	0.0229***	0.0123	0.0239*
GRNREG	0.1276***	0.1709***	0.0351	0.1315***
GRNSOLAR	0.0930***	0.0902***	0.1067***	0.0832*
GRNWIND	0.1098***	0.0278***	0.0590***	0.0511**
Panel B: ETC				
SPGTCED	0.1294***	0.0106**	0.0112	0.0256**
ECO	0.1045***	0.0300***	0.0100	*-0.0116*
GRNBIO	0.0649***	0.1390***	0.0908***	0.1209***
GRNFUEL	0.0665***	0.0520***	***-0.0352****	0.0888***
GRNGEO	0.0714***	0.0000	0.0000***	0.0000***
GRNREG	0.1206***	0.0303***	0.0034	0.1364***
GRNSOLAR	0.0875***	0.0277***	0.0825***	0.1178***
GRNWIND	0.0837***	0.0120	0.0365***	*-0.0313*
Panel C: BCH				
SPGTCED	0.1294***	0.0423***	0.0112	0.0351***
ECO	0.0896***	0.1179***	0.0090	0.0428
GRNBIO	0.0677***	0.2037***	0.0621***	0.0713*
GRNFUEL	0.0722***	0.0845***	***-0.0409****	0.0855***
GRNGEO	0.0741***	0.0113***	0.0192***	0.0211***
GRNREG	0.1085***	0.1224***	0.0590***	0.12945***
GRNSOLAR	0.0637***	0.1033***	0.0781***	0.0602
GRNWIND	0.0849***	0.0050	0.0282***	0.0024
Panel D: LTC				
SPGTCED	0.1459***	0.0113***	0.0187***	0.0312***
ECO	0.1246***	0.06745***	0.0144	0.0564***
GRNBIO	0.1056***	0.1057***	0.0827***	0.1322***
GRNFUEL	0.0946***	0.0232***	0.0064	0.0996***

Table 6 continued from previous page

GRNGEO	0.0611***	0.0162***	0.0139**	*-0.0014*
GRNREG	0.1471***	0.0474***	0.0418***	0.1378***
GRNSOLAR	0.1044***	0.0268***	0.0816***	0.0802***
GRNWIND	0.1143***	0.0130***	0.0237***	0.0015
Panel E: ETH				
SPGTCED	0.1440***	0.0472***	0.0244**	0.0862***
ECO	0.1185***	0.1023***	0.0241	0.0927***
GRNBIO	0.1058***	0.1408***	0.0557***	0.0746**
GRNFUEL	0.10648***	0.0420***	***-0.0262****	0.0746***
GRNGEO	0.0632***	0.0110*	0.0198**	0.0367***
GRNREG	0.1233***	0.1181***	0.0858***	0.1829***
GRNSOLAR	0.0885***	0.0454***	0.1274***	0.1014***
GRNWIND	0.1184***	0.0157***	0.0103*	0.0662***
Panel F: ADA				
SPGTCED	0.1572***	0.0218***	0.0224***	0.0996***
ECO	0.1310***	0.0649***	0.0246**	0.0902***
GRNBIO	0.1209***	0.0994***	0.0639***	0.1181***
GRNFUEL	0.1041***	0.0284***	***-0.0230****	0.0580***
GRNGEO	0.1081***	0.0061	0.0360***	0.0125
GRNREG	0.1476***	0.0441***	0.0693***	0.1518***
GRNSOLAR	0.1252***	0.0147**	0.0947***	0.0997***
GRNWIND	0.0705***	0.0330***	0.0664***	0.1344***
Panel G: MIOTA				
SPGTCED	0.1499***	0.0349***	0.0183**	0.0741***
ECO	0.1320***	0.1042***	0.0112	0.0680**
GRNBIO	0.1262***	0.1621***	0.0530***	0.0728**
GRNFUEL	0.1034***	0.0443***	0.0091	0.11048***
GRNGEO	0.1194***	0.0064***	0.0102***	0.0095**
GRNREG	0.1423***	0.0813***	0.0586***	0.1382***
GRNSOLAR	0.1318***	0.0395***	0.0663***	0.0610***
GRNWIND	0.0826***	0.0296***	0.0700***	0.0987***
Panel H: XRP				
SPGTCED	0.1256***	0.0709***	0.0198	0.1580***
ECO	0.1363***	0.1293***	0.0287	0.1164***
GRNBIO	0.10245***	0.1356***	0.0581***	0.0858***
GRNFUEL	0.1250***	0.0443***	0.0384*	0.18847***

GRNGEO	0.0568***	0.0069**	0.0127***	0.0141**
GRNREG	0.1147***	0.0672***	0.0749***	0.1734***
GRNSOLAR	0.0894***	0.0647***	0.12545***	0.1266***
GRNWIND	0.0654***	0.0160***	0.0309***	0.0239**
Panel I: XLM				
SPGTCED	0.1702***	0.0420***	0.0150***	0.0437***
ECO	0.1479***	0.1262***	0.0207	0.0520**
GRNBIO	0.1422***	0.1242***	0.0795***	0.1346***
GRNFUEL	0.1049***	0.0720***	***-0.0295***	0.0315
GRNGEO	0.0957***	0.0088**	0.0174***	0.0108
GRNREG	0.1562***	0.1181***	0.0364**	0.1066***
GRNSOLAR	0.1263***	0.0708***	0.0920***	0.0951***
GRNWIND	0.0903***	0.0276***	0.0348***	0.0591***
Panel J: NANO				
SPGTCED	0.1567***	0.0100**	0.0252***	0.0350***
ECO	0.1535***	0.0827***	0.0051	0.0495***
GRNBIO	0.0858***	0.1009***	0.0572***	0.1079***
GRNFUEL	0.1143***	0.0093***	0.0010	0.0081***
GRNGEO	0.0690***	*-0.0039*	0.0187***	0.0130
GRNREG	0.1381***	0.0969***	0.0480***	0.1693***
GRNSOLAR	0.1242***	0.0501***	0.0707***	0.0725***
GRNWIND	0.0940***	0.0139*	0.0450***	*-0.0255*

Notes:

1. Modified Equation 6 was used;

2. ***, ** and * denote the rejections of the null hypothesis at the significance level of 1%, 5% and 10%, respectively.

4.2. Spillover effects

4.2.1. Return spillovers

We used an optimal lag length of 1 selected by the Akaike Information Criterion (AIC) for the VAR model to calculate the TS, DS, NS for the return series. Following Saeed et al. [2021], Aharon et al. [2021], Zeng et al. [2020], 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 7, the average dynamic total return connectedness from January 2018 to September 2021 was 63.25%, which is about medium-high level. From Figure 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 assets at that time from DCCs plots (Appendix A). However, if we dig into the total connectedness table, we can see that the the average total spillovers between either of the cryptocurrency markets and clean energy markets were relatively low during the period, despite the fact that SPGTCED and ECO were the two largest spillover transmitters (101.96% and 101.86%). The FROM connectedness between clean energy indices and cryptocurrency indices was much lower than that between clean energy and general stock markets (SP&500), and were at the same level of that between clean energy and gold. The TO connectedness shows that cryptocurrency market transmitted more information to gold than to clean energy markets on average. Gold market was the most isolated as it was 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%).

Table 7: 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

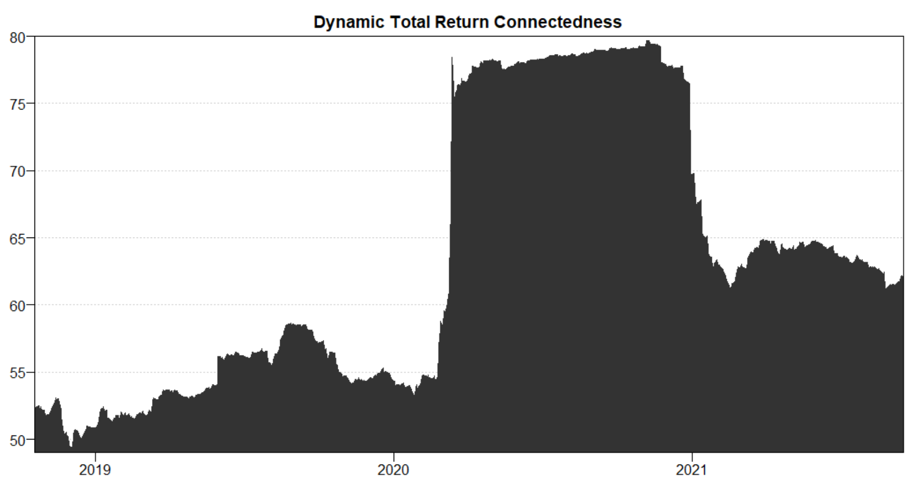

Figure 1: Dynamic total return connectedness

Figure 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 affected by other markets as they continued receiving the highest spillover effects during the whole period. Clean energy markets were greater spillover receivers than cryptocurrency markets, while gold was 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.

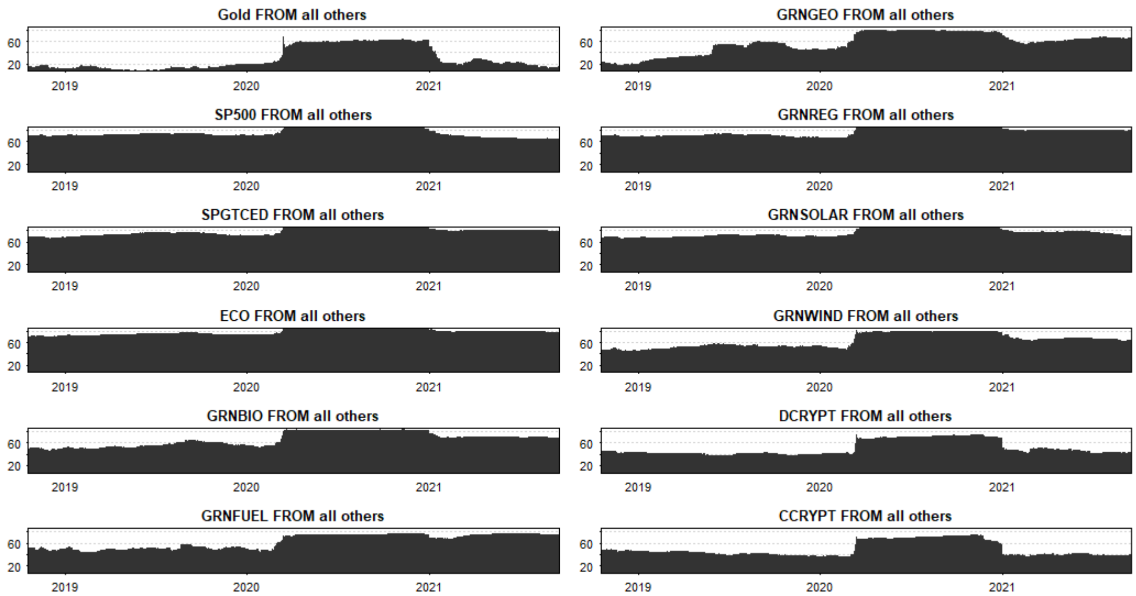

Figure 2: Dynamic directional return connectedness FROM others

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

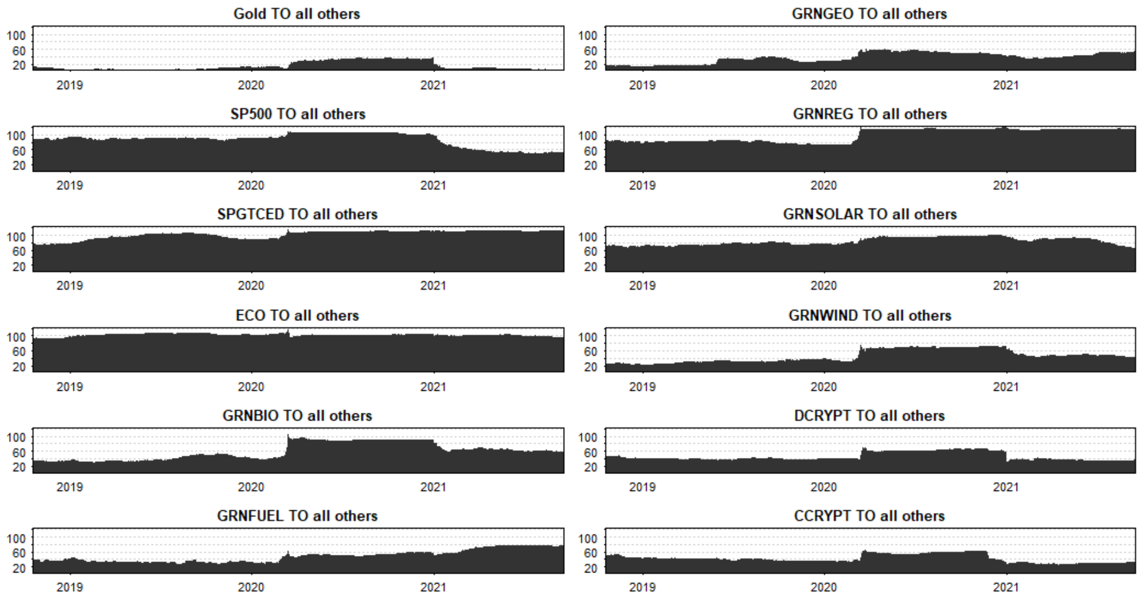

Figure 3: Dynamic directional return connectedness TO others

If look at the net spillovers (Figure 4), we can easily tell that both of the gold, dirty and clean cryptocurrency markets were spillover receivers during the whole sample period. General market (s&p500) had received much more spillovers from other markets since 2021. More interestingly, the role of clean energy indices played in terms of spillovers varied from sectors to sectors. Half of the clean energy indices were spillover transmitter in the whole period, including SPGTCED, ECO, GRNREG, and GRNSOLAR, while GRNFUEL, GRNGEO, and GRNWIND were spillover receivers. GRNBIO switched from receivers to transmitters in the April of 2020 and then switched back from 2021 onward.

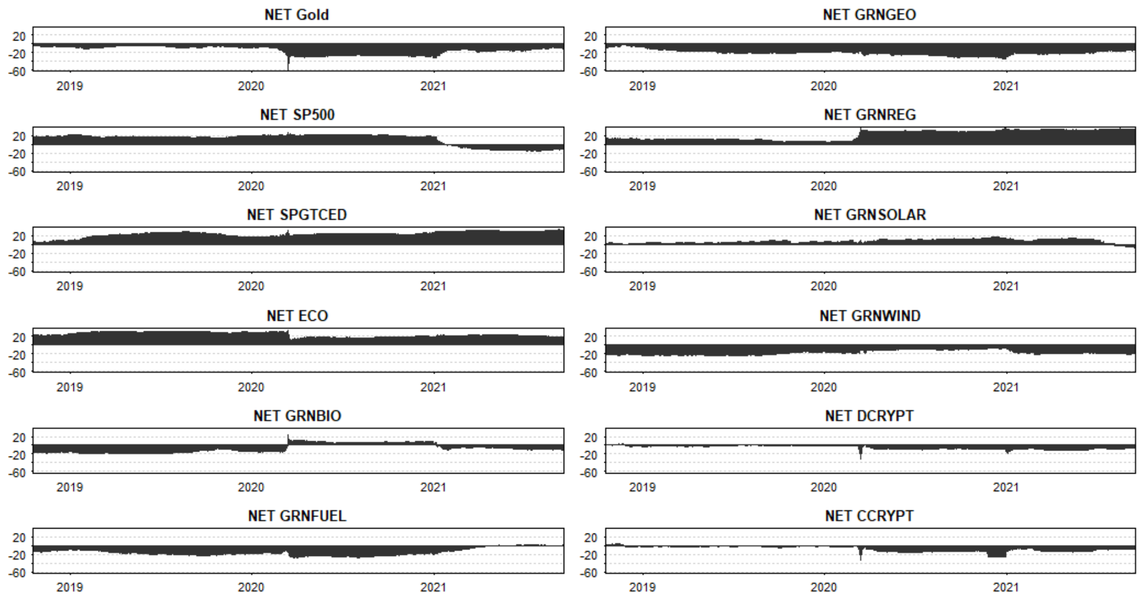

Figure 4: Total net return connectedness

Figure 5 and Figure 6 are the net pairwise directional return connectedness for dirty and green 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 were spillover receivers of the general stock market and most of the clean energy markets. Both DCRYPT and CCRYPT were transmitters for gold.

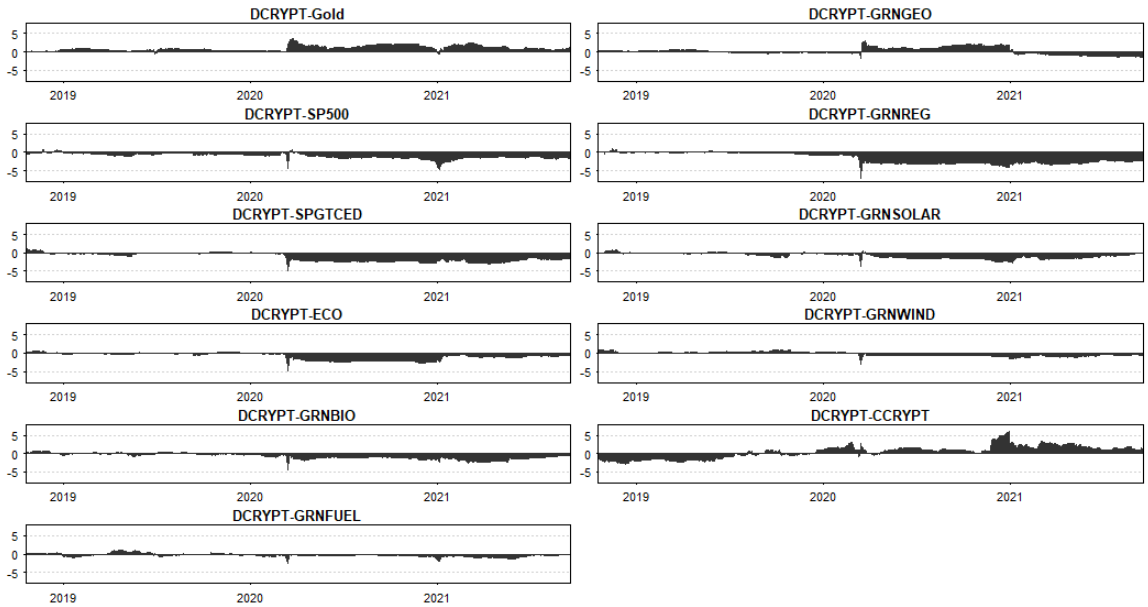

Figure 5: Net pairwise directional return connectedness for DCRYPT

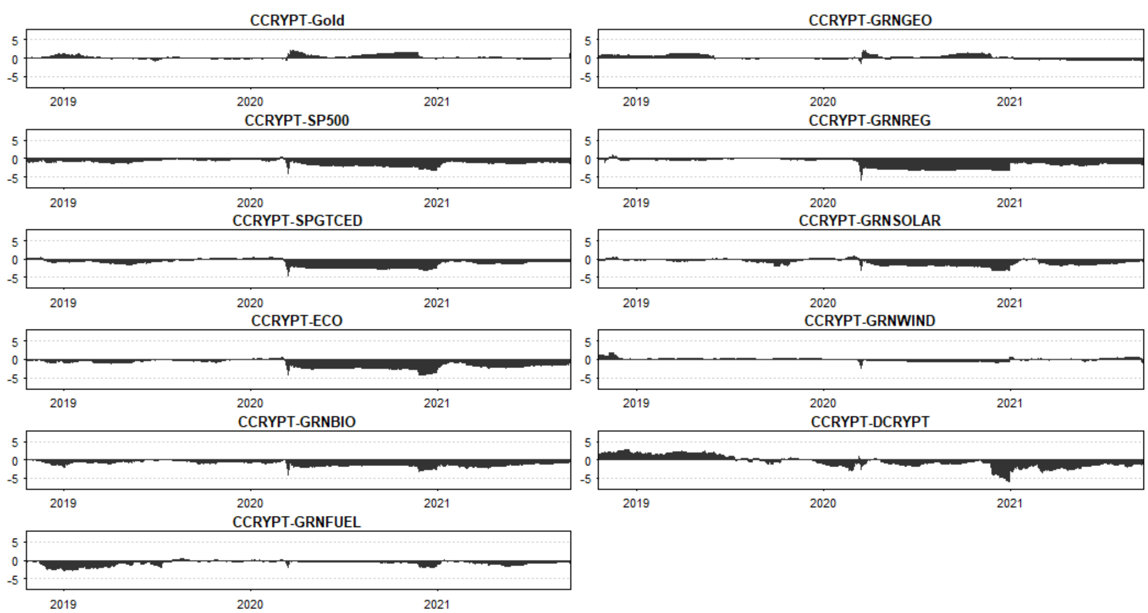

Figure 6: Net pairwise directional return connectedness for CCRYPT

4.2.2. Volatility spillovers

The volatility series were estimated using standard GARCH(1,1) model. We chose 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 8, the average dynamic total connectedness of volatilities from January 2018 to September 2021 was 64.12%, which is slightly higher than that of returns. Figure 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 were increased at the same time (Appendix A). If we zoom in total spillovers table, we can see that the the average total spillovers between either of the cryptocurrency market and clean energy markets were still relatively low during the period, but were higher than the that observed in return connectedness. SPGTCED and ECO were the largest transmitters, followed by GRNREG and S&P500. Half of the clean energy markets were larger receivers than the general stock market. The cryptocurrency and the gold market generally involved the least in the volatility transmission. The level of FROM and TO connectedness between clean energy indices and cryptocurrency indices were slightly higher than that of return connectedness, but were still slightly lower than that between clean energy and gold on average. Gold market remained as the most isolated market as it was the smallest spillover receiver (43.02%) and transmitter (26.09%) again.

Table 8: 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

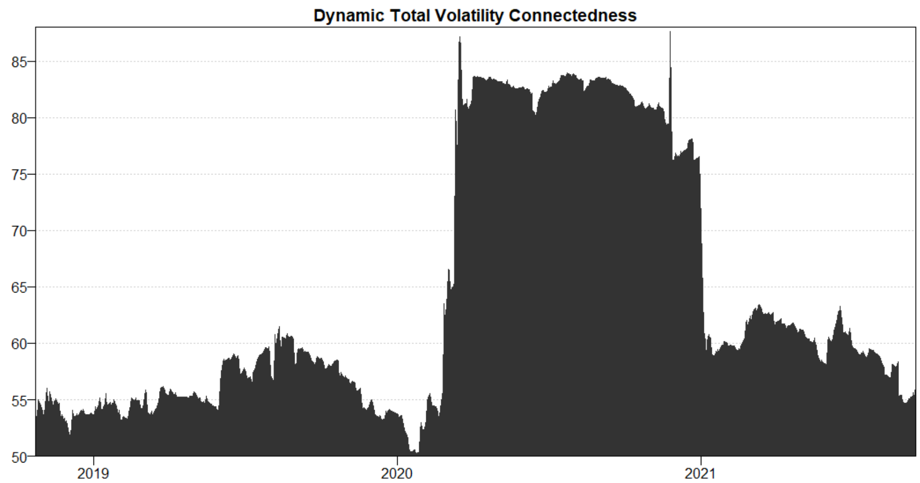

Figure 7: Dynamic total volatility connectedness

Figure 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 were the largest receivers. Most of the other clean energy subsectors shared similar pattern, but not for the case in GRNFUEL which was more volatile. Clean cryptocurrency received more spillovers than dirty cryptocurrency before the mid of 2020, but received much less afterwards. All market received much more spillovers from other markets in 2020 than in other periods.

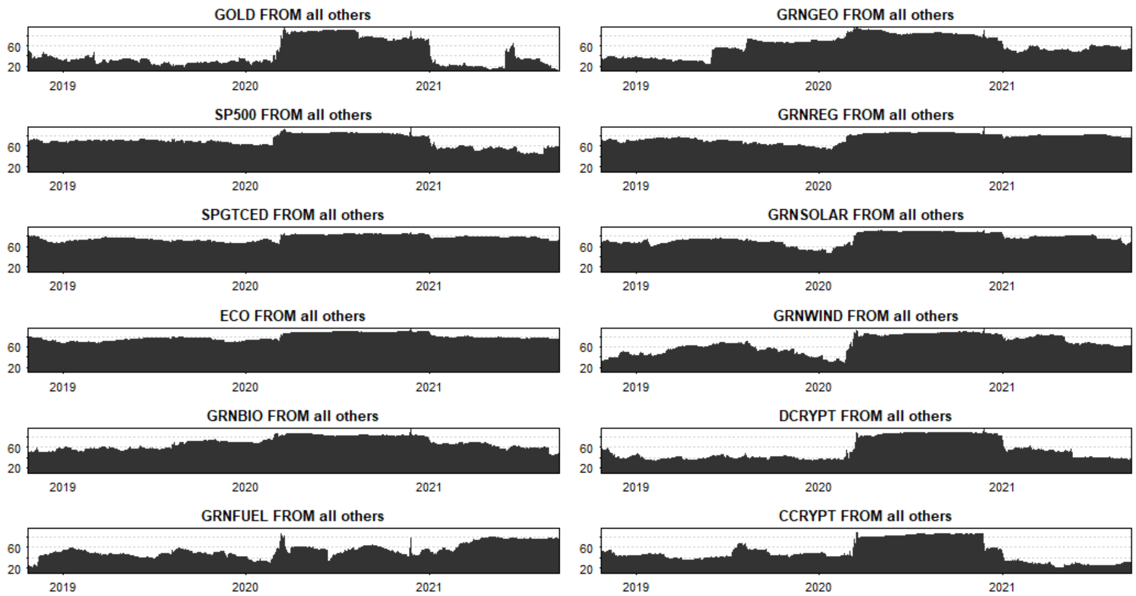

Figure 8: Dynamic directional volatility connectedness FROM others

Figure 9 presents the dynamic directional volatility spillovers of one market transmitted to other markets. S&P500 and some of the clean energy indices had relatively higher spillover effects to others than the others. Dirty cryptocurrency conveyed slightly higher spillover effects to others than clean cryptocurrency and gold on average. Gold, similar to previous result, had 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.

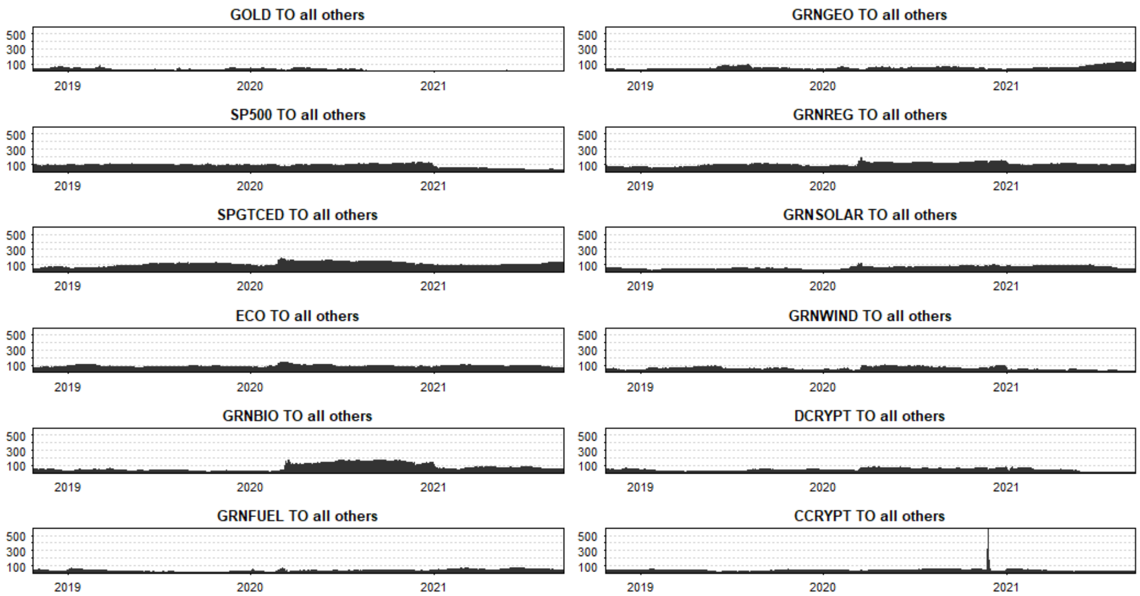

Figure 9: Dynamic directional volatility connectedness TO others

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

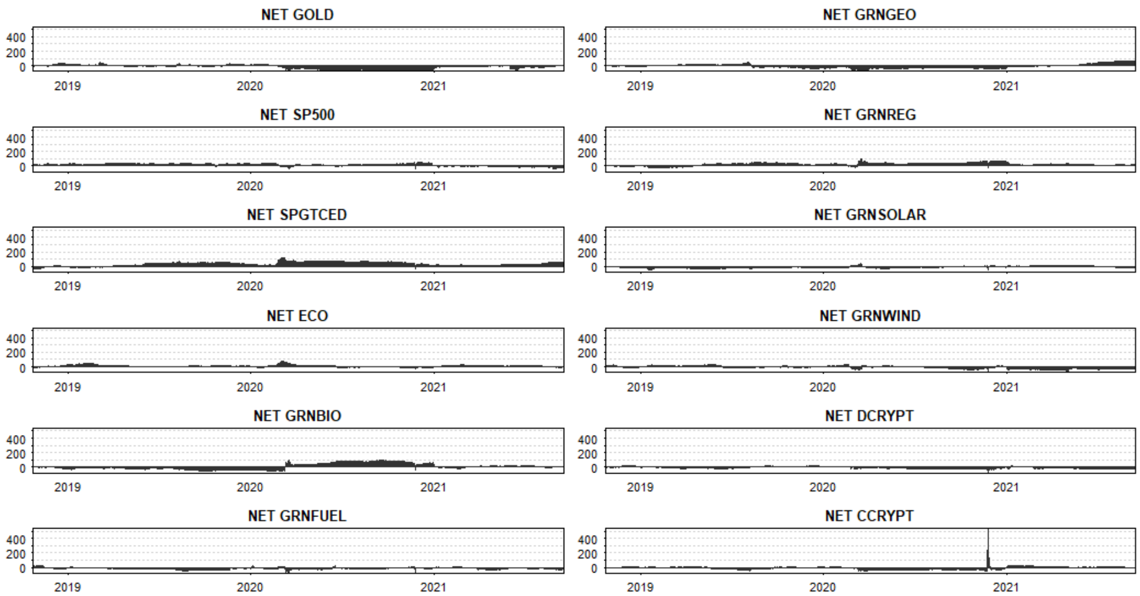

Figure 10: Total net volatility connectedness

Figure 11 and Figure 12 are the net pairwise directional volatility connectedness for dirty and green cryptocurrency indices, respectively. Surprisingly, the net spillovers from dirty to clean cryptocurrency was positive, but became negative following a extreme negative shock at the end of 2020. This tells us that when clean cryptocurrency was experiencing high volatility, the dirty cryptocurrency market got affected. In addition, the net volatility spillover from dirty cryptocurrency to gold became quite negative from 2020 April to December, which suggests that investments had been somehow transferred from dirty cryptocurrency to gold market when the former was experiencing high uncertainty. Another interesting pattern is that clean cryptocurrency had extreme volatility spillover effects to all other market near the end of 2020. Similar to previous findings, the net spillovers between cryptocurrencies and clean energy are different and there was no unified pattern among them.

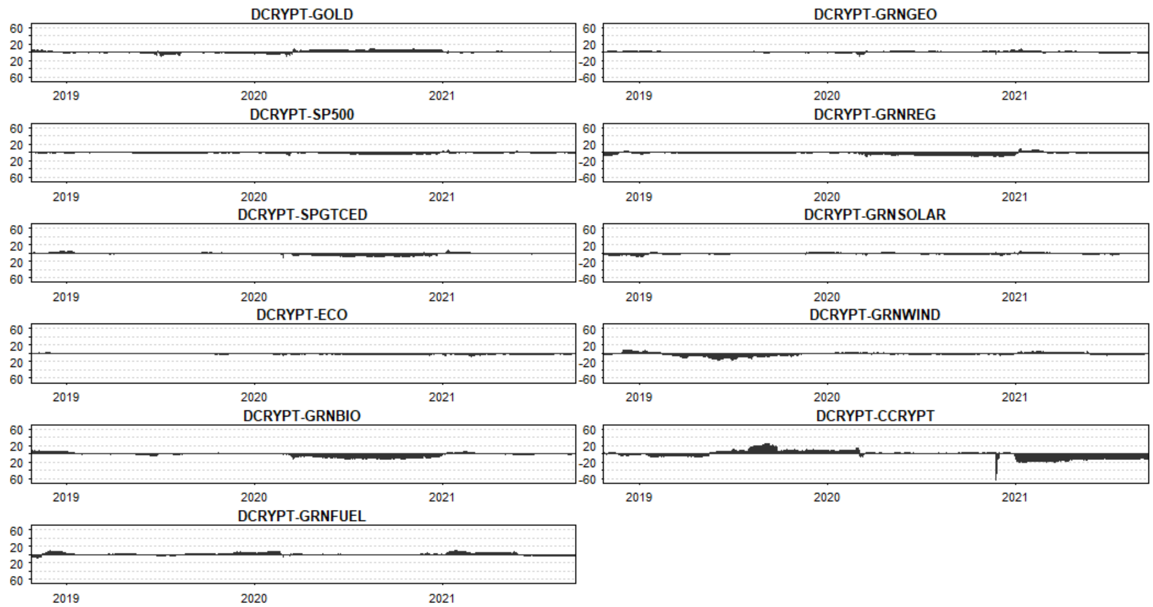

Figure 11: Net pairwise directional volatility connectedness for DCRYPT

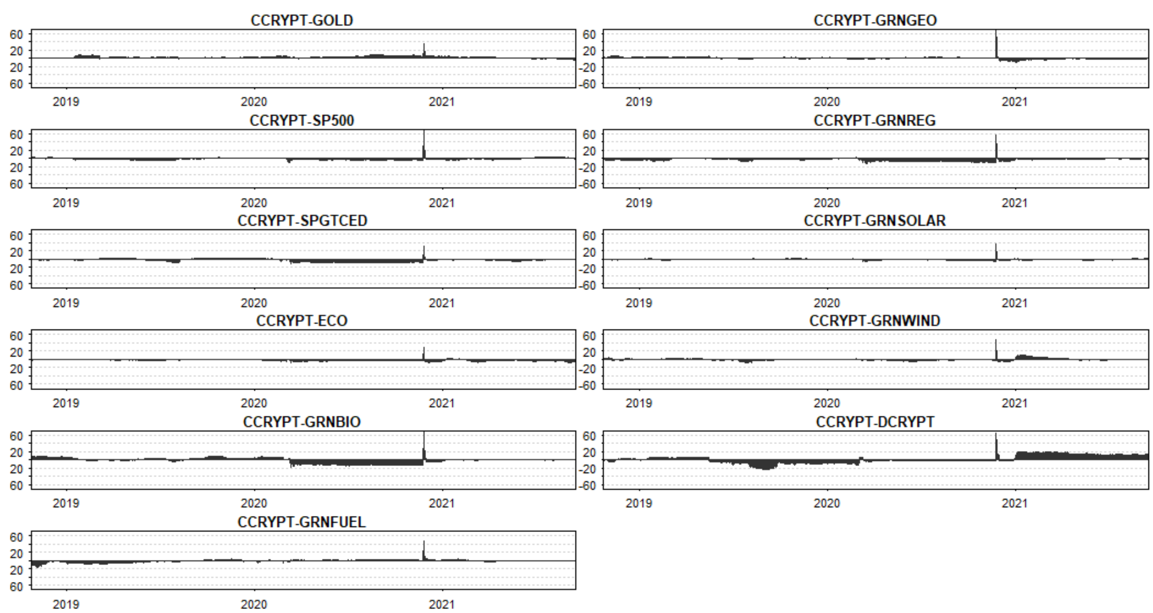

Figure 12: Net pairwise directional volatility connectedness for CCRYPT

Overall, the return and volatility connectedness between clean energy and general market or between clean energy subsectors were 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 considered 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_{2012} (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 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 initiated 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 were introduced to the step of generalized forecast error variance decomposition in the DY_{2012} approach so that we could calculate the spillover indicies TS, $DS_{i\leftarrow j}$, $DS_{i\rightarrow j}$, and NS.

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

By using the TVP-VAR model, we avoided the loss of the first 200 observations, and we showed 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_{2012} and TVP-VAR models happened in the period from 2020 April till the year end. To better illustrate the difference, we dropped the first 200 results of total connectedness obtained using the TVP-VAR model, and scaled both results obtained by DY_{2012} and TVP-VAR models to 100 at the start. Figure 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 spillovers calculated using the TVP-VAR model was decaying after the peak. This is not surprising as the DY_{2012} approach is more sensitive to outliers than the TVP-VAR method as the latter is smoothed by a Kalman filter. Overall, both approaches provide qualitatively similar information and our findings remain robust.

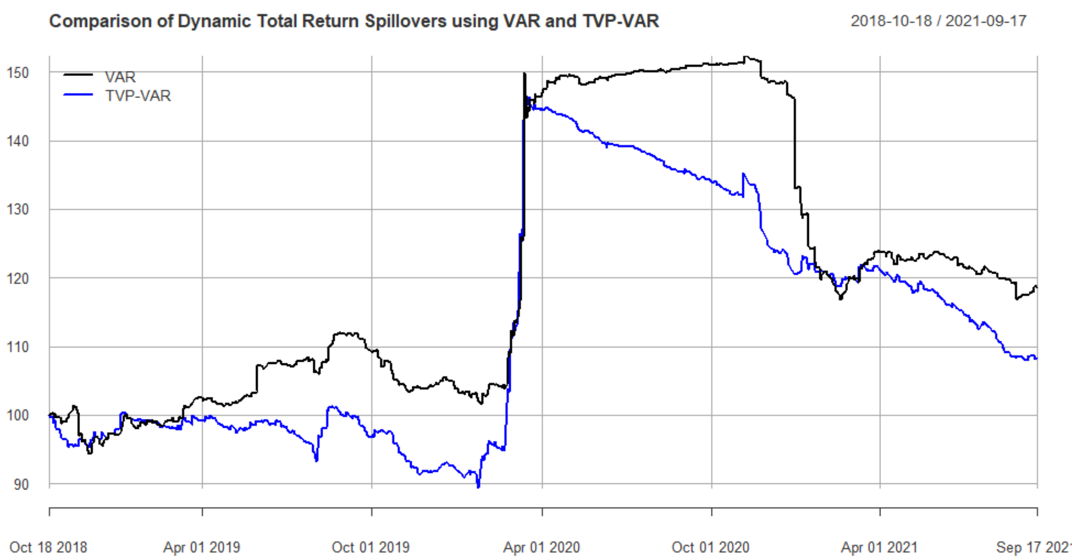

Figure 13: Dynamic total return spillovers using VAR and TVP-VAR

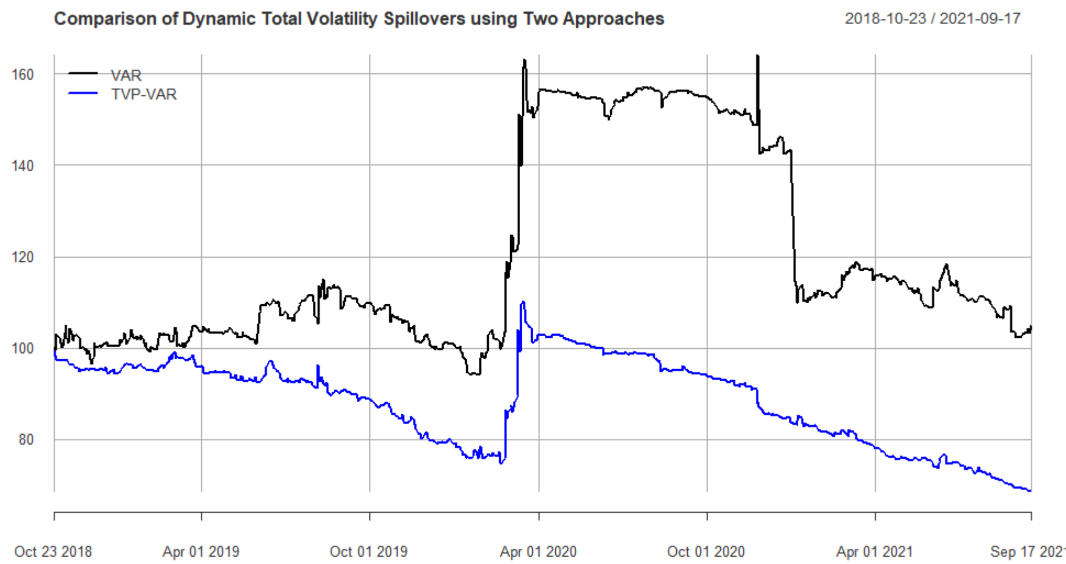

Figure 14: Dynamic total volatility spillovers using VAR and TVP-VAR

6. Conclusions

Previous studies such as Naeem and Karim [2021] and Pham et al. [2021] suggested that green investments such as clean energy could be used as diversification or hedge tool for cryptocurrency investors. However, in this paper, we showed that the time-varing dynamic conditional correlations between clean energy indices and cryptocurrencies was positive the majority of the time, regardless of cryptocurrency types, which implies that clean energy indices might not be a direct hedge for either black and green cryptocurrencies.

Furthermore, we tested 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 confirmed our previous finding that clean energy stocks have not yet become an effective direct hedge for cryptocurrencies. However, we found compelling evidence that clean energy *can* be viewed as a safe haven for both black or green 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, cryptocurrencies are not in general safe havens for clean energy stocks. We believe that retail investors or institutional managers who have used or is seeking to use clean energy stocks to hedge cryptocurrencies would find this study beneficial for their investments and portfolio constructions. Furthermore, it suggests that while cryptocurrencies have a significant negative ecological impact this can be perhaps mitigated by investors in these assets also choosing clean energy assets to act as safe havens. Portfolio stability and ecological protection are not necessarily incompatible.

Finally, we adopted a widely used spillover measure by Diebold and Yilmaz [2012] to calculate the spillover indices across selected markets. Overall, we found that the return and volatility connectedness between clean energy and cryptocurrencies was 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 claimed isolation of Bitcoin market. 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 or safe haven in the future. However, investors should be also aware that clean energy stocks do not homogeneously react to the movements of other markets in our case, while Pham [2019] discovered similar evidence in the oil market.

Our study also provides useful implications for policymakers, regulators, and cryptocurrency founders. Apparently, the current policy of promoting greener energy is not appealing enough for cryptocurrency investors as investors seem to be indifferent to investing in black and green cryptocurrencies. The development of green energy and green cryptocurrencies has brought significant environmental benefits compared to fossil energy and dirty cryptocurrencies. Restrictions and legal constraints are still weak. Greater efforts should be made by the society to promote greener investments and arouse the environmental awareness of investors and founders of dirty cryptocurrency.

Acknowledgements

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Contributor Roles

REN : Methodology, Formal Analysis, Writing - Original Draft

LUCEY : Conceptualization, Methodology, Writing - Review and Editing, Project Administration

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

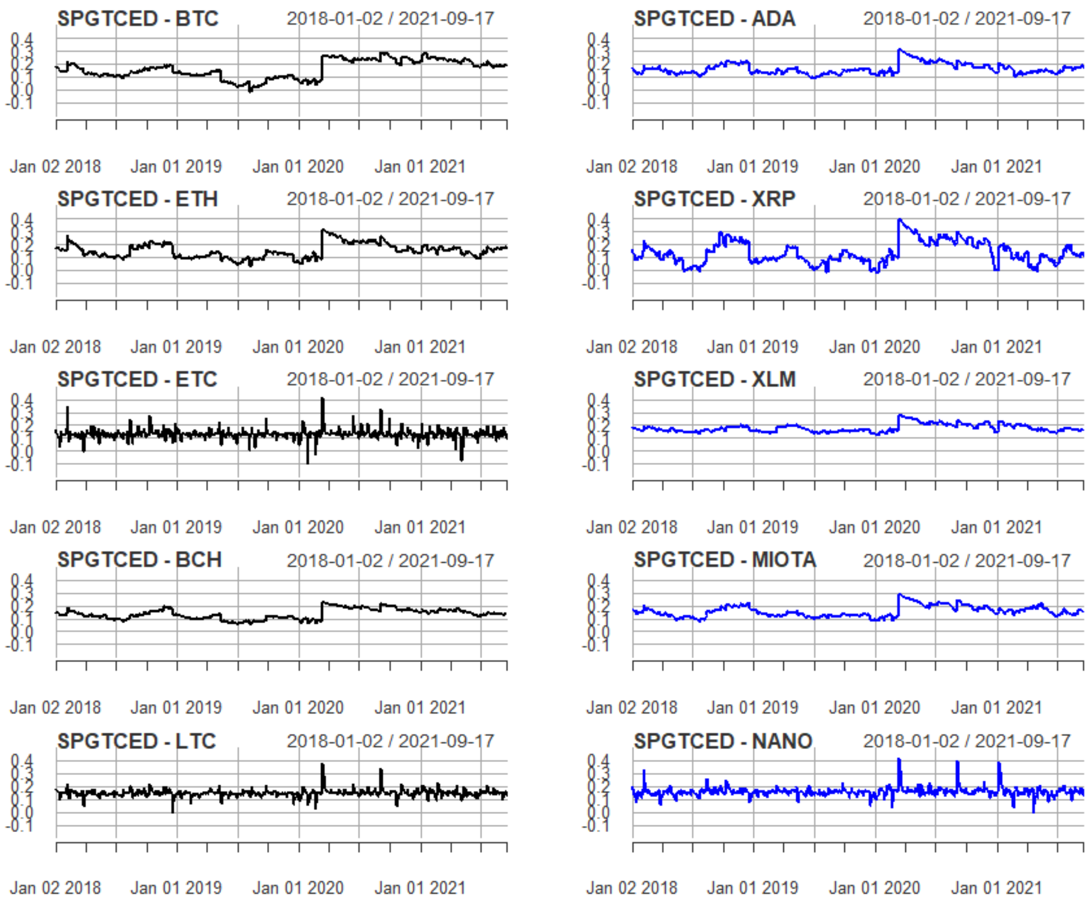

Figure Appendix A.1: DCCs between SPGTCED and cryptocurrencies

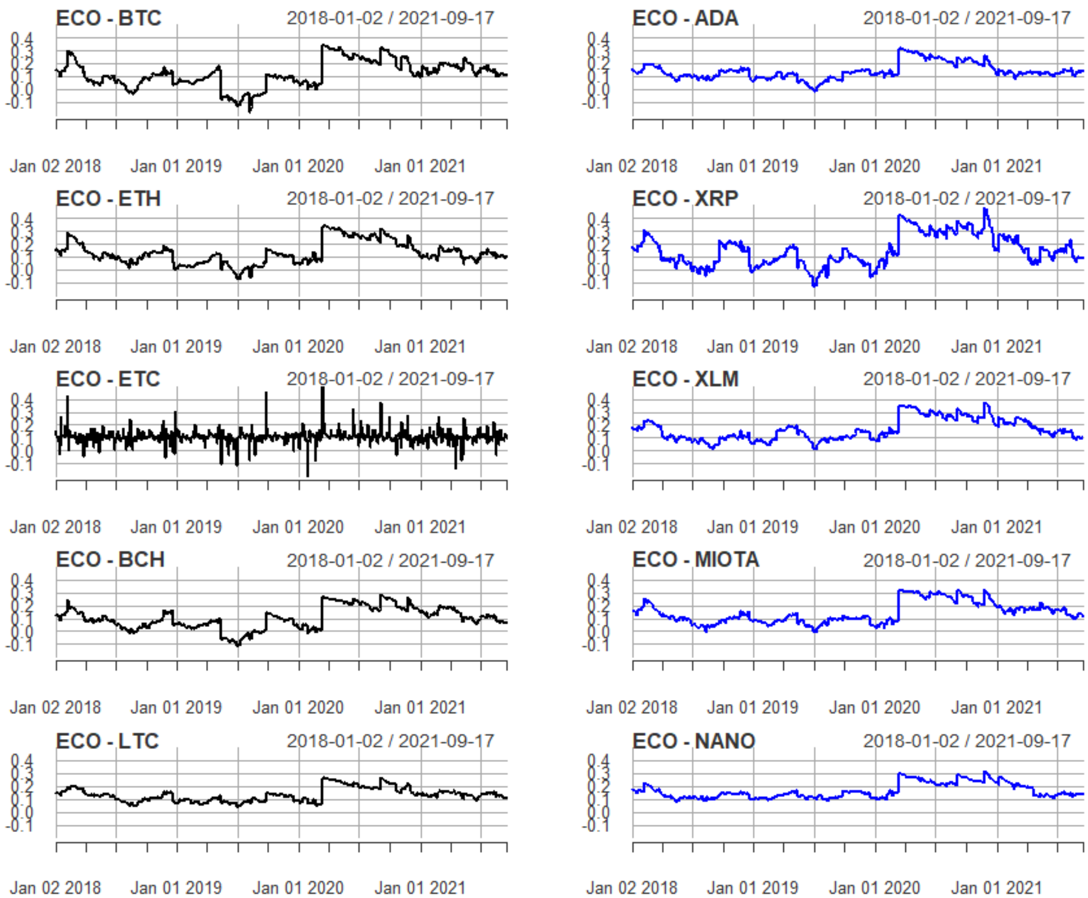

Figure Appendix A.2: DCCs between ECO and cryptocurrencies

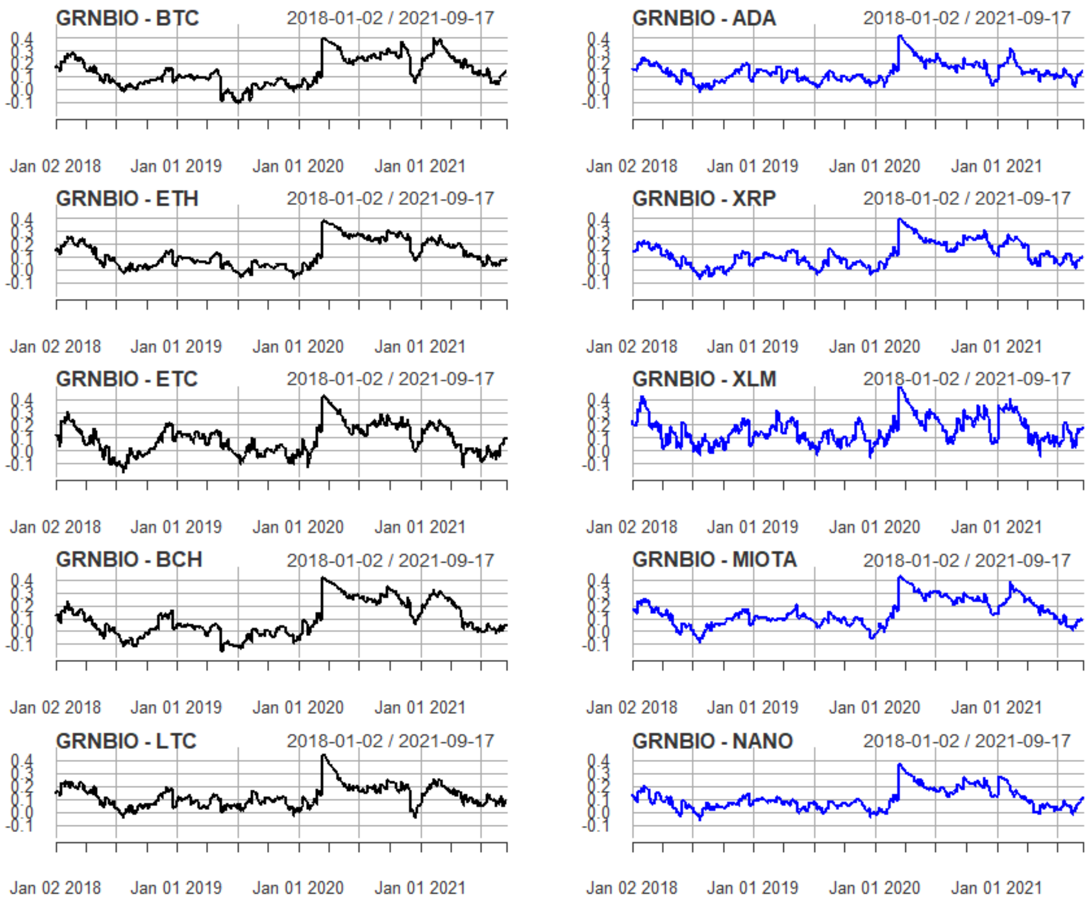

Figure Appendix A.3: DCCs between GRNBIO and cryptocurrencies

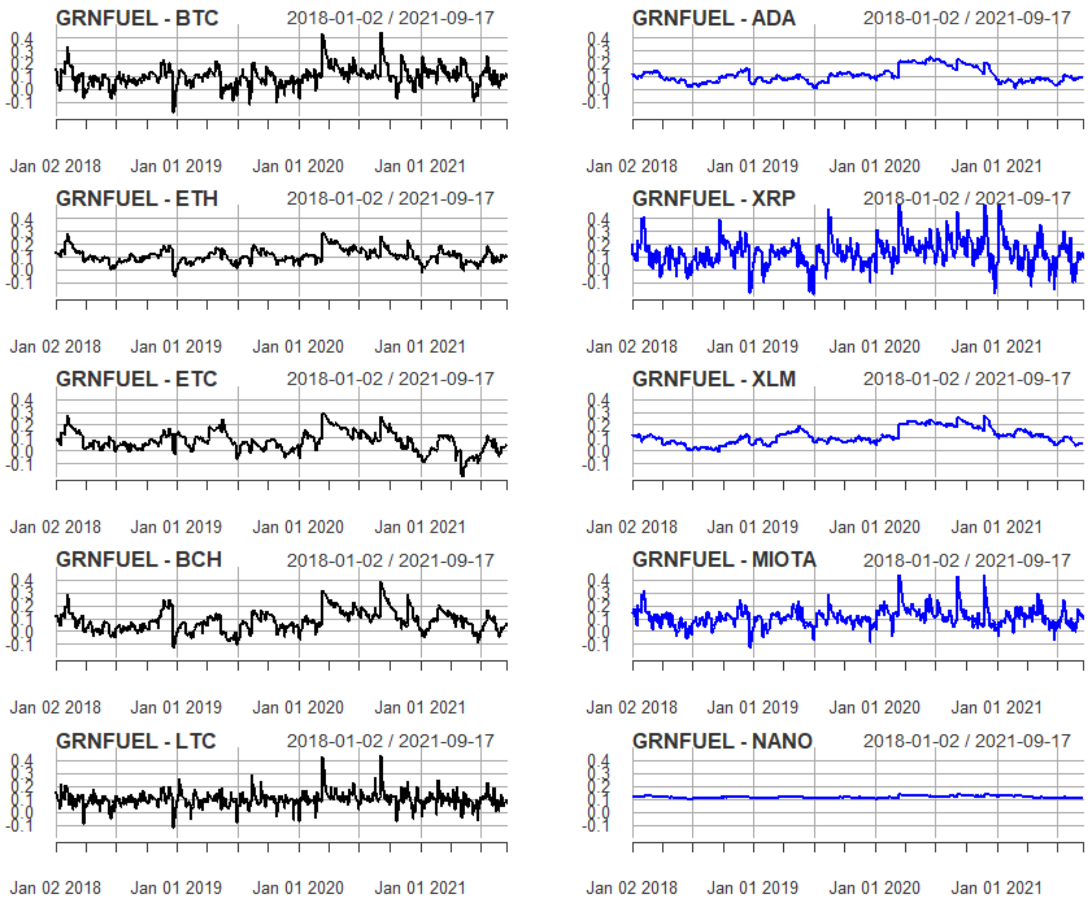

Figure Appendix A.4: DCCs between GRNFUEL and cryptocurrencies

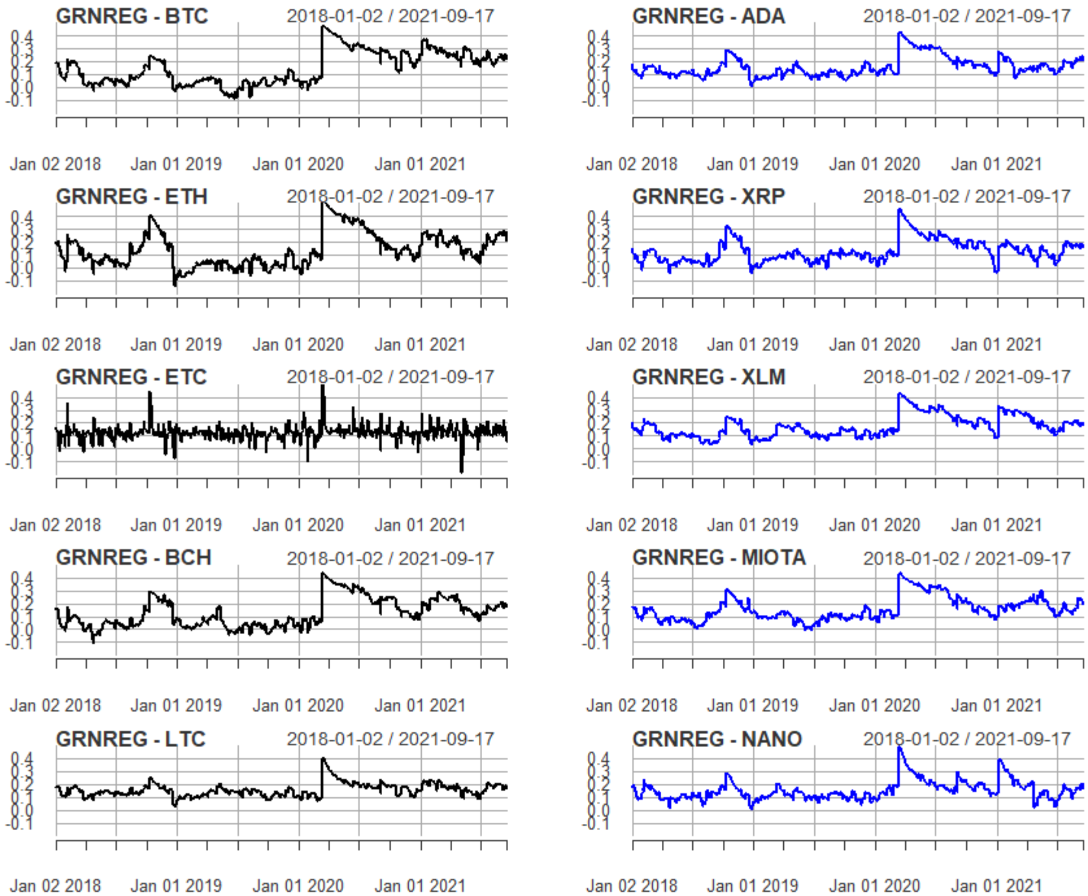

Figure Appendix A.5: DCCs between GRNREG and cryptocurrencies

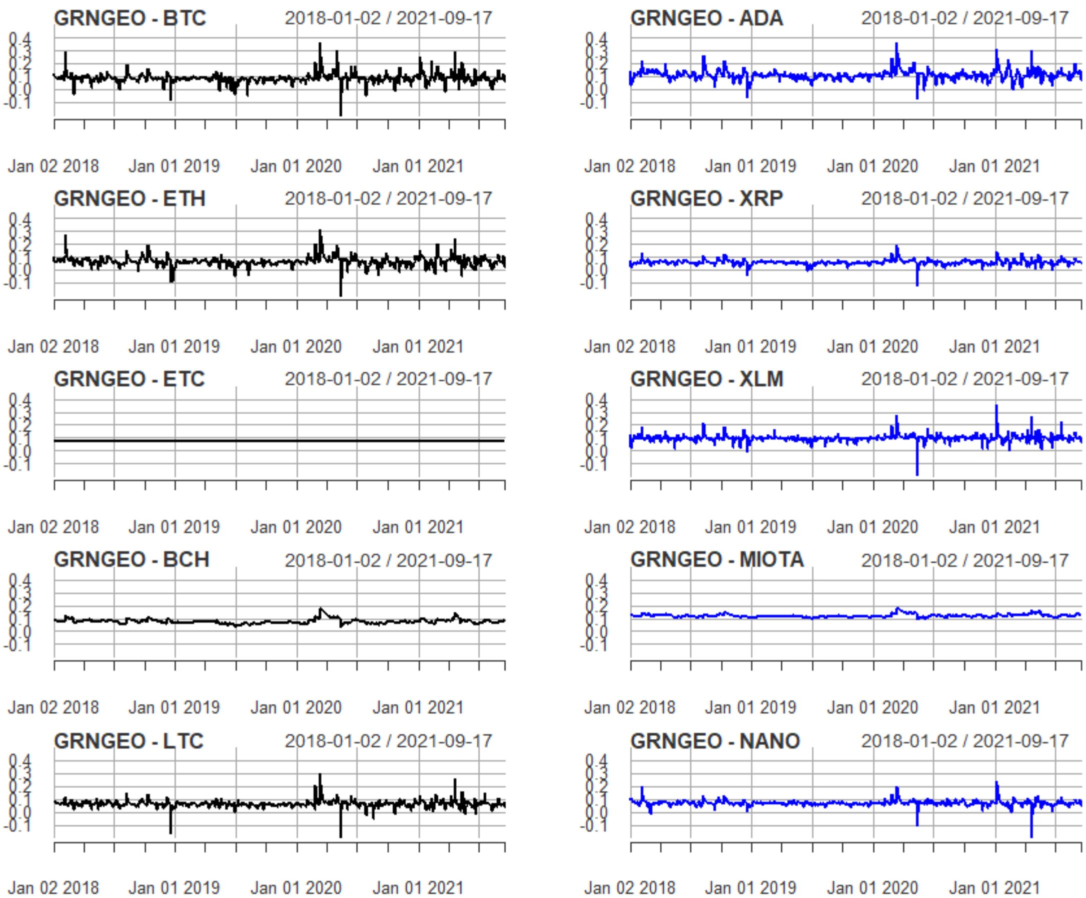

Figure Appendix A.6: DCCs between GRNGEO and cryptocurrencies

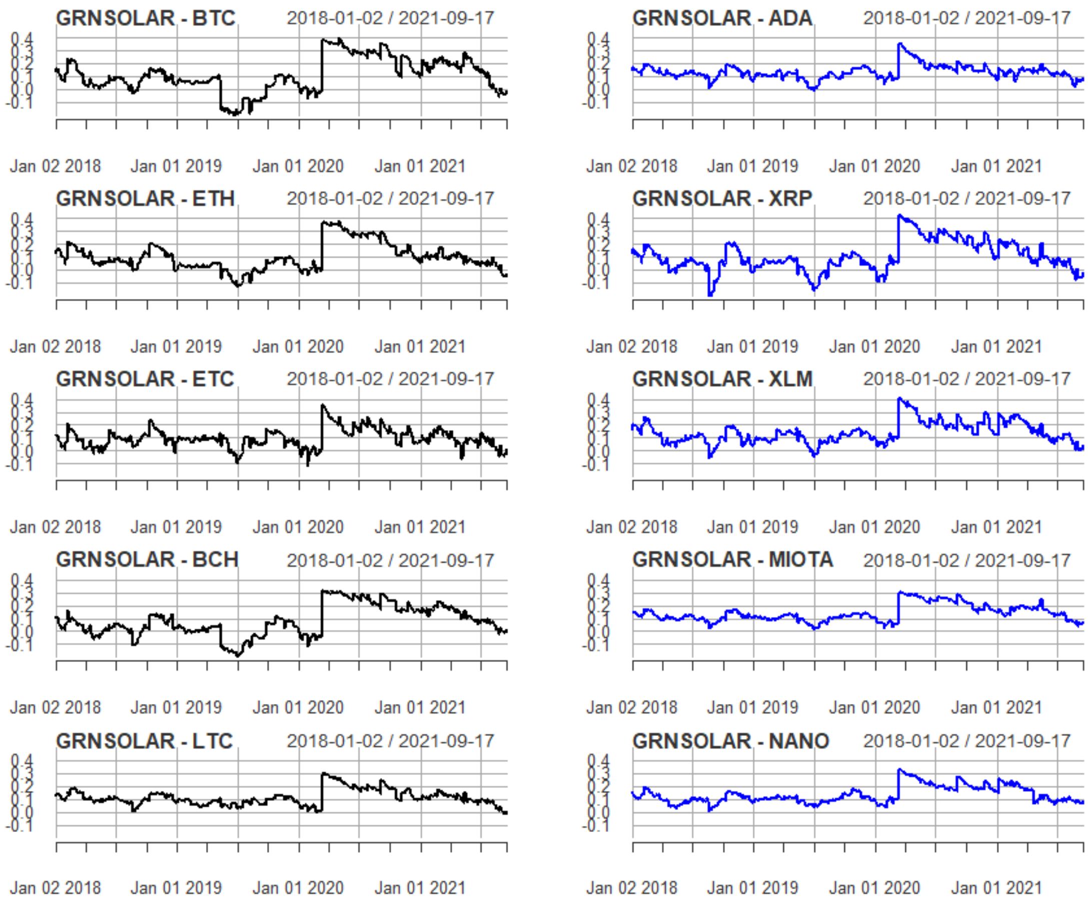

Figure Appendix A.7: DCCs between GRNSOLAR and cryptocurrencies

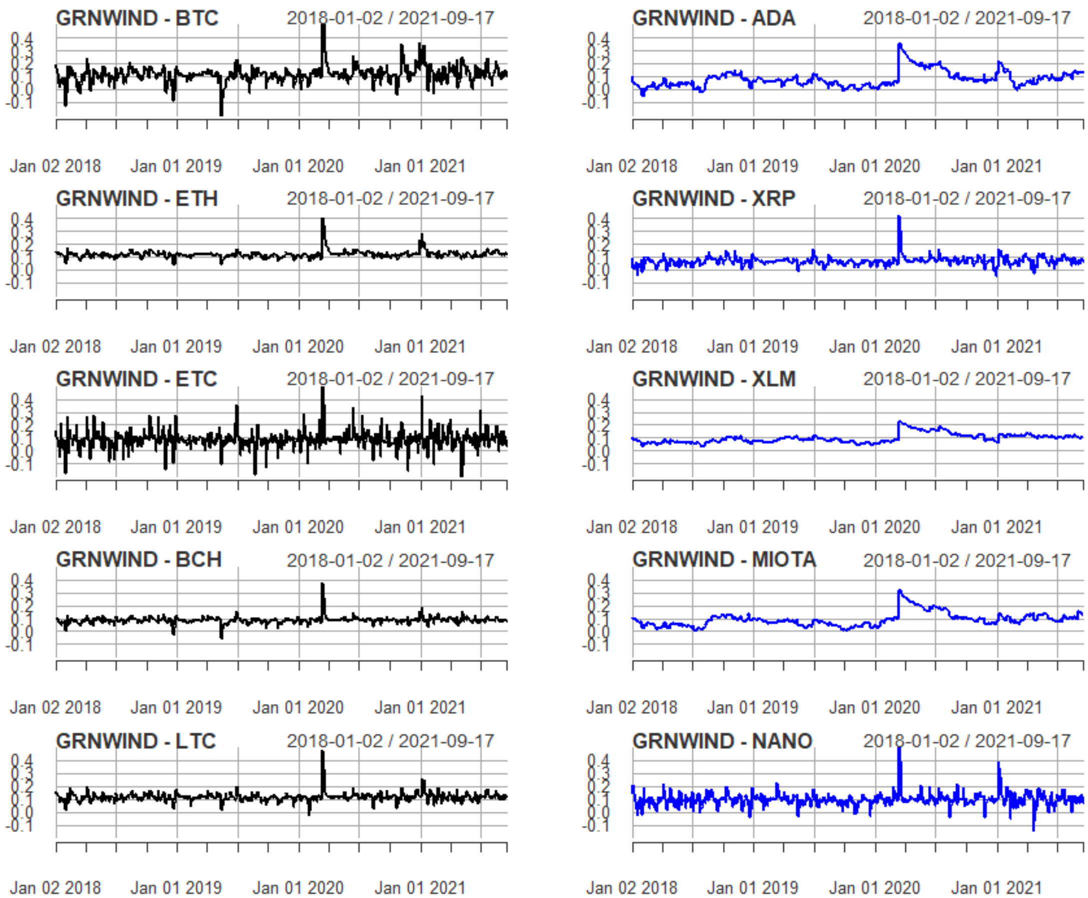

Figure Appendix A.8: DCCs between GRNWIND and cryptocurrencies

Appendix B. Return spillovers analysis using TVP-VAR

Table Appendix B.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

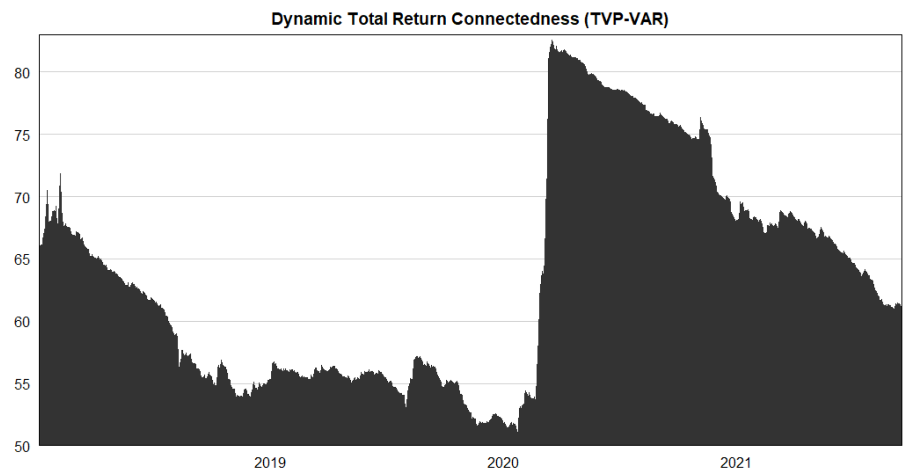

Figure Appendix B.1: Dynamic total return connectedness (TVP-VAR)

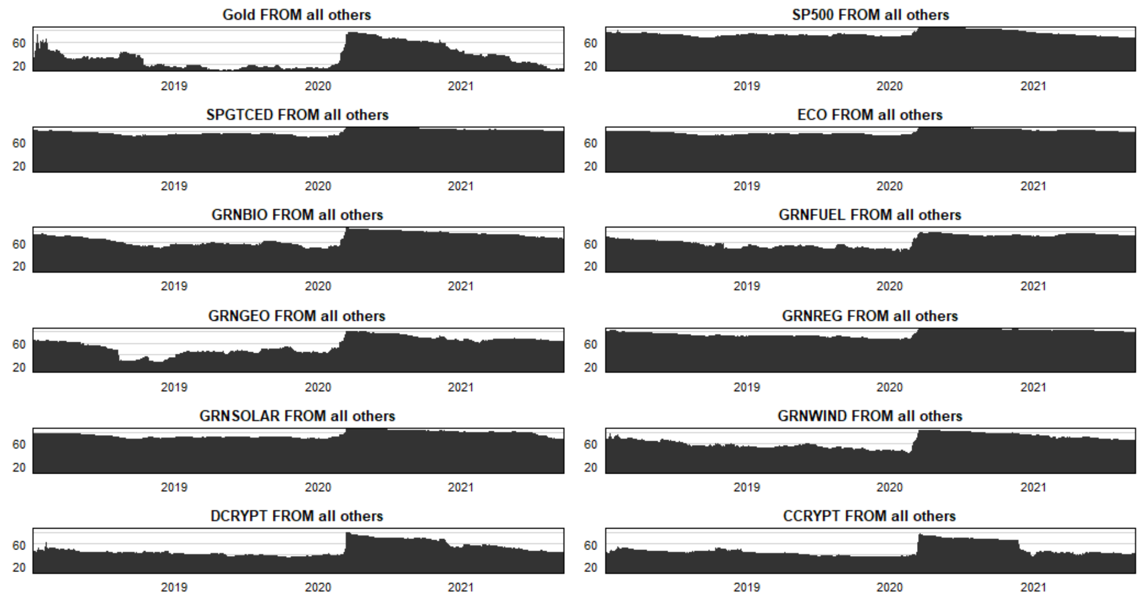

Figure Appendix B.2: Dynamic directional return connectedness FROM others (TVP-VAR)

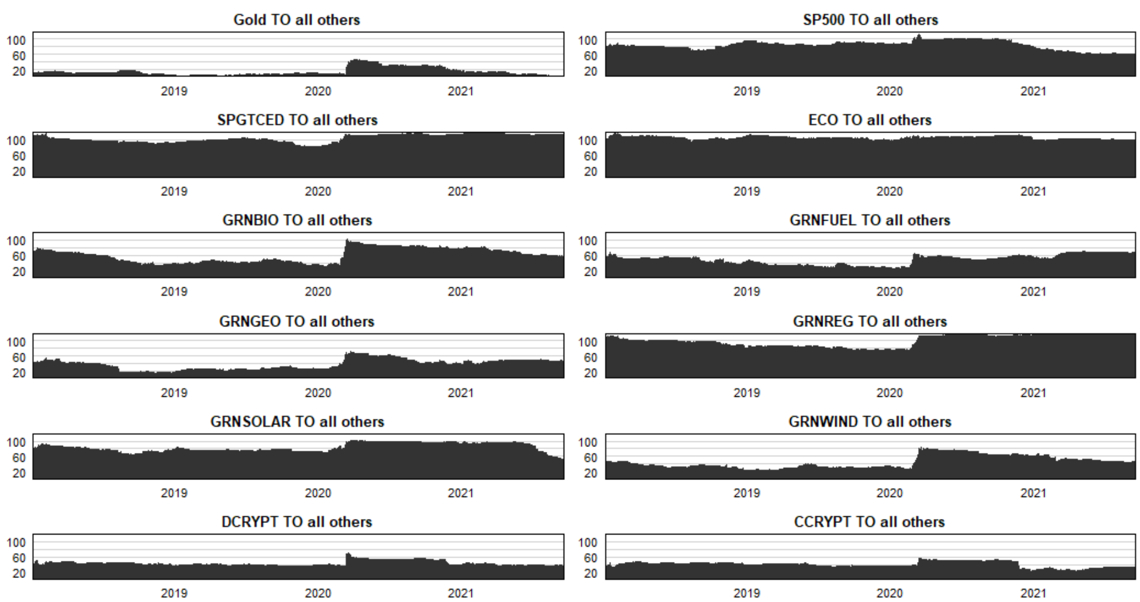

Figure Appendix B.3: Dynamic directional return connectedness TO others (TVP-VAR)

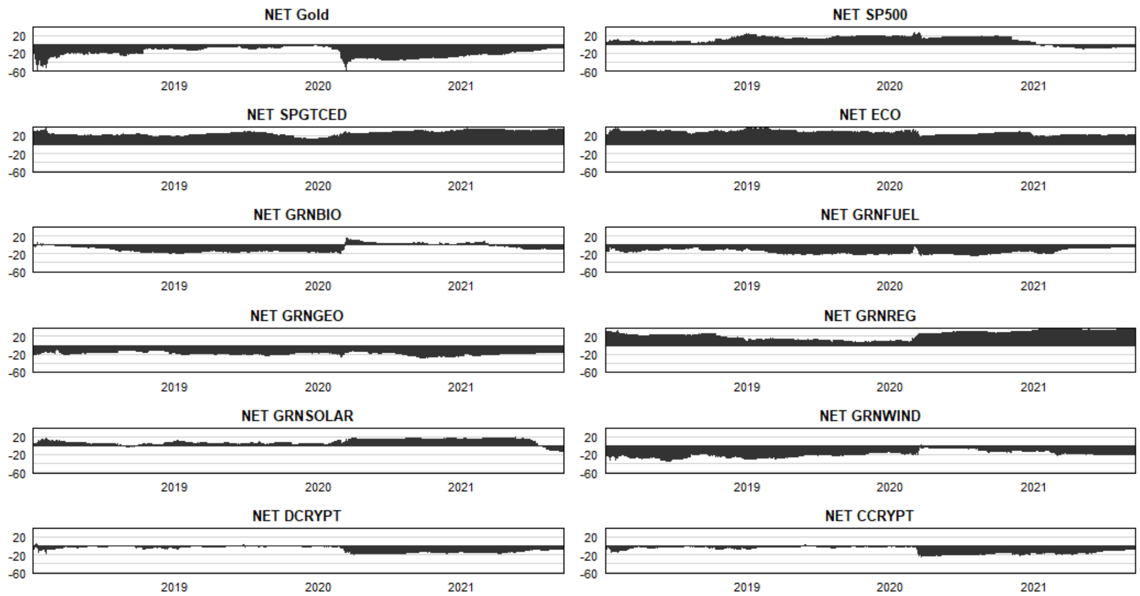

Figure Appendix B.4: Total net return connectedness (TVP-VAR)

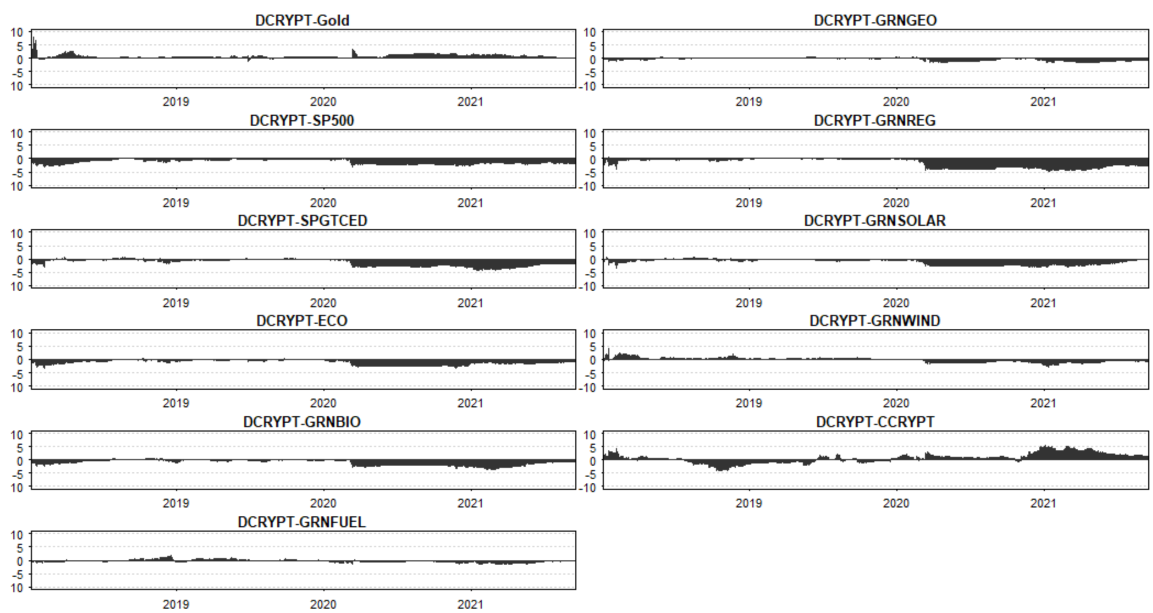

Figure Appendix B.5: Net pairwise directional return connectedness for DCRYPT (TVP-VAR)

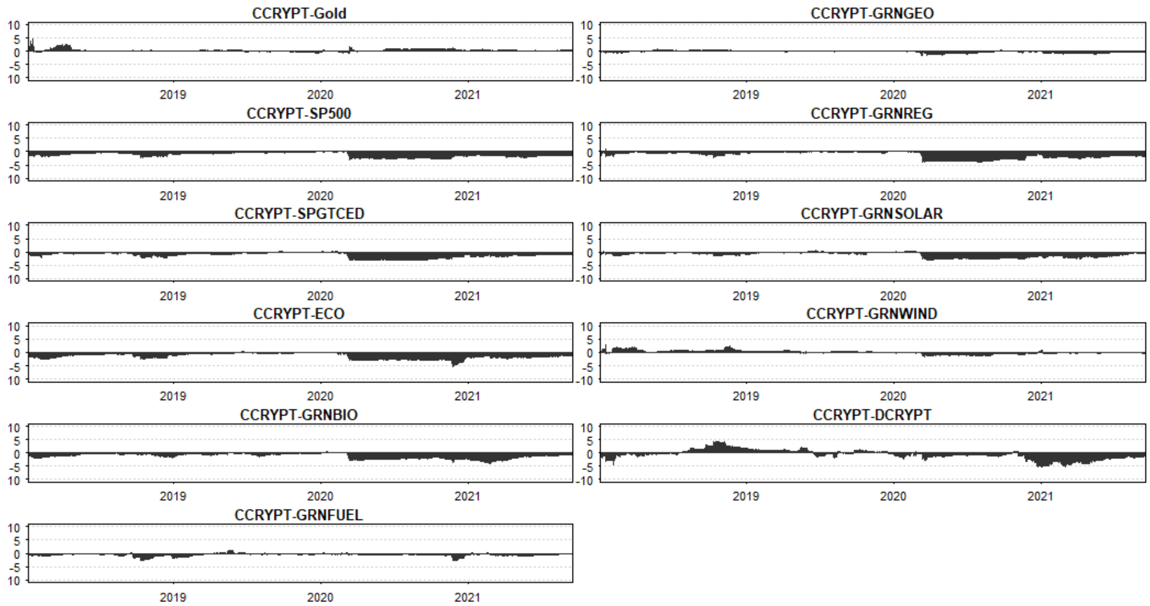

Figure Appendix B.6: Net pairwise directional return connectedness for CCRYPT (TVP-VAR)

Appendix C. Volatility spillovers analysis using TVP-VAR

Table Appendix C.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

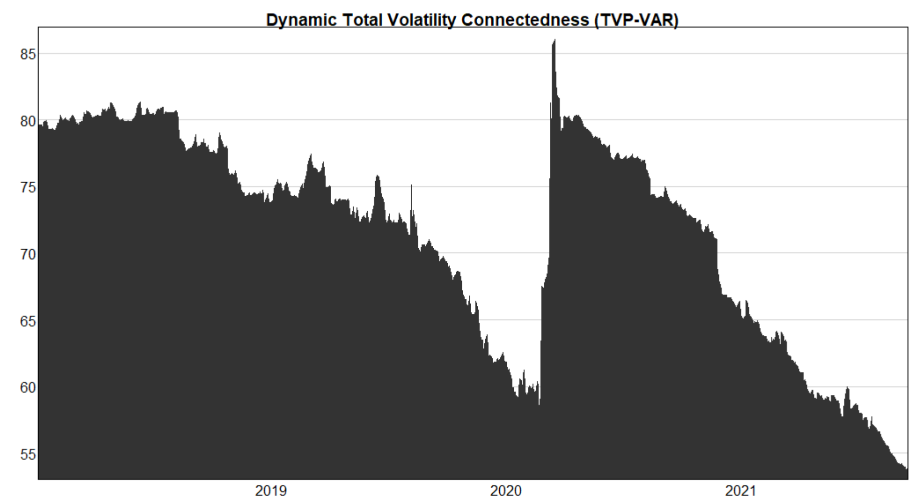

Figure Appendix C.1: Dynamic total volatility connectedness (TVP-VAR)

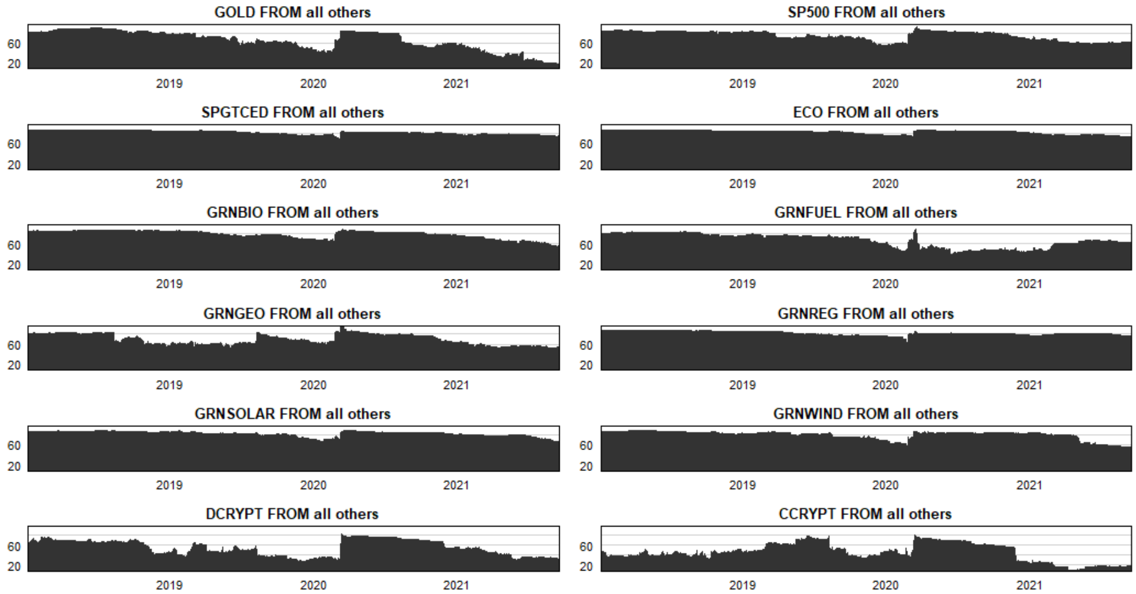

Figure Appendix C.2: Dynamic directional volatility connectedness FROM others (TVP-VAR)

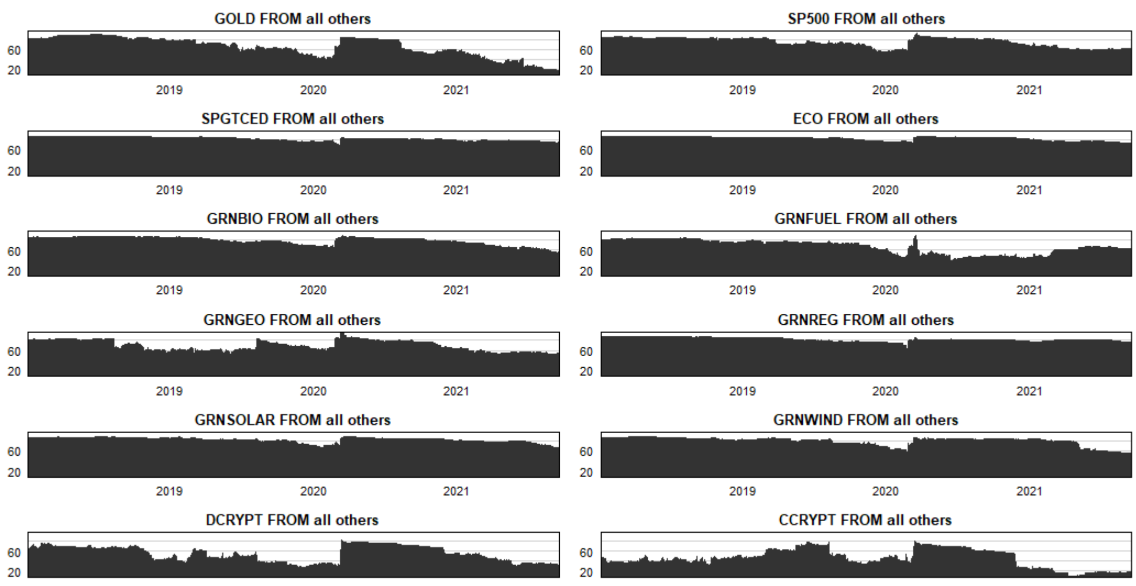

Figure Appendix C.3: Dynamic directional volatility connectedness TO others (TVP-VAR)

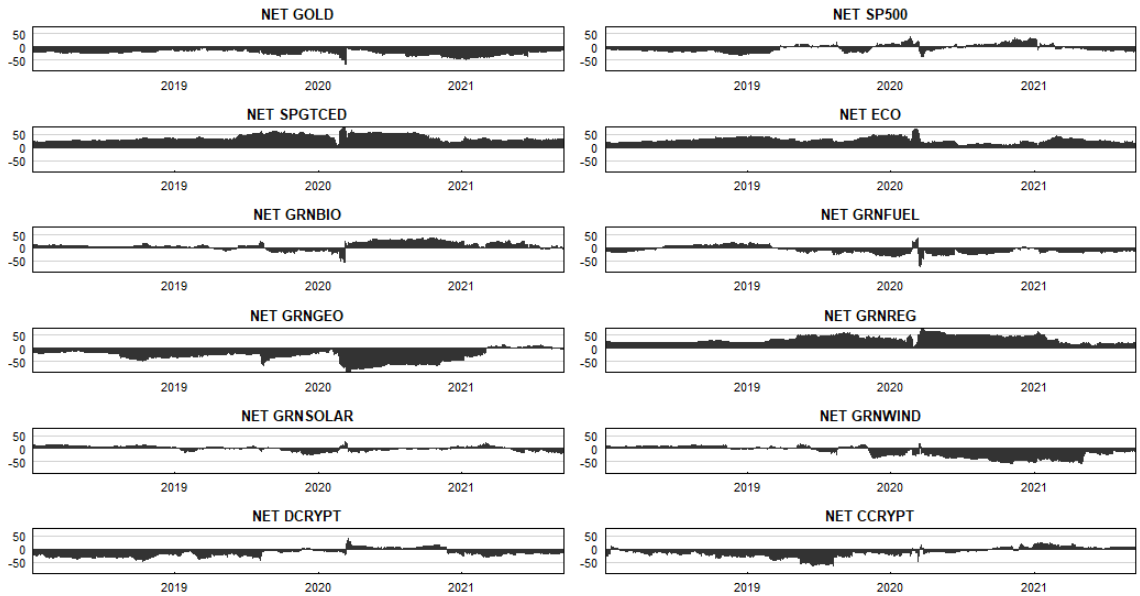

Figure Appendix C.4: Total net volatility connectedness (TVP-VAR)

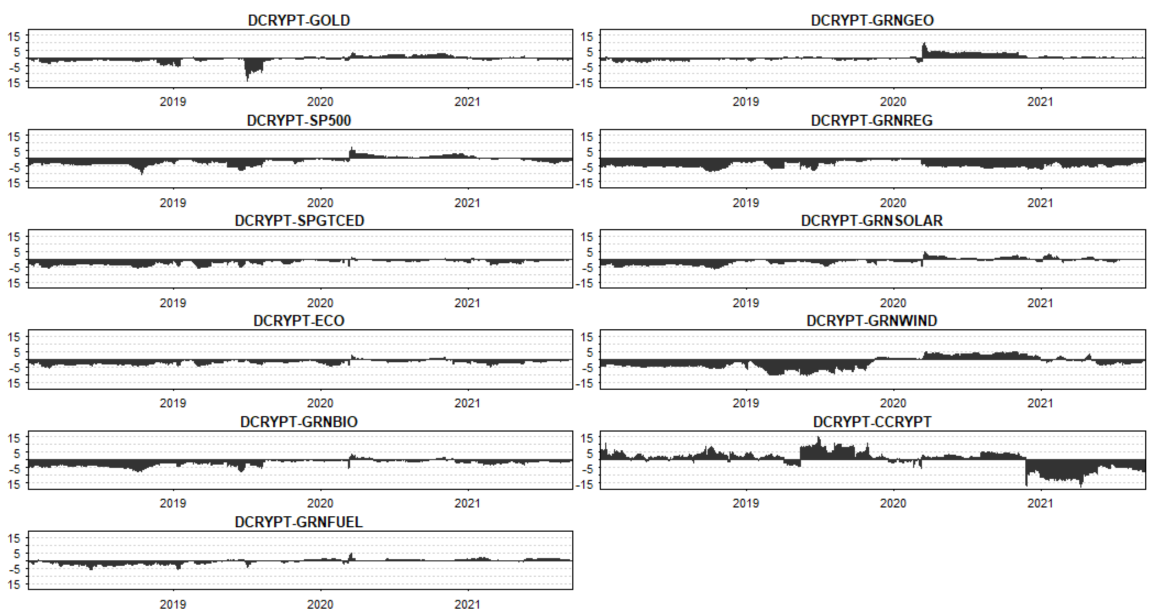

Figure Appendix C.5: Net pairwise directional volatility connectedness for DCRYPT (TVP-VAR)

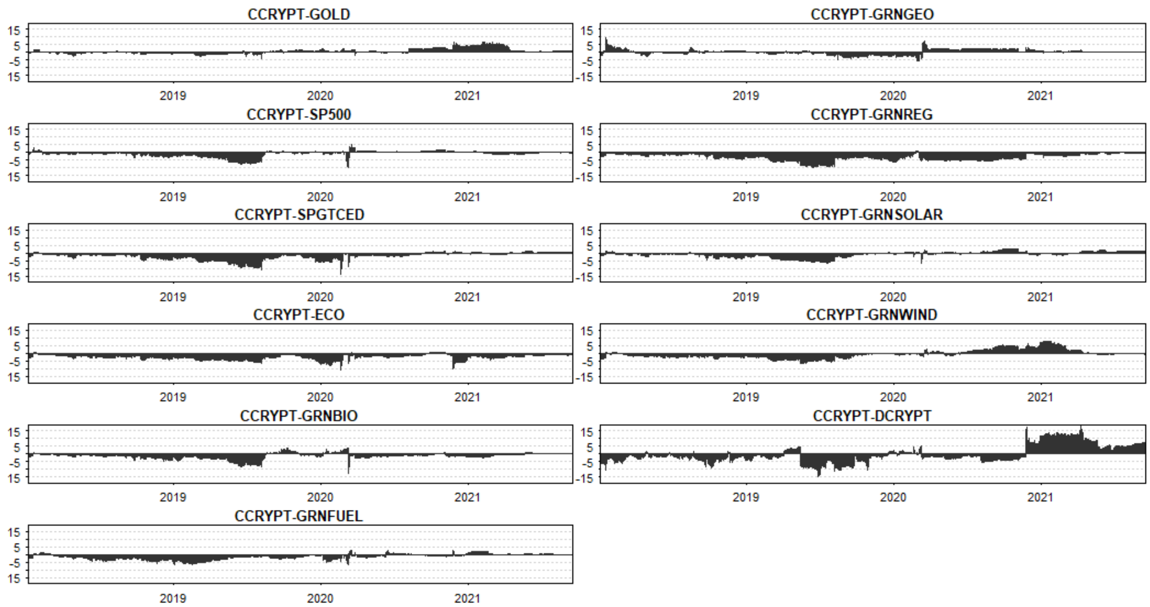

Figure Appendix C.6: Net pairwise directional volatility connectedness for CCRYPT (TVP-VAR)

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