Co-movement between Cryptocurrencies, NFTs, DeFi assets and Energy Market

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Abstract

Energy consumption for cryptocurrencies is increasing dramatically following the growing mining difficulty and a more comprehensive range of applying blockchain technology such as NFT and DeFi. In May 2021, Elon Musk, the CEO of Tesla, also tweeted about his worry about the environmental footprint of Bitcoin and indicated that "*Tesla will not sell any Bitcoin and we intend to use it for the transaction as soon as mining transactions to more sustainable energy*"[1]. It might start transition waves from "dirty" to "clean" energy used for such activities. These concerns raise questions about the relationship between cryptoassets and the energy markets and whether it varies among crypto groups and energy classes. Employing the time-varying parameter VAR model, this study can complement the existing literature on the liaison between cryptoassets and energy markets. Unlike most existing scholars, our study approaches not only leading and famous energy-consuming cryptocurrencies, Bitcoin and Ethereum, but also other blockchain-based assets.

Keywords: Cryptocurrency, NFT, DeFi, energy

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[1] See: https://www.bloomberg.com/opinion/articles/2021-05-14/elon-musk-bitcoin-tweet-the-latest-tesla-governance-worry

1. Introduction

Cryptocurrencies have been developing rapidly and have become sought-after assets and gaining tremendous attention from investors, media, policymakers, and academia because of their technical characteristics with the critical idea of decentralization and attractive wide-range volatility feature. In late November 2021, the total market capitalization of cryptocurrencies reached over USD 2900 billion, and the 24-hour transaction volume peaked at nearly USD 140 billion. In early 2020 those figures were USD 200 billion and USD 70 billion, respectively[1]. However, apart from Bitcoin, Ethereum, and other major conventional cryptocurrencies, the new technology platforms such as Non-fungible token (NFT) and Decentralized Finance (DeFi) assets occupy a prominent place in the cryptocurrency market (Dowling, 2022*a*). In the meantime, researches on NFTs and Defi assets are quite scarce. The authors attempt to uncover these new platforms (Aharon and Demir (2022) and Karim et al. (2022)) and give the idea of efficiency (Dowling (2022*a*), Dowling (2022*b*)). Recent research investigates their connectedness with conventional cryptocurrencies and financial assets, among others (Yousaf and Ali (2020), Karim et al. (2022) and Aharon and Demir (2022)).

Our research mainly focuses on their recent sounding point relating to the environmental footprint issues of cryptoassets. The enormous power consumption of cryptocurrencies, particularly Bitcoin and Ethereum, has been documented in Mora et al. (2018), Jiang et al. (2021) and Schinckus (2021). This energy cost mainly derives from the "Proof of Work" (PoW) consensus operation on which almost all cryptocurrencies are based. A cryptocurrency could be created to enter circulation through the mining process primarily based on the decentralized PoW consensus mechanism. In this process, the miners must solve complicated math puzzles and reward new crypto coins. As more cryptocurrencies were created, these mining activities became much more difficult and consumed more power. Given the strong dependencies between cryptocurrency operation and electrical energy consumption, the relationship between cryptocurrencies and the energy market is clear. Some researchers provided evidence that an increase in crude oil prices could lead to an appreciation in

[1]See https://coinmarketcap.com/charts/

Bitcoin's prices and vice versa (Das and Dutta (2020), Ciaian et al. (2016), Bouri et al. (2017), Li et al. (2019), Okorie and Lin (2020), Rehman and Kang (2021) and Huynh et al. (2022)). However, Bitcoin was shown to have negatively co-moved (Das et al., 2018) while weakly depended on crude oil in Charfeddine et al. (2020) and Bouri et al. (2017).

By investigating the co-movement between cryptocurrencies and energy markets, this paper can contribute to the existing literature but differs from the others by answering the following research questions. First, in addition to Bitcoin and Ethereum, do other emerging cryptoasset groups, including NFT and DeFi, co-move with energy markets? The relationship between NFT and DeFi assets is yet examined despite their potential energy consumption throughout their operation. Given environment tightening control from various governments, energy usage may cause diver among different types of energy, especially renewable energy. We, therefore, investigate the second question, do cryptoassets correlate differently among crude oil, coal, natural gas, and renewable energy prices? This idea is partly examined in Symitsi and Chalvatzis (2018), Ren and Lucey (2022), Corbet et al. (2021), Naeem and Karim (2021), Pham et al. (2022) and Pham et al. (2021) but we attempt to see the dynamic correlation at one time. Third, we study whether technology-based could explain the correlation differences among the cryptoassets. In other words, the correlation between cryptoassets depends on the mechanism of energy consumption. If so, the findings could help policymakers and governments design policies to ensure market efficiency and environmental sustainability. Last, by analyzing the dynamic correlation between cryptoassets and energy markets, we can show if cryptoassets and energy could be considered a safe haven or hedging tool in the portfolio.

To answer those questions, we employ daily price data of cryptocurrencies, NFT, and Defi assets in `https://coinmetrics.io/`. In each group, we choose two candidates to get the most extended data time series. We additionally collect daily WTI Crude Oil Spot (USD/Barrel)[2], Coal Intercontinental Exchange(ICE) (USD/Metric Tonne), Natural Gas (USD), and Global Renewable Energy (USD) from Refinitiv to illustrate for oil, coal and renewable price, respectively. We utilize

[2]Crude Oil-West Intermediate Spot Prices

a time-varying parameters vector auto-regression (TVP-VAR) model introduced Primiceri (2005) to describe the case of the cross-correlation between the cryptoassets and energy market. This method allows for capturing structural changes in the time series.

Our paper is structured as follows: section 2 gives a brief review of the literature; the following is the sample data description and the method to estimate return and liquidity in section 4. Section 3 presents the methodology, and its empirical results are discussed in section 5. The conclusions are provided in section 6.

2. Literature Review

There are four mainstreams of the existing literature about conventional cryptocurrencies. First, the authors investigate if the cryptocurrencies could be considered as financial assets (Dyhrberg (2016), Polasik et al. (2015)), Baur et al. (2018), Yermack (2015). Second, cryptocurrency market efficiency is also examined in Urquhart (2016), Nadarajah and Chu (2017), (Al-Yahyaee et al. (2018), Grobys and Sapkota (2019), Zhang et al. (2018)). Third, cryptocurrencies are urged to be either hedging and safe heaven tool in the portfolio (Corbet et al. (2018); Giudici and Abu-Hashish (2019) Guesmi et al. (2019) and Briere et al. (2015)). Last, being categorized as a financial asset (Baur et al., 2018), the authors also concern about the connectedness of Bitcoin and other cryptocurrencies to their peers (Borgards (2021), Cerqueti et al. (2020), Yi et al. (2018)) and other conventional financial markets such as equity, bond, commodity (Rehman and Kang (2021), Wang et al. (2019), Okorie and Lin (2020) and Corbet et al. (2021)). Also playing an important role in the crypto market, NFTs and DeFi recently received enormous attention from the media, regulators and investors. DeFi is recently considered as a technological evolution milestone in the world of global finance (Chohan (2021) and Zetzsche et al. (2020). Research on NFTs and Defi assets is at the initial steps of exploring (Aharon and Demir (2022) and Karim et al. (2022)) and analyzing their efficiency (Dowling (2022*a*), Dowling (2022*b*)) but growing recently. In particular, an increasing study documented the relationship between NFT and DeFi assets and conventional cryptocurrencies (Corbet et al. (2021) and Yousaf and Yarovaya (2022*a*)) and other conventional financial assets such as oil, gold, stock and fiat currencies (Yousaf and Ali (2020), Karim et al. (2022) and Aharon and Demir (2022)).

A single transaction of Bitcoin is estimated to have consumed about 1469.84 kWh [3] equivalent to the average US household power consumption in 50.38 days. Annualized Bitcoin electrical energy consumption is 132.57 TWh, comparable to Argentina's power consumption in a year. Jiang et al. (2021) also argues that 296.59 TWh are required to maintain the Bitcoin blockchain in 2024. Besides, the figures for Ethereum energy consumption estimated were still high. Each transaction of Ethereum consumes 215.06 kWh, equivalent to the U.S household power consumption in 7.27 days on average[4] In addition, the annualized electrical energy usage of Ethereum is estimated to be comparable to Finland's power consumption of 83.89 TWh. Not an exception, an NFT is estimated to use about 340 kWh of energy for the whole process from minting to bidding, then selling and transferring at the end. This power consumption is equivalent to one-third of the energy consumed by a US household in a month [5].

The scholars recently also highlighted the Bitcoin footprint on the environment and sustainability. For example, Mora et al. (2018) warned that global warming could live more than two degrees Celsius in thirty years, given the continuous Bitcoin trading. Di Febo et al. (2021) additionally provides evidence of significant Bitcoin impact on carbon allowances, especially in the lower quantiles. The necessity of eliminating mining activities and using PoW substitutes is precisely highlighted in Schinckus (2021). Indeed, using non-PoW and eco-friendly cryptoassets becomes à la mode (Ren and Lucey, 2022). Not stopping at the finance field, the PoW blockchain-based technology is now applied throughout the economic sectors (Schinckus (2021) and Pham et al. (2021)) such as Andoni et al. (2019), research and development activities (van der Waal et al., 2020), supply chain management (Saberi et al., 2019), social manufacturing (Leng et al., 2019) and e-commerce Yang et al. (2022).

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[3] According to `https://digiconomist.net/bitcoin-energy-consumption` on September 5, 2022

[4] `https://digiconomist.net/ethereum-energy-consumption/` on September 5, 2022.

[5] `https://cyberscrilla.com/how-much-energy-do-nfts-use/`

Studies on the dependence of cryptoassets on energy give different arguments. Starting with Ji et al. (2019), the study presents the unexpectedly weak connectedness between cryptocurrencies and energy. Still, their integration into the energy market, including natural gas, unleaded gas, and heating crude oil, is performed through static and dynamic entropy-based spillover tests. This relationship exists weakly but increasingly, as shown in Zeng et al. (2020). Okorie and Lin (2020) examine the volatility connectedness and hedging chance between crude oil and cryptocurrencies. It shows uni-directional and bi-directional connectedness between them, and crude oil can act as a hedging tool in cryptocurrency portfolios. In Jiang et al. (2022), the authors give further evidence of volatility transmission among Bitcoin, gold, equity, foreign exchange, and energy represented by crude oil and natural gas. Specifically, natural gas and the stock market act as volatility receivers while Bitcoin, gold, foreign exchange, and crude oil gas play transmitter role. This finding is partly in line with Rehman and Kang (2021) in which Bitcoin, crude oil, and natural gas is shown to have lead-lag linkage without the presence of coal, while the power in a big part of miners' origin, China, is mainly generated from coal. Indeed, Wang et al. (2019) presents that the dynamic correlation between Bitcoin and coal indices is increasing, especially around extreme mining points implemented in China. The correlation and volatility spillovers between cryptocurrencies and electricity markets are further investigated in Okorie (2021) and Corbet et al. (2021).

Closely to our study, some recent researchers have moved to focus on the co-movement between cryptocurrencies and clean energy markets. Particularly, from starting point of energy consumption amount, Corbet et al. (2021) examine how prices and mining characteristics of Bitcoin affected the energy market, utility companies, and green ETFs. It shows that Bitcoin volatility has great effects on the energy market, including fossil fuels and clean energy stock, confirmed before by Symitsi and Chalvatzis (2018); but no evidence of significant volatility linkage between Bitcoin and the largest green ETFs markets. Naeem and Karim (2021) also indicates the results of no tail dependence between Bitcoin and clean energy after testing time-varying copula to analyze the extreme dependence between Bitcoin and green financial assets. The result is concluded by the possibility that clean energy can be a hedging instrument for Bitcoin in the portfolio. Pham et al. (2021) further hypothesizes that green investments could be diversification tools for cryptocurrencies in the non-crisis period, given the weak connectedness between Bitcoin, Ethereum, and green assets. Our research supplements to Pham et al. (2022) when adding coal to energy markets to see their co-movement and extend the cryptoasset group to NFT and Defi, which is only studied in Yousaf and Ali (2020).

3. Methodology

As discussed, the strong dependence on cryptoassets and energy may eventually lead to a time variation in the observable effects of energy price shocks on the cryptoassets. As such, the constant parameter or sub-sample VAR method might not be sufficient to capture the dynamic correlation among the variables. We investigate the time-varying co-movement between cryptoassets and energy by estimating the TVP-VAR model developed by utilizing Primiceri (2005). This model allows for time-varying coefficients and the variance-covariance matrices. We first evaluate the time-varying parameter VAR model as defined following:

$$y_t = c_t + B_1 y_{t-1} + ... + B_s y_{t-s} + v_t \tag{1}$$

where y_t is a k x 1 vector of each sample variable i; $B_{i,t}$ are matrices of k x k of time-varying coefficients; c_1 is a vector of intercept and v_t is innovation covariance matrix of k x 1. Following Farooq Akram and Mumtaz (2019), all variable data is HP-filtered and lag length is fixed at $s = 2$ in the interest of parsimony. We premise the coefficients models as:

$$\tilde{\phi}_{s,t} = \tilde{\phi}_{s,t-1} + \eta_t \tag{2}$$

where $\tilde{\phi}_{s,t} = \{vec(c_t), vec(B_{i,t})\}$ provides the time-varying coefficient vector and η_t is the conformable innovation vector.

As in Primiceri (2005), v_t is assumed to be normally distributed with zero mean, heteroskedastic disturbance term and time-varying variance-covariance matrix Ω_t.

$$VAR(v_t) \equiv \Omega_t = A_t^{-1} H_t (A_t^{-1})' \tag{3}$$

Where A_t is lower triangular, measuring the simultaneous relationships among the observed variables. H_t is a matrix $diag(h_{1,t}, h_{2,t}..., h_{N,t})$. h_t is considered an independent geometric random walk.

$$\ln h_{i,t} = \ln h_{i,t-1} + \tilde{v}_t \tag{4}$$

According to Primiceri (2005) matrix A_t is postulated with non-zero and non-one constituents following random walk processes.

$$\alpha_t = \alpha_{t-1} + \tau_t \tag{5}$$

Vector $[v_t', \eta_t', \tau_t, \tilde{v}_t']$ is assumed to be distributed as:

$$\begin{bmatrix} v_t \\ \eta_t \\ \tau_t \\ \tilde{v}_t \end{bmatrix} \sim N(0, V), \text{with } V = \begin{bmatrix} \Omega_t & 0 & 0 & 0 \\ 0 & Q & 0 & 0 \\ 0 & 0 & S & 0 \\ 0 & 0 & 0 & G \end{bmatrix} \text{ and } G = \begin{bmatrix} \sigma_1^2 & 0 & 0 & 0 & 0 \\ 0 & \sigma_2^2 & 0 & 0 & 0 \\ 0 & 0 & \sigma_3^2 & 0 & 0 \\ 0 & 0 & 0 & \sigma_4^2 & 0 \\ 0 & 0 & 0 & 0 & \sigma_5^2 \end{bmatrix} \tag{6}$$

Next, we examine the time-varying trend of each variable by estimating their time-varying unconditional means. Equation 1 can be stacked as:

$$Y_t = \mu_t + F_t Y_{t-1} + V_t \tag{7}$$
$$VAR(V_t) = \Omega_t^*$$

where μ_t are VAR intercepts, F_t are the coefficients, and Ω_t^* is error covariance. The time-varying unconditional mean is estimated as:

$$E(Y_t) = e_N (I - F_t)^{-1} \mu_t \tag{8}$$

where N is the number of first elements of $E(Y_t)$ picked out to matrix e_N.

Then the spectral density matrix of each variable is investigated at time t as:

$$\hat{f_t(}\omega = (I - F_t^{-i\omega})^{-1} \frac{\Omega_t^*}{2\pi} [(I - F_t^{-i\omega})^{-1}], \tag{9}$$

Where ω represents the frequency. This spectral density matrix can describe the relationship between variables at different frequency levels ω. We also follow Croux et al. (2001) method to measure the dynamic correlations between variable i and j at the frequency ω as:

$$\frac{\hat{c}_{ij}(\omega)}{\sqrt{\hat{f}_t^{ii}(\omega)\hat{f}_t^{jj}(\omega)}}, \tag{10}$$

where $\hat{c}_{ij}(\omega)$ is the co-spectrum between two variables i and j at ω frequency. These dynamic correlations vary in range from -1 to 1. At the dynamic correlation level of 1, two series i and j are completely synchronized at the frequency ω.

4. Data and Estimation

4.1. Cryptocurrencies, NFTs and DeFi assets

For study purposes, we collect cryptocurrency, NFTs, and Defi assets representatives from `https://coinmetrics.io`. We select the cryptoassets whose data time series is longer to investigate the long-run comovement. Bitcoin (BTC) and Ethereum (ETH), the two most popular PoW blockchain-based implementations, are selected to represent the cryptocurrency group. In 2009, Bitcoin was first introduced by Satoshi Nakamoto with the idea of the Proof of Work (PoW) as a technical blockchain background (Nakamoto, 2008). This consensus creates a cross-border system for transferring value among the parties without centralized authorities. In other words, blockchain can be understood as a new way to combine network and database organization where the information is not stored in a center but through the network. All pieces of information and updates are recorded in the distributed ledger, and all nodes in the network can reach them. Therefore, blockchain can offer two features, transparency and traceability. When a new node block is added to the distributed ledger, associated cryptographic puzzles will be generated and shared with all computer nodes, who compete to solve them and gain a small amount of Bitcoin, along with transaction fee rewards. The computer node winner is called a miner. As more and more new blocks were added, the mining activity became more complex and consumed much more power. With the idea of wasting less energy and allowing significant transactions, Ethereum was later born with alternative technology of PoW called Proof of Stake (PoS). The PoS algorithm consumes less computational power because a new information block is randomly chosen to add to the distributed ledger instead of accepting all large transactions.

Non-fungible token (NFT) is a non-interchangeable digital asset. The main characteristic making them different from cryptocurrencies is non-fungibility. Bitcoin is fungible, meaning that one Bitcoin is the same as and interchangeable with another existing Bitcoin. The most popular NFTs are collectibles, artworks, virtual objects, and digitalized characters found in games and sports. With the same idea of eliminating the intermediaries in every single financial transaction, Decentralized finance (DeFi) is created based on a blockchain network and smart contracts where financial services and products are decentralized. Following Yousaf and Yarovaya (2022*b*) and Yousaf et al. (2022) we choose, Decentraland (MANA) and Digibyte (DGB), Chainlink (LINK), and Maker (MKR) to represent for NFT and DeFi asset group.

Next, daily oil, coal, natural gas, and renewable prices are collected from Refinitiv presented by WTI Crude Oil Spot (USD/Barrel)[6], Coal Intercontinental Exchange(ICE) (USD/Metric Tonne), Natural Gas (USD), and Global Renewable Energy (USD), respectively.

Table 1: Descriptive statistics of the cryptoasset and energy prices

Variable	Code	Time series	Obs	Mean	Std. Dev.	Min	Max
Bitcoin	BTC	2010 - 2022	4429	8332.271	14603.380	0.051	67541.760
Ethereum	ETH	2012 - 2022	2582	780.809	1125.490	0.420	4811.156
Digibyte	DGB	2015 - 2022	2761	0.019	0.023	0.000	0.158
Decentraland	MANA	2012 - 2022	1834	0.516	0.897	0.009	5.185
Chainlink	LINK	2017 - 2022	1799	8.950	10.659	0.147	51.747
Maker	MKR	2017 - 2022	1711	1186.256	997.503	201.066	6066.121
Oil	OIL	2012 - 2022	2584	65.742	22.858	-37.630	123.700
Coal	COAL	2012 - 2022	2584	91.176	65.843	38.450	439.000
Natural Gas	NG	2012 - 2022	2584	333.176	30.527	235.840	391.230
Renewable Energy	RE	2012 - 2022	2584	70.460	44.045	18.060	229.520

Descriptive statistics of the price series are presented in Table 1 while Figure 1 and 2 provide the daily prices of all cryptoasset and energy prices. Each variable's time span differs; the Bitcoin

[6] Crude Oil-West Intermediate Spot Prices

series is the longest, from 2010 to 2022, with 4429 observations. Chainlink and Maker have the smallest time length, just since 2017, with 1799 and 1711 observations, respectively. It can be seen that among cryptoassets, Bitcoin, Ethereum, and Maker have the much higher mean and standard deviation than others. In particular, Maker owns the highest minimum price of over USD 201, while the lowest prices of other cryptoassets are all less than USD 1, especially, Digibyte, with nearly zero price. However, Bitcoin always takes the lead with the highest maximum price, over USD 67541, so its average price and standard deviation are the highest compared to the others.

4.2. Correlation matrix

Table 2: Correlation matrix of all variables

	BTC	**ETH**	**DGB**	**MANA**	**LINK**	**MKR**	**Oil**	**Coal**	**NG**	**RE**
BTC	1									
	4429									
ETH	0.9381*	1								
	2582	2582								
DGB	0.7340*	0.6535*	1							
	2761	2582	2761							
MANA	0.7396*	0.8492*	0.2960*	1						
	1834	1834	1834	1834						
LINK	0.9219*	0.8156*	0.7145*	0.5767*	1					
	1799	1799	1799	1799	1799					
MKR	0.8787*	0.8786*	0.7935*	0.6245*	0.8820*	1				
	1711	1711	1711	1711	1711	1711				
Oil	0.1418*	0.6461*	0.3109*	0.5742*	0.2254*	0.3903*	1			
	2584	1844	1973	1310	1285	1223	2584			
Coal	0.4997*	0.5843*	0.1544*	0.5251*	0.1996*	0.2852*	0.5257*	1		
	2584	1844	1973	1310	1285	1223	2584	2584		
NG	0.4901*	0.4792*	0.5219*	0.2229*	0.2333*	0.4107*	0.3447*	0.3045*	1	
	2584	1844	1973	1310	1285	1223	2584	2584	2584	
RE	0.8844*	0.7710*	0.5879*	0.5175*	0.8668*	0.6885*	-0.0052	0.4187*	0.3895*	1
	2584	1844	1973	1310	1285	1223	2584	2584	2584	2584

Note: The numbers below each line in the table is the number of observation. * represents 5% significant levels. BTC, ETH, DGB, MANA, LINK, MKR, Oil, Coal, NG and RE denote Bitcoin, Ethereum, Digibyte, Decentraland, Chainlink, Maker, Oil, Natural gas and Renewable Energy.

Before investigating the dynamic correlation among the cryptoassets and energy markets, we check their pairwise correlation matrix as shown in table 2. At the 5% significant level, all cryptoasset - energy are positively correlated. Specifically, the correlation between Bitcoin and renewable energy is strongest at 0.8844, followed by Chainlink and Renewable pairwise. Additionally, the cryptocurrency group has stronger correlations with energy markets than NFT and DeFi groups. Moreover, the correlations between renewable energy and cryptoassets are stronger than fossil fuels.

5. Results

5.1. Estimation and Unconditional mean

We follow the Seemingly Unrelated Regression (SUR) model constituting all equations 1 - 6. Following Chib and Greenberg (1995), we use the Bayesian methods and Gibbs sampling algorithm to estimate the posterior distribution. We first estimate the initial values of parameters as shown in table 3. All posterior mean values of parameters $\beta_{t,i}$ and $h_{t,i}$ are within the confidence interval. f_t provides the spectral density level of all variables.

Table 3: TVP-VAR model estimation results

Variables	**BTC**	**ETH**	**MANA**	**DGB**	**LINK**	**MKR**	**Oil**	**Coal**	**NG**	**RE**
Time-varying coefficients										
Parameters	$\beta_{t,1}$	$\beta_{t,2}$	$\beta_{t,3}$	$\beta_{t,4}$	$\beta_{t,5}$	$\beta_{t,6}$	$\beta_{t,7}$	$\beta_{t,8}$	$\beta_{t,9}$	$\beta_{t,10}$
Posterior mean	0.784	0.072	0.312	0.021	0.835	0.074	0.088	0.01	0.066	0.106
Stdev	0.01	0.014	0.094	0.038	0.132	0.108	0.075	0.125	0.025	0.017
95%D	0.784	0.071	0.308	0.019	0.829	0.069	0.085	0.005	0.065	0.105
95%U	0.784	0.073	0.316	0.023	0.841	0.079	0.091	0.015	0.067	0.107
Independent geometric random walks										
Parameters	$h_{t,1}$	$h_{t,2}$	$h_{t,3}$	$h_{t,4}$	$h_{t,5}$	$h_{t,6}$	$h_{t,7}$	$h_{t,8}$	$h_{t,9}$	$h_{t,10}$
Posterior mean	1.688	1.9	1.998	5.293	3.655	3.548	1.158	0.908	0.901	0.971
Stdev	0.492	0.727	1.065	1.075	0.527	0.251	0.536	0.503	0.06	0.009
95%D	1.674	1.872	1.958	5.244	3.631	3.536	1.137	0.889	0.899	0.971
95%U	1.702	1.928	2.038	5.342	3.679	3.560	1.179	0.927	0.903	0.971
Density										
Parameters	f_t									
Posterior mean	0.01									
Stdev	0.014									

Note: Stdev stands for the standard deviation. BTC, ETH, DGB, MANA, LINK, MKR, Oil, Coal, NG and RE denote Bitcoin, Ethereum, Digibyte, Decentraland, Chainlink, Maker, Oil, Natural gas and Renewable Energy.

Figure 3 and 4 provide the unconditional mean estimation of each cryptoasset price series following 8. Except for Chainlink, the figures present that the estimated long-run mean of cryptoasset seems to have no change throughout the period despite big structural changes in actual blue line prices. Chainlink's estimated means show a depreciation over time but are always positive. In the meantime, the figures also indicate that the estimated means of Bitcoin, Digibyte, and Decentraland are close to zero over the estimation period.

5.2. Dynamic Correlations

Figures 5, 6 and 7 shows the estimation of the dynamic correlation of each cryptoasset group to each energy type at the long-run frequency. This long-run comovement can provide insights on potential structural shifts and account for high-frequency erratic movements in the data. Generally, all cryptoasset groups correlate with both fossil fuels, in line with the conclusion of Corbet et al. (2021), Symitsi and Chalvatzis (2018) and Pham et al. (2022) even though the posterior median correlation between NFTs with energy prices is quite small and not statistically significant. We also find that the cryptocurrency group, represented by Bitcoin and Ethereum, strongly correlates with renewable energy prices against weak connectedness evidence in Naeem and Karim (2021) and Pham et al. (2021). The correlations between renewable energy, NFTs, and DeFi assets are not statistically significant except for Marker.

In addition, the figures show structural shifts in the period 2018-2019. The correlation between Bitcoin and Oil decreased suddenly from late 2018 to early 2019. At that time, the Bitcoin - natural gas Bitcoin - Natural got a peak while Bitcoin - renewable energy correlation hit its bottom. The movement in the correlations of Ethereum and Energy fluctuated in 2018-2019 while remaining stable for the remaining time. The highest value of Digibyte correlations is also found in 2019 between Digibyte and fossil fuels, including oil and natural gas, between Chainlink and coal and between Maker and oil. The findings can be explained by the events of the switch to the blockchain of China, Libra's introduction, Trump's tweet, and the explosive rise of Decentralized Finance (DeFi) with a big name MakeDAO whose governance token is Maker. In 2021, given the highlight event of banning mining activities in China, we can see the close-to-zero correlations between Bitcoin and coal, Bitcoin and natural gas but not with oil and renewable energy. Indeed, in May 2021, Bitcoin mining still grabbed over 21‰ the total hash rate in the world and made China the second mining hub despite the ban[7].

[7]See `https://www.bloomberg.com/news/articles/2022-05-17/`

In figure 5, it can be seen that the correlation between cryptocurrencies with fossil fuels and renewable energy is different between Bitcoin and Ethereum. The correlation of renewable energy is negative with Bitcoin but positive with Ethereum. All remaining cryptocurrency-energy correlations are positive. Specifically, a relatively stable and positive correlation was seen in the relationship between Bitcoin and crude oil, except for a slight reduction in the first half of 2018. The pairwise correlation of Bitcoin - natural gas is coincidentally the same as Bitcoin - renewable energy but in a different direction. The correlation between Bitcoin and natural gas did not exhibit from 2012 to 2014, then gradually climbed to a peak at 0.8 in 2019 before falling to zero in late 2021. However, the correlation value was positive over time. Reversely, the median correlation between Bitcoin and the Renewable Energy price index remained negative throughout the observed time. It kept stable in 2012 - 2015, then increased its strength to peak at nearly -0.6 in 2019 and slightly increased afterward. Regarding the second cryptocurrency, Ethereum, the observed results are surprisingly different. Generally, the correlation between Ethereum with all energy-type prices was relatively stable and positive in the 2015 - 2022 period. The median correlation between Ethereum, coal and natural gas was small and not statistically significant. The pairwise correlation of the Ethereum - crude oil and Ethereum - renewable energy index was around 0.4 and almost stable. In 2018, the correlation between Ethereum and renewable energy prices faintly declined, which was also found in Bitcoin - renewable energy.

Moving focus on the NFT group, in figure 6, it can be seen that the correlation patterns are not the same between Digibyte and Decentraland. The first impression is that almost the posterior median of the correlation between Digibyte and Decentraland and energy prices were pretty small and not statistically significant. It is surprising in contrast to the fact that NFT operation could consume tremendous energy, as mentioned in 2, so their correlation should eventually be strong. However, that may depend on which algorithm was employed to mint an NFT. Notably, despite being an utterly PoW blockchain, Digibyte can be mined with five separate mining algorithms,

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`china-makes-a-comeback-in-bitcoin-mining-despite-government-ban?leadSource=uverify%20wall` including Sha256, Scrypt, Skein, Qubit, and Odocrypt[8] so it may consume energy less than 814 times than Bitcoin[9]. Unlike Digibyte, as folk of Bitcoin, Decentraland is based on Ethereum utilizing Proof of Stake (PoS), where transaction validation only depends on certain trusted users instead of all computational nodes in PoW. It, therefore, can limit mining activities. Next, the correlation between Digibyte, Decentraland, and fossil fuel energy prices had relatively the same strength but different signs. The Digibyte prices negatively correlated to coal and crude oil, while these results were recorded positively with Decentraland. The peaks of Digibyte - crude oil, Digibyte - natural gas, and Decentraland - crude oil were found in 2019 at -0.3, 0.4, and 0.2, respectively. Third, we observe that the correlation between these two NFT assets with energy prices tentatively increased throughout the time, especially after 2021. That can be explained that NFTs got a huge of attention, "from a sub-billion-dollar market to a multi-decabillion industry" in 2021[10].

Figure 7 shows that the correlation between Chainlink and coal has decreased by about 0.1 since 2019. Until then, its correlation slightly increased in the 2017-2019 period and peaked at 0.6 in 2019. Meanwhile, other correlations with other types of energy gradually decreased before climbing and stabilizing from late 2018 to date. The median correlation between LINK and renewable energy prices was around zero, giving us the idea of no relationship between LINK trading with the renewable energy index. On the other hand, different from Chainlink, Maker seemed to be significantly correlated with oil and renewable energy. These correlations were steady and high over the period 2017 - 2022. The main difference between Chainlink and Maker is the based blockchain technology. Chainlink is a blockchain platform connecting smart contracts universally by utilizing Oracles. Oracle's technology makes Chainlink unique as allowing the integration of on/off-chain smart contracts [11]. Maker blockchain is based on Ethereum, so by coincidence, Maker prices are more correlated with oil than coal. These findings are also observed with Ethereum and

[8]See `https://digibyte.org/#blockchain`

[9]Estimated by `https://josiah-digibyte.medium.com/how-green-is-digibyte-6e2ad24a6308`

[10]See `https://www.ft.com/content/e95f5ac2-0476-41f4-abd4-8a99faa7737d`

[11]See `https://blog.chain.link/blockchains-and-oracles-are-redefining-the-energy-industry/`

Ethereum blockchain-based cryptoasset, Decentraland.

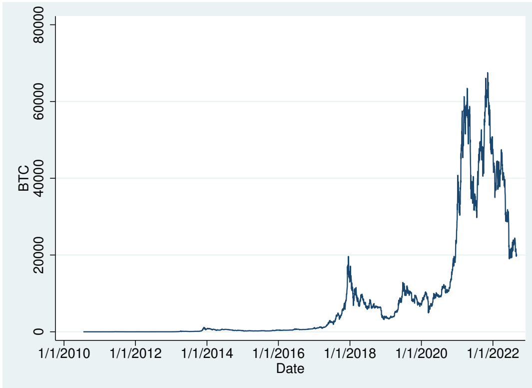
Last, we also find evidence that the median correlation values of cryptoassets with renewable energy are higher than fossil fuels. In the fossil fuel group, except for Bitcoin, natural gas seems not to be the user choice of blockchain operation as its correlations with the cryptoasset are poorly estimated, given the non-significant results. The correlation of renewable energy with Bitcoin is -0.6 while Ethereum, Decentraland, Chainlink, and Marker are about 0.4. This could imply two findings. First, the correlations are transitioning from fossil fuel to clean energy, given the higher values. Second, cryptoassets could act as either hedging or diversification tools for the renewable energy market thanks to the different correlation directions between Bitcoin - renewable energy and other cryptoassets with renewable energy.

6. Conclusion

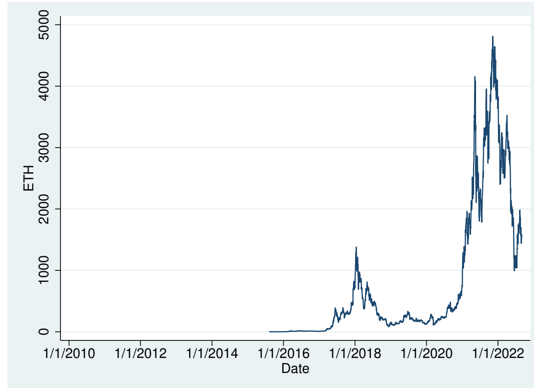
This study investigates the time-varying dynamic correlations of cryptocurrencies, NFTs, DeFi assets, and energy markets. We analyze each pairwise cryptoasset-energy to see how the co-movements shift through time. The observation time varies according to each pairwise. Using Bitcoin and Ethereum, Digibyte and Decentraland, Chainlink and Maker, besides the objective of collecting the most extended sample time length, we expect that the findings could be implied for cryptocurrencies, NFT, and DeFi groups because of their significant market capitalization percentage. Regarding the energy group, we choose oil, coal, and natural gas as representatives of the fossil fuel group and renewable energy price index standing for clean energy type.

This paper contributes to the existing co-movement literature between cryptoassets and energy markets in some following points. First, supporting previous authors, we shed light on the strong correlation between all cryptoassets, including cryptocurrencies, NFTs, and DeFi assets, with fossil fuels, especially oil and coal. However, only cryptocurrencies give evidence of correlating with renewable energy. Second, the ban on mining activities does not affect the correlation between cryptoassets and energy markets, as the estimated values remained stable in 2021. Third, having a strong correlation with fossil fuels, but the Bitcoin, Ethereum, and Ethereum-based cryptoasset highly correlate with oil rather than coal. Next, the correlation relationship between cryptoassets and energy markets may vary due to the difference in technology base that affects the mining activities. Last, we highlight a transition from "dirty" to "clean" energy, given the correlation values of renewable energy and cryptoassets in both statistical and time-varying dynamic estimation are increasing and higher than other energy types.

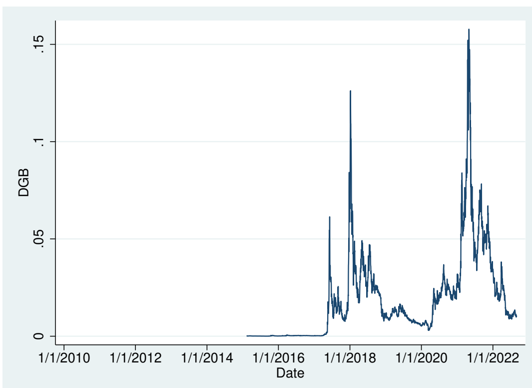
With the above findings, this paper can have specific implications for investors and policy-makers with environmental sustainability consciousness. In particular, provided negative correlation values over the sample period, Bitcoin can be selected as a hedging asset for the renewable energy index, while Ethereum and Maker can be diversification candidates. Digibyte and Decentraland can be safe haven assets as non-significant results are found. However, the effect of hedging, diversification, and haven is not yet studied in this paper, which may inspire an idea for future research to give better implications for investment strategy. As correlations between cryptoassets and fossil fuels are still high over the period despite the bans in various countries, the policy may care more about mining technology-based to have a more accommodative policy to limit the carbon footprint of crypto markets.



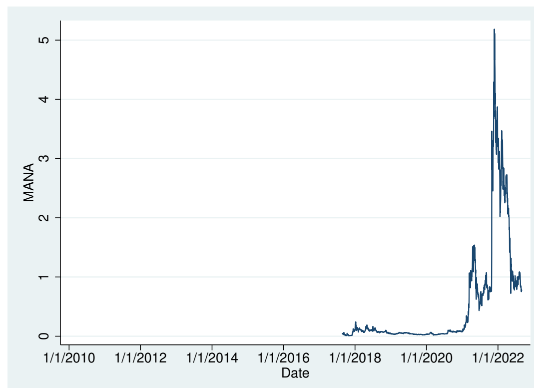
(a) Bitcoin



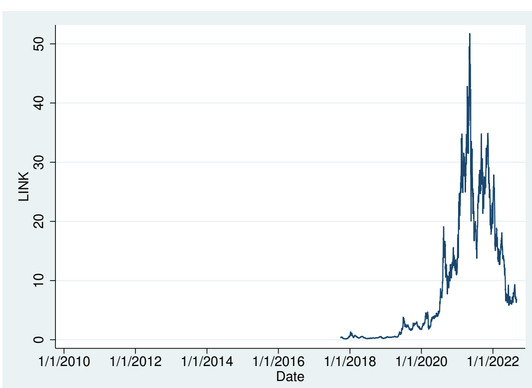
(b) Ethereum



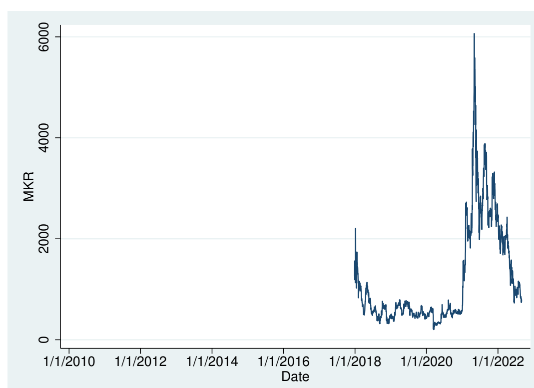
(c) Digibyte



(d) Decentraland



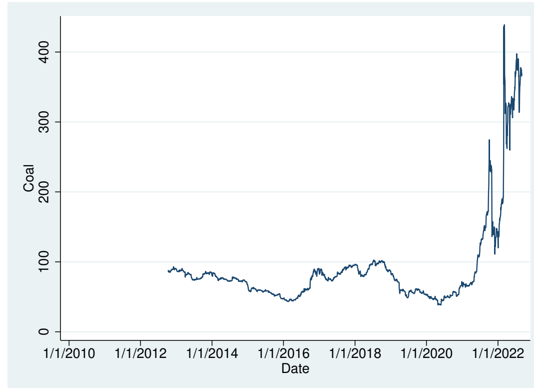
(e) Chainlink



(f) Maker

Figure 1: Daily prices of cryptoassets

(a) Oil

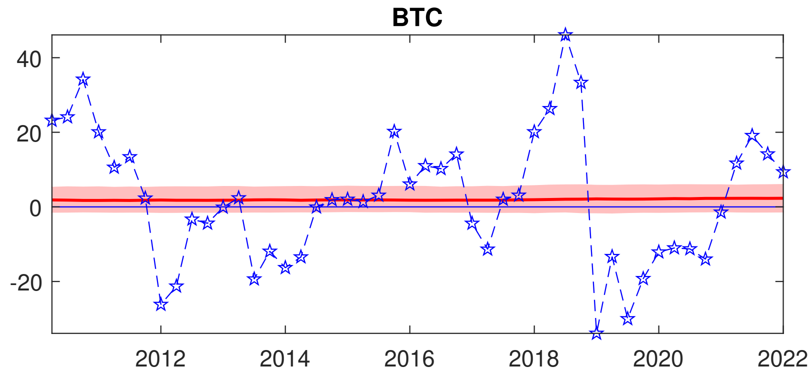


(b) Coal

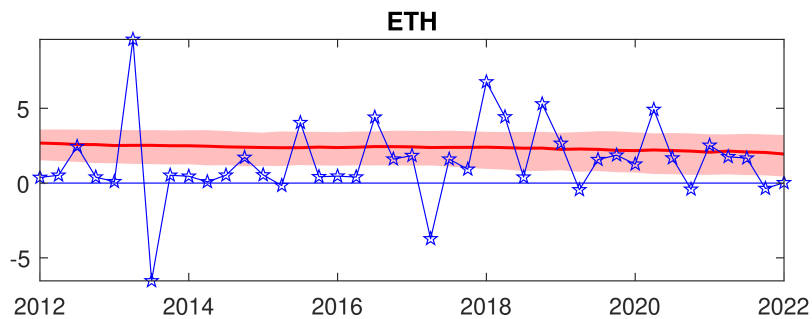
(c) Natural Gas

(d) Renewable Energy

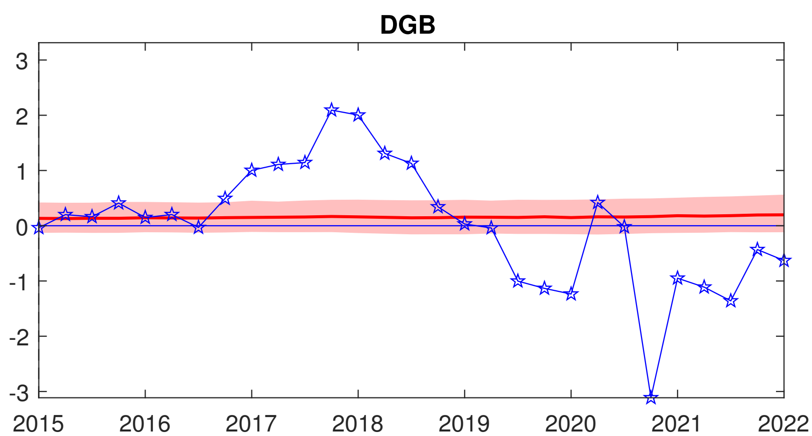
Figure 2: Daily prices of energy



(a) Bitcoin

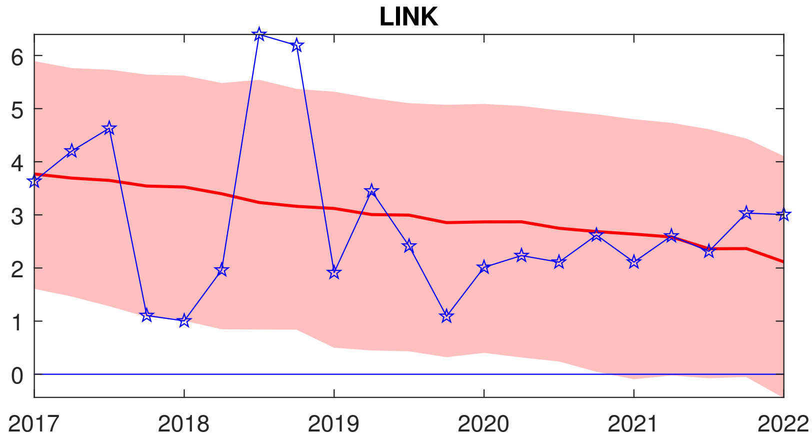


(b) Ethereum

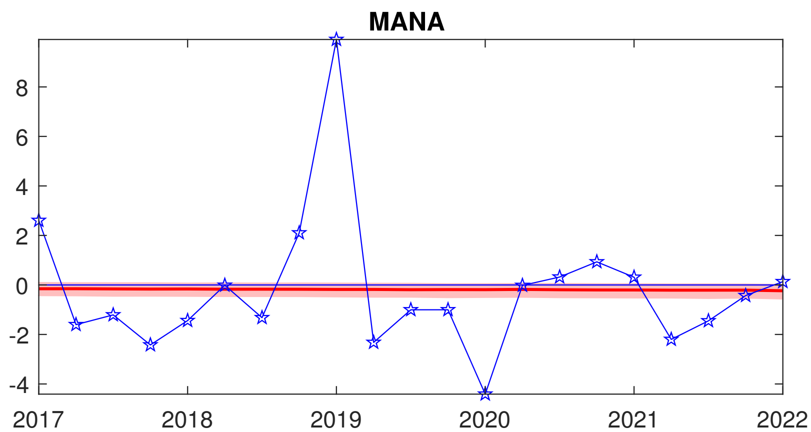


(c) Digibyte

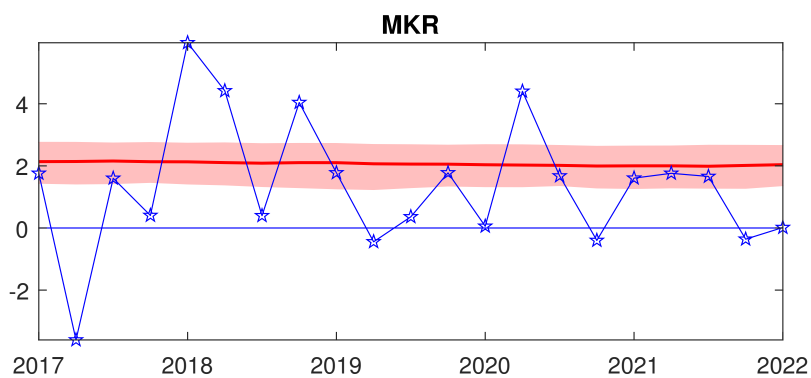
Figure 3: Time-varying unconditional means of cryptoassets and actual data (blue line). The red line shows the estimated posterior median, and the shaded areas indicate the 68% error bands.



(a) Decentraland

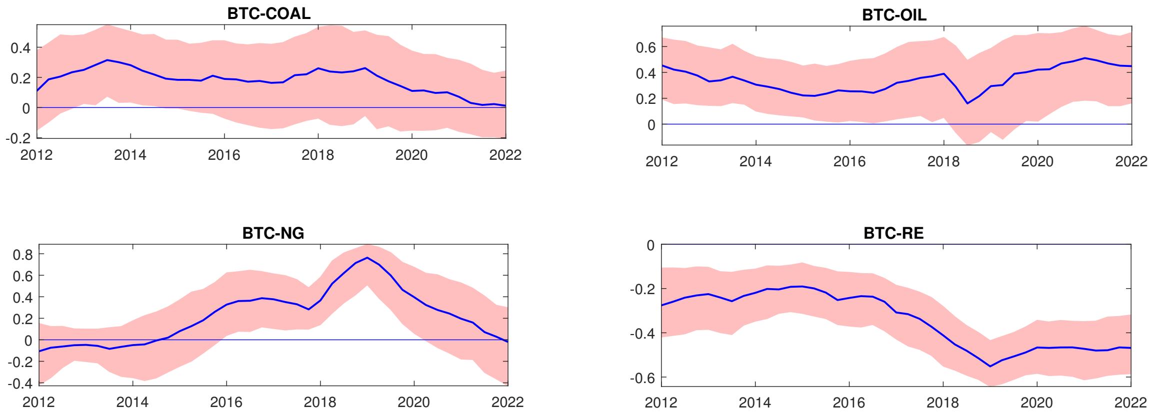


(b) Chainlink

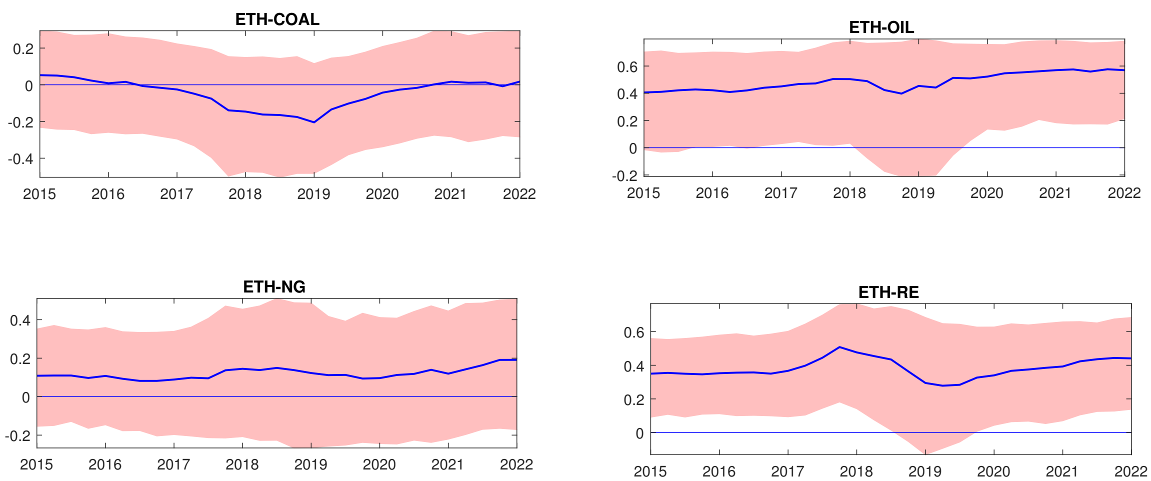


(c) Maker

Figure 4: Time-varying unconditional means of cryptoassets and actual data (blue line). The red line shows the estimated posterior median, and the shaded areas indicate the 68% error bands.



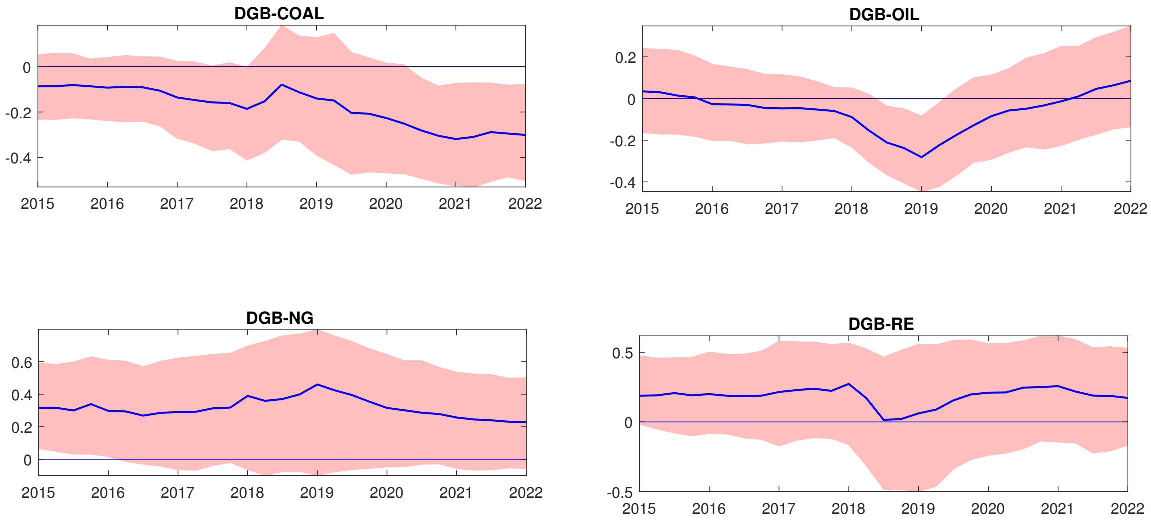
(a) Bitcoin



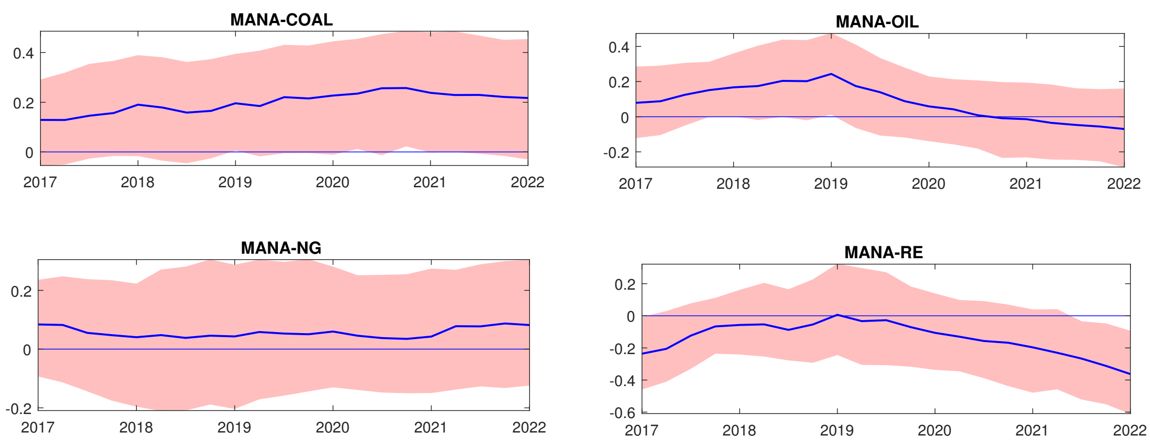
(b) Ethereum

Figure 5: Dynamic Correlations at the frequency zero. The solid lines show the median estimates, and the shaded regions represent the 68% error bands.

Note: BTC, ETH, DGB, MANA, LINK, MKR, Oil, Coal, NG and RE denote Bitcoin, Ethereum, Digibyte, Decentraland, Chainlink, Maker, Oil, Natural gas and Renewable Energy.



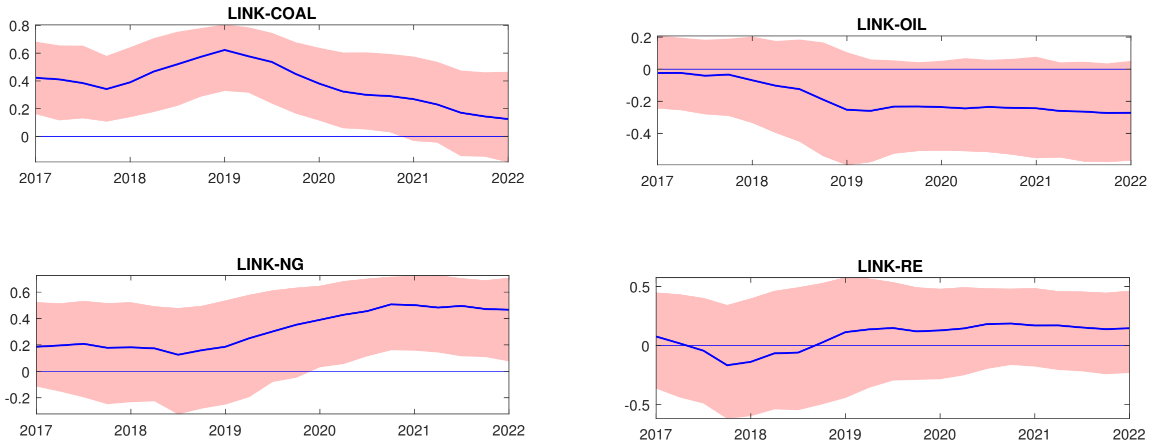
(a) Digibyte



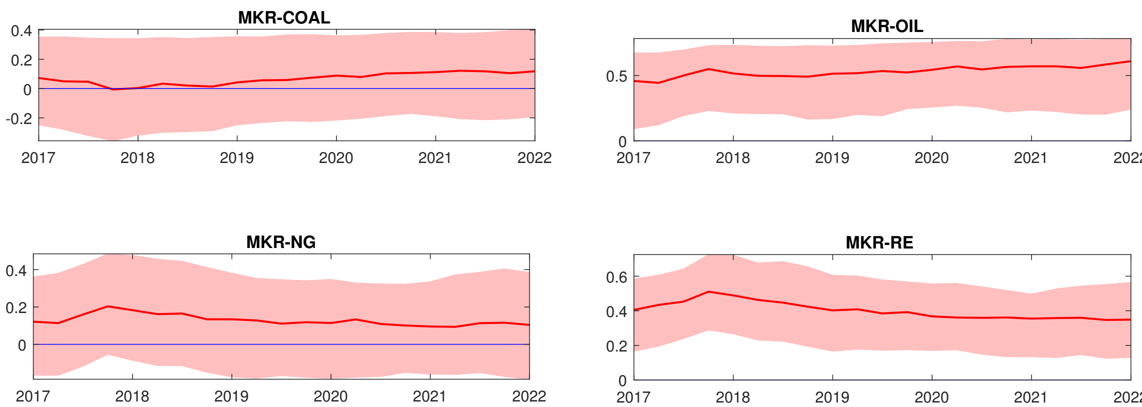
(b) Decentraland

Figure 6: Dynamic Correlations at the frequency zero. The solid lines show the median estimates and the shaded regions represent the 68% error bands.

Note: BTC, ETH, DGB, MANA, LINK, MKR, Oil, Coal, NG and RE denote Bitcoin, Ethereum, Digibyte, Decentraland, Chainlink, Maker, Oil, Natural gas and Renewable Energy.



(a) Chainlink



(b) Maker

Figure 7: Dynamic Correlations at the frequency zero. The solid lines show the median estimates, and the shaded regions represent the 68% error bands.

Note: BTC, ETH, DGB, MANA, LINK, MKR, Oil, Coal, NG and RE denote Bitcoin, Ethereum, Digibyte, Decentraland, Chainlink, Maker, Oil, Natural gas and Renewable Energy.

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