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Do clean and dirty cryptocurrencies connect with financial assets differently? The role of economic policy uncertainty

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ABSTRACT

This paper analyzes time-varying networks of clean and dirty cryptocurrencies with green and traditional assets through a dynamic connectedness approach established by the time-varying parameter vector autoregressive (TVP-VAR) model. The underlying asymmetry of the dynamic pairwise connectedness when facing uncertainty shocks is further studied through a non-parametric quantile causality method. Our results demonstrate a limited information transmission of volatility from cryptocurrencies to both traditional and green assets, while the connection of clean cryptocurrencies (CI) with the financial system is even weaker compared to that of dirty cryptocurrencies (DI), especially after the COVID-19 pandemic. In contrast, connection within the financial system is found to be relatively closer. Moreover, causal relationships between economic policy uncertainty (EPU) and cryptocurrency-financial asset linkages are generally enhanced after the pandemic onset, while such the causality of uncertainty with DI related asset linkages tends to be even stronger. Most of the above causalities are shown to be negligible during market depression, further implying the sheltering role of the market linkages against uncertainty.

1. Introduction

Since the introduction of the first cryptocurrency, Bitcoin, there has been a rapid growth in the size and number of cryptocurrencies given their promising independence from political and economic unrest of Sovereign nations and ability to serve as an underlying investment shelter for financial markets. Despite economic benefits, conventional cryptocurrencies built on Proof-of-Work (PoW) algorithms feature heavy carbon footprints due to massive energy consumption for mining and trading activities, leading to widespread attention to their environmental impact in terms of global warming (Corbet and Yarovaya, 2020). Due to complex and heavy PoW algorithms, the estimated annualized electrical energy usage of Bitcoin has now reached 204.5 TWh, being comparable to the power consumption of Argentina.[1] The urgency of reducing and/or replacing energy-intensive cryptocurrencies to environmentally-friendly ones has been recently highlighted by the general public (Schinckus, 2021). Accordingly, relatively cleaner cryptocurrencies built on energy-efficient algorithms involving Proof-of-Stake (PoS), Ripple Protocol, and Stellar Protocol etc (Ren and Lucey, 2022) have experienced ongoing development, contributing to low-carbon transition of the cryptocurrency market. At the same time, to combat global warming, green assets have also raised widespread attention against traditional assets, shaping a promising direction for financial market development (Naeem and Karim, 2021).[2]

Moreover, with rising popularity and volumes of cryptocurrency trading over time, there are emerging exposures of investment portfolios to cryptocurrency-related products (Conlon et al., 2020). The dynamics of cryptocurrencies and its connection with the financial system have therefore attracted heated discussion, while no consensus has been reached by far.[3] On the one hand, widespread adoption of cryptocurrency-related products in financial investments could strengthen such the connection (Elsayed et al., 2022). On the other hand, cryptocurrencies are known to perform a weak or even negative

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[1] Data are sourced from https://digiconomist.net/bitcoin-energy-consumption on 10 June 2022.

[2] According to the IMF, ESG-related debt issuance more than tripled to $190 billion in 2021.(Data source: https://blogs.imf.org/2022/03/01/sustainable-finance-in-emerging-markets-is-enjoying-rapid-growth-but-may-bring-risks/).

[3] See a detail discussion of the extant literature in Section of Literature Review. An intuitive summary of the related key literature is further summarized in Appendix B.

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linkage with financial assets due to the investment sheltering role of the former (Huang et al., 2021; Bouri et al., 2020). Moreover, several important questions also remain to be answered. Whether and how do energy-intensive (dirty) cryptocurrencies and energy-efficient (clean) cryptocurrencies connect with financial assets differently? How do the above connections differ for different asset types, i.e., traditional and green assets? Whether and how would these cross-market connections be altered in the face of various uncertainty degrees and the COVID-19 pandemic?

Against the above backdrop, our paper fills the gap by studying the dynamic and bi-directional market networks in volatility of clean cryptocurrencies (CI) and dirty cryptocurrencies (DI) with traditional and green assets over time by using a time-varying parameter vector autoregressive (TVP-VAR) framework. The asymmetric and non-linear causal relationship between the above-obtained various market networks and uncertainty is further examined using a non-parametric causality test. In addition, the potential changes of the market networks and the role of uncertainty are investigated when facing the COVID-19 pandemic shock. In terms of the target variables, CI and DI are two value-weighted market indices that are constructed based on major clean and dirty cryptocurrencies, respectively, following Ren and Lucey (2022). Four major stock indices including S&P500 Index (SP500), Financial Times Stock Exchange 100 Index (FTSE), Toronto Stock Exchange Index (TSX), and Australian Securities Exchange Index (ASX) are identified as traditional assets, while green assets are represented by four leading indices of Dow Jones Sustainability World Index (SWI), S&P ESG Leader Index (ESGLI), S&P Green Bond Index (GBI), and S&P Global Clean Energy Index (GCEI), in spite of the extant literature (e.g., Huang et al., 2021, 2023). Our sample period spans from 01 March 2018 to 31 March 2022, wherein the whole sample are split as sub-samples of before and after the pandemic onset, being in line with the existing studies (see, e.g., Goodell and Goutte, 2021; Huang et al., 2021).

Our paper contributes to the existing research in the following aspects. Unlike missing the fact that cryptocurrencies can be energy-intensive or -efficient, we provide an in-depth comparison on the underlying different linkages of clean and dirty cryptocurrencies with financial assets. Our research is among the firsts to analyze the dynamic differential linkages of clean and dirty digital currencies with green and traditional assets, contributing to not only enhanced understanding of the above cross-market spillover but also low-carbon transition of the economic and financial system. In addition, we further extend the literature by analyzing the causal relationship between the above built spillover networks and uncertainty in the economy in a non-linear setting. Through this, whether and how would the linkages of cryptocurrencies and financial assets be affected by changing uncertainties over the data distribution can be captured. Moreover, our employed time-varying parameter (TVP) VAR model advances the traditional DY-type of connectedness approach proposed by Diebold and Yılmaz (2012, 2014) by better accommodating underlying time variations of the cross-market spillover. That is, rather than relying on the rolling window approach to allow for the time-varying spillover, our employed TVP-VAR method is known to well capture the potential time variation of the spillover.

Noteworthy, while there exists similar research (e.g., Ren and Lucey, 2022) to ours, we are different from it in the following main aspects. First, rather than only focusing on the linkage of cryptocurrencies with the clean energy sector, we further extend the literature by providing a comparison of the market linkage of (clean and dirty) cryptocurrencies with traditional and green financial assets, respectively. In particular, we have followed the extant literature (Naeem and Karim, 2021) by using a comprehensive representation of the green asset through a value-weighted index, which involves not only the clean energy sector but also other aspects including Sustainability, ESG Leadership, and Green Bonds archived from the S&P Dow Jones Indices database. The traditional asset is also represented in a comprehensive manner that includes important stock markets worldwide. Through this, potentially different market linkages depending on whether the target asset is clean/green or not can be studied. Second, in addition to building the market linkage, we move a step further by studying the potentially asymmetric response of the same when facing uncertainty shocks over the data distribution. This further enhances the interpretation on dynamics of the cross-market connection in the cryptocurrency and financial system under uncertainty and stress.

We find that the information transmission between cryptocurrency and both traditional and green assets is limited, and the connection of energy-efficient 'clean' cryptocurrency (CI) with financial assets is even weaker especially after the pandemic onset against that of energy-intensive dirty one (DI), revealing the hedge and safe heaven role of cryptocurrency. At the same time, the market nexus between different asset types within the ecosystem of traditional and green assets is relatively closer. The implications of the above-obtained spillovers are further explored by employing the optimal hedge ratios and portfolio weights, supporting that dirty and clean cryptocurrencies can provide diversification gains against most green and traditional assets, especially during the COVID-19 pandemic period. Moreover, the causal relationship between the above-obtained market nexus and uncertainty is shown to feature evident asymmetry and non-linearity. Specifically, the causal relationship is found to be generally enhanced after the outbreak of the pandemic, and such the relationship of uncertainty with the DI-financial system nexus is relatively stronger, further confirming better performance of CI for diversification and risk mitigation. In addition, most of the above causal relationship appears to be negligible during the period of market depression at extremely low quantiles. This indicates the investment sheltering role of the cryptocurrency-financial asset nexus for uncertainty irrespective of whether target assets are carbon-intensive and/or -friendly. We further discuss that our findings are consistent with both our expectations and existing related literature.

The remainder of the paper proceeds as follows. Section 2 presents the data and preliminary analysis. Section 3 describes employed estimation techniques. Section 4 discusses our empirical results and corresponding theoretical explanations. Section 5 concludes with a discussion of results in the context of policy.

2. Literature review

Our paper is connected to the extant literature in the following strands, notably involving the market linkages of clean/dirty cryptocurrencies with financial assets, and the role of the uncertainty level in the economy in the above linkages. Key related literature has been summarized in the table in Appendix B to report existing findings in this regard. Existing research has studied the market nexus between traditional assets and cryptocurrencies with a particular focus on the potential investment sheltering role of cryptocurrencies notably including Bitcoin (Dutta et al., 2020; Bouri et al., 2020; Conlon et al., 2020). However, little attention has been brought to the sheltering role of a broad set of cryptocurrencies against the emerging green asset class.

The limited literature to date studies the role of dirty cryptocurrencies, where Dutta et al. (2020) employ DCC-GARCH models and point out the role of Bitcoin as a diversifier for crude oil fluctuations in a time-varying setting. Wang et al. (2019) study the investment sheltering role of Bitcoin for financial assets in China, and find the hedging role of Bitcoin for stocks, bonds and the monetary market, while its safe haven role occurs in the latter at extreme conditions. Charfeddine et al. (2020) also support the viewpoint that cryptocurrencies can be applied for the investment diversification, while they also find that the relationship between Bitcoin/Ethereum and traditional assets is sensitive to external economic and financial shocks. Conlon et al. (2020) test the safe haven properties of Bitcoin, Ethereum, and Tether during the COVID-19 pandemic, and suggest that two of the three are not safe havens for most international equity markets examined. Rehman and Kang (2021) examine the time–frequency relationship between Bitcoin and energy commodity markets by suggesting that a lead–lag price connection exists between oil and gas with Bitcoin.

At the same time, existing research also studies clean cryptocurrencies, although the corresponding eco-friendly feature of the latter is neglected. For example, Gil-Alana et al. (2020) exhibit the bilateral linkages of two clean and four dirty cryptocurrencies with stock market indices using fractional integration techniques. Both clean and dirty cryptocurrencies are decoupled from the mainstream financial and economic assets, which implies the role of cryptocurrencies as a diversifier. Hsu et al. (2021) apply a diagonal BEKK model to examine the risk spillovers of Bitcoin (dirty), Ethereum (dirty), and Ripple (clean) to ten leading traditional currencies and two gold prices. While the two types of cryptocurrencies display different co-volatility spillovers with various financial assets, both have hedging or safe haven opportunities for the traditional currency market. Ghorbel and Jeribi (2021) point out that Ripple (clean), Ethereum (dirty), and Monero (dirty) are more volatile than Bitcoin (dirty) and Dash (clean) concerning the dynamic correlations with Cboe Volatility Index (VIX).

Moreover, recent empirical evidence finds that the market linkage of between cryptocurrencies and financial assets could be uni- or bi-directional and be varying over time (see, e.g., Symitsi and Chalvatzis, 2018; Okorie and Lin, 2020). For example, Le et al. (2021) establish a time and frequency domain VAR system to examine the spillovers among Fintech, green bonds, and Bitcoin. They suggest that Bitcoin acts as a net contributor of volatility shocks in the system, whereas green bonds are net receivers. Pham et al. (2021) elaborate on the time-varying market connection, and suggest that the spillovers between cryptocurrencies and green/fossil fuel investment are small during non-crisis periods but increase during crisis periods. Similarly, Naeem and Karim (2021) investigate the asymmetric and time-varying dependence structure between Bitcoin and green financial assets, and further confirm the hedging effect of green assets by using AGDCC-GARCH models. However, Ren and Lucey (2022) demonstrate that clean energy is not a direct hedge for either clean or dirty cryptocurrencies. Using a generalized VAR model, they suggest that clean energy is more likely to be a safe haven for dirty cryptocurrencies than that for clean cryptocurrencies, especially in periods of high uncertainty. In addition, Wang et al. (2020) document the safe haven property of stablecoins against traditional cryptocurrencies in specific status, and find that such the property tends to vary across market conditions.

As for the role that economic policy uncertainty (EPU) plays in the market linkage between cryptocurrencies and financial assets, existing research is scant, while the attention is more focused on searching for instruments to hedge against EPU. Wang et al. (2019) use the US EPU index, equity market uncertainty index, and VIX as proxies for the uncertainty level to determine the risk spillover effects from uncertainty to Bitcoin, and conclude that the spillover is negligible in most of the market conditions. Cheema et al. (2020) argue that cryptocurrencies might not act as a hedge or safe haven against other financial assets during uncertain times due to the strong predictability of EPU for the cryptocurrency returns over different time horizons. Using an non-parametric causality-in-quantile approach, Fasanya et al. (2021) demonstrate that the connectedness between Bitcoin and precious metals with the US EPU is stronger around the median and higher quantiles, indicating that the connectedness might not act as an investment shelter for the uncertainty. Elsayed et al. (2022) investigate the dynamic connectedness of return- and volatility spillovers among cryptocurrency index, gold, and uncertainty by showing that gold is susceptible to uncertainty shocks and affected by cryptocurrency markets.

Overall, existing literature has widely discussed the relationship of cryptocurrencies notably Bitcoin with traditional financial assets, while no consensus has been reached by far in regard to the direction, strength, and significance. Moreover, whether generation of the specific cryptocurrency is energy intensive or eco-friendly, and its potentially distinct linkages with traditional and green financial assets still lack in-depth research. How does the cross-market linkage vary in the face of uncertainty shocks under different market conditions also entails careful investigation. Having been jointly inspired by extant literature and the nature of energy consumption for target assets of our research, the following research hypotheses can be developed. That is, while there is an increasing popularity of cryptocurrency in investment activities, it could perform a weak or even negative linkage with financial assets, showing as an investment shelter. Whether the target asset is energy-intensive or energy-efficient could alter the linkage of cryptocurrency and financial assets. Fluctuations in uncertainty could affect the above linkage, and the impact varies over the data distribution.

Our research fills the gaps by first distinguishing between clean cryptocurrencies (CI) and dirty cryptocurrencies (DI) depending on the relatively low- and high-energy consumption of their built algorithms. We then study the dynamic and potentially time-varying cross-market linkage between cryptocurrencies (including both CI and DI) and financial assets (with both the traditional and green types) by using a time-varying parameter vector autoregressive (TVP-VAR) framework. The asymmetric response of the above obtained cross-market linkage when encountering the uncertainty shocks over the data distribution and its potential dynamics before and after the COVID-19 pandemic is further analyzed by using a non-parametric causality test.

3. Data and preliminary analysis

We have follow Ren and Lucey (2022) by constructing two value-weighted indices of dirty and clean cryptocurrencies (i.e., DI and CI). DI is built based on five major dirty cryptocurrencies including Bitcoin (BTC), Ethereum (ETH), Bitcoin Cash (BCH), Ethereum Classic (ETC), and Litcoin (LTC); CI is built based on five major clean cryptocurrencies including Cardano (ADA), Ripple (XRP), IOTA (MIOTA), Stellar (XLM), and Nano (NANO). We select the above five dirty and five clean cryptocurrencies following the existing literature (e.g., Ren and Lucey, 2022; Pham et al., 2022). The daily data of cryptocurrencies are from CoinMarketCap.[4] Moreover, in spirit of the extant literature (e.g., Huang et al., 2021, 2023), the traditional asset dynamics are captured by four major stock indices worldwide involving S&P 500 Index (SP500), Financial Times Stock Exchange 100 Index (FTSE), Toronto Stock Exchange Index (TSX), and Australian Securities Exchange Index (ASX), and the corresponding data are from Investing.[5] These are four of the largest and well-respected stock exchanges in the world and therefore represent traditional assets. Regarding green assets, they are represented by the following four leading sources including Dow Jones Sustainability World Index (SWI), S&P ESG Leader Index (ESGLI), S&P Green Bond Index (GBI), and S&P Global Clean Energy Index (GCEI), and are from S&P Dow Jones Indices database.[6] In addition, the data of US Economic Policy Uncertainty Index (EPU) are from Baker et al. (2016).[7] A detailed description of each incorporated variable is summarized in Table 1.

To clearly capture the potential variation of the market linkage as well as the role of EPU on the linkage when facing the onset of the COVID-19 pandemic, our whole sample is divided into two sub-samples on 11 March 2020, which is the first day of the COVID-19 being announced as a pandemic by the WHO.[8] Accordingly, in spirit of the extant literature (see, e.g., Goodell and Goutte, 2021; Huang et al., 2021), pre- and post-COVID-19 periods are represented by the

[4] Data source from https://coinmarketcap.com.
[5] Data source from https://www.investing.com.
[6] Data source from https://www.spglobal.com.
[7] Data source from http://www.policyuncertainty.com.
[8] See details about key dates of COVID-19 announced by the WHO at https://www.who.int/emergencies/diseases/novel-coronavirus-2019/interactive-timeline.

Table 1
Variable description.

Market/ Uncertainty index	Variable	Label	Description
Cryptocurrency	Dirty cryptocurrency index	DI	The value-weighted index of five major dirty cryptocurrencies including Bitcoin (BTC), Ethereum (ETH), Bitcoin Cash (BCH), Ethereum Classic (ETC) and Litcoin (LTC)
	Clean cryptocurrency index	CI	The value-weighted index of five green cryptocurrencies including Cardano (ADA), Ripple (XRP), IOTA (MIOTA), Stellar (XLM), and Nano (NANO)
Financial assets	Canadian stock index	TSX	Toronto stock exchange index
	UK stock index	FTSE	Financial times stock exchange 100 index
	Australian stock index	ASX	Australian securities exchange index
	US stock index	SP500	S&P 500 index
Green assets	Sustainability index	SWI	Dow Jones Sustainability World Index
	ESG leader index	ESGLI	S&P ESG Leader Index
	Green bond index	GBI	S&P Green Bond Inde
	Clean energy index	GCEI	S&P Global Clean Energy Index
Uncertainty	Economic policy uncertainty	EPU	Policy-related economic uncertainty

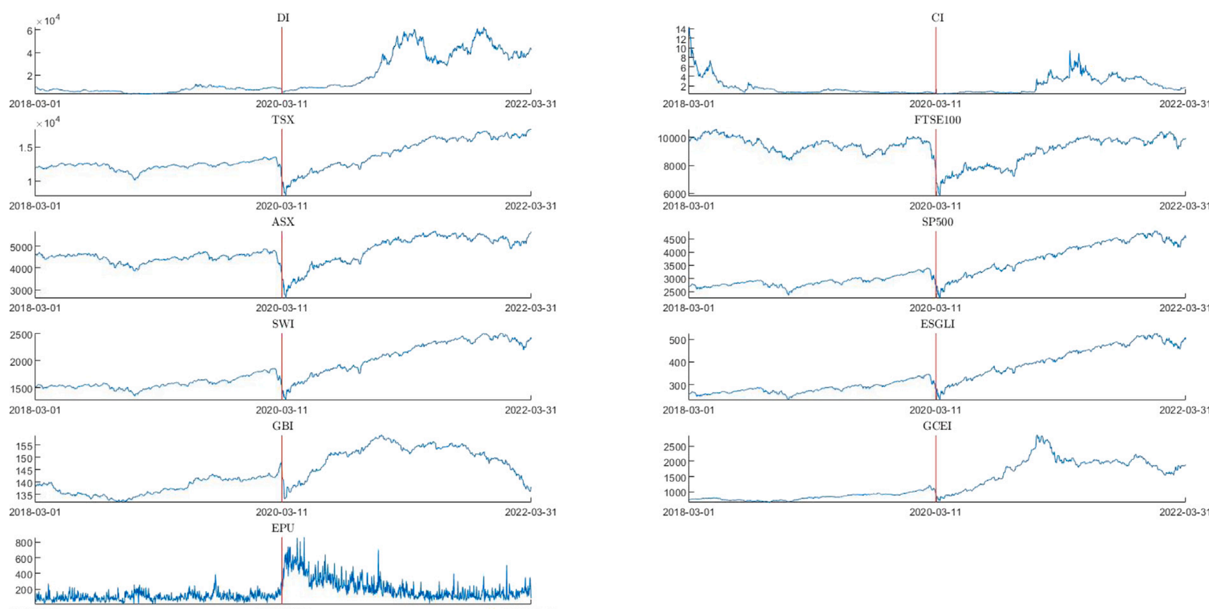


Fig. 1. Dynamics of Price series of variables.
Note: This figure plots the time-varying dynamics of eleven target series under research including dirty and clean cryptocurrency indices (i.e., DI and CI), four financial assets (i.e., TSX, FTSE, ASX, and SP500), four green assets (i.e., SWI, ESGLI, GBI, and GCEI), and US Economic Policy Uncertainty Index (EPU). Red line denotes the first day of the COVID-19 being announced as a pandemic by the WHO, which is 11 March 2020. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

sub-samples of 01 March 2018–10 March 2020 and that of 11 March 2020–31 March 2022, respectively.

The time-varying evolution of the price series of (dirty and clean) cryptocurrency indices, (traditional and green) assets, and EPU is shown in Fig. 1. Generally, it is clear that most of the series being considered have witnessed a marked fluctuation on 11 March 2020, i.e., the announcement date of COVID-19 as a pandemic. Although the indices of dirty and clean cryptocurrencies remained relatively stable in the coming pandemic period, both of them vary dramatically thereafter. At the same time, the dynamics of financial assets have witness a gradual recovery after the sudden slump caused by the pandemic shock. In contrast, EPU suffered from a short-run skyrocket since the pandemic onset, and then its magnitude declined gradually. The above therefore provides an intuitive demonstration of further splitting the whole sample before and after the pandemic onset and examining the potential difference in the financial market network.

In our case, to explore the volatility spillover of cryptocurrencies with financial assets, each of the incorporated variables is transformed in the format of the realized volatility via $Y_t = ((\log(P_t) - \log(P_{t-1})) \times 100)^2$ where P is the price series of the target series. As for EPU, it is employed in the logarithmic format to ensure the stationarity. Table 2 summarizes the descriptive statistics for all the transformed series in both sub-samples of pre- and post-COVID-19 periods, respectively. Generally, all the transformed series are found to possess larger mean values with higher standard deviations since the COVID-19 was announced as a pandemic. Moreover, it is worth noting that the standard deviations of the cryptocurrencies indices after the pandemic are much greater than that before the pandemic, indicating marked fluctuations in the cryptocurrency market after the pandemic onset. In addition, the large positive skewness and kurtosis values of all incorporated series except for the EPU depict non-normality of the data feature. This indicates the necessity of using a quantile framework to depict the asymmetric

Table 2
Summary statistics.

	Mean	Std. Dev.	Minimum	Maximum	Skewness	Kurtosis
Panel A: Pre-Covid-19						
DI	11.8987	27.5808	0.0000	233.9221	4.4469	24.1759
CI	42.7051	87.7133	0.0000	697.3695	4.3626	23.6273
TSX	0.5873	5.8309	0.0000	156.8665	26.0916	696.2151
FTSE	0.6996	2.3031	0.0000	47.0268	12.5721	226.9174
ASX	0.6352	2.5305	0.0000	58.3833	16.8521	367.2354
SP500	0.7976	3.2017	0.0000	62.4264	11.8430	195.6027
SWI	0.4443	1.8754	0.0000	43.6714	17.4474	383.4870
ESGLI	0.8552	3.3051	0.0000	61.9114	11.0084	169.8628
GBI	0.0340	0.0758	0.0000	0.8529	5.2625	38.0429
GCEI	0.8274	4.8558	0.0000	123.6402	22.3188	553.6142
EPU	4.5067	0.5303	1.3987	5.9563	−0.9491	3.3230
Panel B: Post-Covid-19						
DI	16.9905	82.3163	0.0000	2118.2855	22.4227	565.1887
CI	79.9536	392.2437	0.0000	7428.4353	12.7033	196.4408
TSX	1.5228	9.7311	0.0000	181.5971	13.5511	208.2424
FTSE	1.4616	6.7602	0.0000	149.4212	16.0189	320.9157
ASX	1.8574	7.7649	0.0000	138.1113	10.7995	150.7337
SP500	1.6773	8.7560	0.0000	162.9507	12.6130	190.8641
SWI	1.0588	5.8275	0.0000	112.3966	13.8617	225.8536
ESGLI	1.7146	9.0124	0.0000	168.5060	12.7405	194.0351
GBI	0.0959	0.3740	0.0000	5.8078	11.3277	152.8140
GCEI	3.5124	10.9818	0.0000	156.1818	8.3090	89.3476
EPU	5.2149	0.6175	3.0267	6.7582	0.1103	−0.5226

response of market linkages between cryptocurrency-financial assets when facing uncertainty shocks.

4. Methodology

In this section, we introduce the methodology employed in the empirical analysis that explores the time-varying volatility spillover networks between dirty/clean cryptocurrency and financial/green assets through a dynamic connectedness approach using a time-varying parameter vector autoregressive (TVP-VAR) framework, and further studies the underlying asymmetry and non-linearity of the above-obtained dynamic connectedness in the face of uncertainty shock (i.e., economic policy uncertainty, EPU) by employing a non-parametric causality-in-quantile test. Our methodology proposed is upon the research objectives and hypotheses to determine whether and how the energy-intensive and energy-efficient cryptocurrencies connect with financial and green assets differently, and how these cross-market linkages would be altered when facing the uncertainty in the economy in an asymmetric and non-linear setting.

4.1. Time-varying parameter VAR: The dynamic connectedness

We adopt the dynamic connectedness measure based on a TVP-VAR model (Antonakakis et al., 2020) to evaluate the cross-market dynamic spillovers of dirty/clean cryptocurrencies with financial and green assets. This method advances the DY connectedness framework proposed by Diebold and Yılmaz (2012, 2014) by allowing for time-variations of the spillover effect without an arbitrary imposition of the window setting as in the rolling analysis. We begin with the TVP-VAR model with a lag order of p formulated as follows:

$$Y_t = B_t X_{t-1} + \epsilon_t, \qquad \sigma_t \sim N(0, \Sigma_t), \tag{1}$$

$$vec(B_t) = vec(B_{t-1}) + u_t, \qquad u_t \sim N(0, U_t), \tag{2}$$

where $X_{t-1} = (Y'_{t-1}, \dots, Y'_{t-p})'$ and $B_t = (B_{1t}, \dots, B_{pt})$. Y_t and X_{t-1} are $n{\times}1$ and $np \times 1$ vectors of variables, B_t represents the matrix of parameters with the dimension of $n{\times}np$, which follows a random walk process, and ϵ_t indicates an $n{\times}1$ vector of i.i.d. error term. Note that the dimensions of time-varying covariance matrices Σ_t and U_t are $n \times n$ and $n^2q \times n^2q$, and $vec(B_t)$ is an $n^2q \times 1$ vector.

By transforming the TVP-VAR model to its vector moving average (VMA) representation following the Wold theorem, we can rewrite Eq. (1) as:

$$Y_t = \sum_{j=0}^{\infty} A_{jt}\epsilon_{t-j}, \tag{3}$$

where A_{jt} denotes an $n \times n$ matrix of coefficients determined as $A_{jt} = M' V_t^j M$ with $M' = (I, 0, \dots, 0)$ and $V_t = \begin{pmatrix} B_t \\ I_{n(p-1)} \quad 0_{n(p-1)\times n} \end{pmatrix}$.

Through a VMA representation of TVP-VAR model, the H-step-ahead forecast error variance is decomposed to measure the impact of variable j on variable i on the basis of its forecast variance share, and then normalized by summing up each row to one, showing that 100 percent of variable i's forecast error variance is illustrated by all variables. In accordance with Antonakakis et al. (2018) and Fasanya et al. (2021), the generalized forecast error variance is calculated as:

$$\varphi_{ij,t}(H) = \frac{\sigma_{jj,t}^{-1} \sum_{t=0}^{H=1} \left(\vartheta_i' A_{H,t} \Sigma_t \vartheta_j\right)^2}{\sum_{t=0}^{H-1} \left(\vartheta_i' A_{H,t} \Sigma_t A_{H,t}' \vartheta_i\right)}, \tag{4}$$

$$\widetilde{\varphi}_{ij,t}(H) = \frac{\varphi_{ij,t}(H)}{\sum_{j=1}^{N} \varphi_{ij,t}(H)'}, \tag{5}$$

where $\sum_{j=1}^{N} \widetilde{\varphi}_{ij,t}(H) = 1$ and $\sum_{i,j=1}^{n} \widetilde{\varphi}_{ij,t}(H) = n$. $\sigma_{jj,t}$ is the standard deviation of the error term ϵ_t for variable j at period t, and ϑ_j is an $N \times 1$ selection vector with one as the jth element, and zero otherwise.

Next, we construct the spillover indices to measure the considered volatility spillover effects. By using the technique of the forecast error variance in Eq. (5), the total spillover (TS_t) that shows how a shock in one variable spills over to other variables is deduced by:

$$TS_t(H) = \frac{\sum_{i,j=1, i\neq j} \widetilde{\varphi}_{ij,t}(H)}{\sum_{i,j=1}^{n} \widetilde{\varphi}_{ij,t}(H)} \times 100 = \frac{\sum_{i,j=1, i\neq j} \widetilde{\varphi}_{ij,t}(H)}{N} \times 100. \tag{6}$$

To further evaluate the directional spillovers through the dynamic connectedness approach, we define the directional spillover from others ($DS_{i\leftarrow j,t}$) used to present shocks in variable i receives from all other variables j, and the directional spillover to others ($DS_{i\rightarrow j,t}$) that indicates variable i transmits its shocks to all other variables j, which are formulated as:

$$DS_{i\leftarrow j,t}(H) = \frac{\sum_{j=1, i\neq j} \widetilde{\varphi}_{ij,t}(H)}{\sum_{i,j=1}^{n} \widetilde{\varphi}_{ij,t}(H)} \times 100 = \frac{\sum_{j=1, i\neq j} \widetilde{\varphi}_{ij,t}(H)}{N} \times 100, \tag{7}$$

$$DS_{i\to j,t}(H) = \frac{\sum_{j=1,i\neq j} \widetilde{\varphi}_{ji,t}(H)}{\sum_{i,j=1}^{n} \widetilde{\varphi}_{ji,t}(H)} \times 100 = \frac{\sum_{j=1,i\neq j} \widetilde{\varphi}_{ji,t}(H)}{N} \times 100. \tag{8}$$

The net total spillover ($NTS_{i,t}$) is then calculated by subtracting directional spillover from others ($DS_{i\leftarrow j,t}$) in Eq. (7) from directional spillover to others ($DS_{i\to j,t}$) in Eq. (8):

$$NTS_{i,t}(H) = DS_{i\to j,t}(H) - DS_{i\leftarrow j,t}(H), \tag{9}$$

This net spillover index denotes the effect of variable i on the analyzed spillover network. Therefore, if $NTS_{i,t} > 0$, variable i has more impact on the network than being impacted, otherwise, variable i is passive in the network.

Finally, we compute the net pairwise spillovers ($NPS_{ij,t}$) to measure the bidirectional connectedness between variables i and j, which is defined as:

$$NPS_{ij,t}(H) = \left(\widetilde{\varphi}_{ij,t}(H) - \widetilde{\varphi}_{ji,t}(H)\right) \times 100, \tag{10}$$

where a positive $NPS_{ij,t}$ stands for variable j being dominates by variable i while a negative $NPS_{ij,t}$ mean variable j dominates variable i.

4.2. Nonparametric causality-in-quantile test

To further examine whether and how the uncertainty affects the dynamic market connectedness between cryptocurrencies and financial assets over the data distribution, we employ a nonparametric causality-in-quantile test initially developed by Nishiyama et al. (2011) and Jeong et al. (2012). This approach has been widely embraced in existing literature to test for the asymmetric Granger causality between factors (see, e.g., Duan et al., 2021). In our analysis, the nonlinear Granger causality in quantile is set to test the hypotheses as follows: the EPU (p_t) does not cause volatility spillovers (s_t) in the ρ-th quantile with respect to a q-lag vector of both EPU and volatility spillovers $Z_{t-1} = (s_{t-1}, \ldots, s_{t-q}, p_{t-1}, \ldots, p_{t-q})$ if

$$Q_\rho(s_t|Z_{t-1}) = Q_\rho(s_t|S_{t-1}), \tag{11}$$

and the p_t is a prima facie cause of s_t in the ρ-th quantile with respect to Z_{t-1} if

$$Q_\rho(s_t|Z_{t-1}) \neq Q_\rho(s_t|S_{t-1}), \tag{12}$$

where $Q_\rho(s_t|\cdot)$ is the ρth quantile of s_t given $(\cdot)$ with $\rho \in (0,1)$, and $S_{t-1} = (s_{t-1}, \ldots, s_{t-q})$ denotes the lag-vector of volatility spillovers. Let $F_{s_t|Z_{t-1}}(s_t|Z_{t-1})$ and $F_{s_t|S_{t-1}}(s_t|S_{t-1})$ represent the conditional distribution functions of s_t given Z_{t-1} and S_{t-1}, respectively, and we assume $F_{s_t|Z_{t-1}}(s_t|Z_{t-1})$ to be absolutely continuous in s_t for almost all Z_{t-1} following Jeong et al. (2012). Then, the probability of $F_{s_t|Z_{t-1}} \{Q_\rho(s_t|Z_{t-1})\} = \rho$ will be 1 if denoting $Q_\rho(Z_{t-1}) \equiv Q_\rho(s_t|Z_{t-1})$. Therefore, the hypotheses to be tested in terms of definitions made in Eqs. (11) and (12) are:

$$H_0 = P\left\{F_{s_t|Z_{t-1}}\left\{Q_\rho(s_t|Z_{t-1})\right\} = \rho\right\} = 1, \tag{13}$$

$$H_1 = P\left\{F_{s_t|Z_{t-1}}\left\{Q_\rho(s_t|Z_{t-1})\right\} = \rho\right\} < 1, \tag{14}$$

To consistently test the hypothesis in Eq. (13), a distance measure proposed by Jeong et al. (2012) is employed, which has the following form:

$$D = E[(F_{s_t|Z_{t-1}}\left\{Q_\rho(s_t|Z_{t-1})\right\} - \rho)^2 f_Z(Z_{t-1})], \tag{15}$$

where $f_Z(Z_{t-1})$ indicates the marginal density function of Z_{t-1}. Note that D is a non-negative number and $D = 0$ holds if and only if H_0 in Eq. (13) is true, while $D > 0$ holds under H_1 in Eq. (14). The distance measure D can thus be a proper indicator for the consistent test of the null hypothesis H_0. Following Jeong et al. (2012), we use a feasible kernel-based method to estimate D as follows:

$$\hat{D_T} = \frac{1}{T(T-1)b^{2q}} \sum_{t=q+1}^{T} \sum_{k=q+1,k\neq t}^{T} K\left(\frac{Z_{t-1} - Z_{k-1}}{b}\right) \hat{\epsilon}_t \epsilon_s, \tag{16}$$

where $K(\cdot)$ is the kernel function with a bandwidth of b. T is the sample size, and $\hat{\epsilon}_t$ is an estimated regression error, specified as $\hat{\epsilon}_t = \mathbf{1}\left\{s_t \leq \hat{Q}_\rho(S_{t-1})\right\} - \rho$. Using the nonparametric kernel method, we can further estimate the ρth conditional quantile of s_t given S_{t-1} as $\hat{Q}_\rho(S_{t-1}) = F^{-1}_{s_t|S_{t-1}}(\rho|S_{t-1})$, where the $\hat{F}_{s_t|S_{t-1}}(s_t|S_{t-1})$ is the Nadaraya–Watson kernel estimator computed by $\hat{F}_{s_t|S_{t-1}}(s_t|S_{t-1}) = \frac{\sum_{k=q+1,k\neq t}^{T} K'\left(\frac{S_{t-1}-S_{k-1}}{b}\right)\mathbf{1}(s_k \leq s_t)}{\sum_{k=q+1,k\neq t}^{T} K'\left(\frac{S_{t-1}-S_{k-1}}{b}\right)}$ with the kernel function of $K'(\cdot)$ and a bandwidth of b.

5. Empirical results

5.1. The dynamic market networks

We begin our analysis by analyzing the directional spillover between the considered variables in volatility, through which the dynamic market networks of (dirty and clean) cryptocurrencies with (traditional and green) assets are investigated. The corresponding results based on the whole sample are presented in Table 3. Specifically, values in the rows depict the individual spillover from the variable placed at the column head (i) to variables in the row (j). The sum of these represents total contribution (TS) of the information spillover from the variable i to others (j), i.e., $DS_{i\to j}$. At the same time, the values in row-wise depict the contribution ($From$) received by the variable in the specific row of the first column (j) from different variables (i), i.e., ($DS_{i\leftarrow j}$). The diagonal values are explained as the own shocks received by and/or obtained from the variable itself. Moreover, the net total spillover index (NTS) implies a variable that gives (receives) more shocks than receiving (or giving) from other variables. A positive value of NTS reveals that the variable is considered as a net giver with more shocks to other variables than it receives, while a negative result depicts a net receiver of the variable that is more influenced to shocks from others. In addition, the net pairwise directional volatility connectedness between variables is denoted as the net piece-wise spillover (NPS) to measure whether a variable affects (gets affected by) other variables.[9]

Based on the whole sample period, Table 3 summarizes the average dynamic market networks of cryptocurrencies with financial assets. Overall, it is shown that the total connectedness index is 67.1%, indicating that more than two thirds of the total variation of the forecast error in the system over the sample can be explained by the information spillovers, while the rest of the variation is explained by idiosyncratic shocks. This finding is also corroborated by the graphical analysis of the total spillover presented in Fig. 2. Regarding the directional spillover across markets, it can be seen that information spillovers between (dirty and clean) cryptocurrency indices and (traditional and green) assets are found to be relatively weak in the system, and vice versa. For example, both dirty cryptocurrencies (DI) and clean cryptocurrencies (CI) are shown to transmit only limited information to financial assets with the largest related case is the transmission from DI to the forecast variance of Financial Times Stock Exchange 100 Index (FTSE) with 4.2%. However, except for the self-transmission, the contribution to the forecast error of financial assets can be as large as 22.2% from the traditional asset S&P 500 Index (SP500) to the green asset S&P ESG Leader Index (ESGLI). Thus, as for the information receiving, the majority of the information received by financial assets are from others within the same group instead of cryptocurrencies.

It is clear that financial assets including both traditional and green assets contribute to most of the information transmission within the market network in our case. Specifically, the green asset, i.e., Dow Jones Sustainability World Index (SWI), is ranked as the largest information giver that contributes to the innovation dynamics of the

[9] The 10-step ahead forecast horizon of the TVP-VAR system is considered, and the optimal lag order is selected as 1 based on the Akaike Information Criterion (AIC) when measuring TS, DS, NTS, and NPS.

Table 3
Volatility spillovers during the whole sample period.

	DI	CI	TSX	FTSE	ASX	SP500	SWI	ESGLI	GBI	GCEI	FROM
DI	53.7	9.7	6.1	6.9	2.3	2.9	7.0	2.7	4.2	4.5	46.3
CI	10.6	67.1	3.6	3.4	1.9	1.6	3.4	1.4	2.1	4.8	32.9
TSX	3.0	1.9	23.7	9.9	7.4	11.9	15.3	11.3	3.6	11.9	76.3
FTSE	4.2	2.2	13.9	28.1	6.7	8.3	15.3	7.9	4.1	9.4	71.9
ASX	1.7	1.5	11.8	7.1	25.7	12.9	13.2	12.5	3.1	10.4	74.3
SP500	1.7	1.0	11.9	6.2	7.3	22.0	16.7	21.7	2.1	9.4	78.0
SWI	3.2	1.7	14.1	10.3	7.1	15.1	20.2	14.8	3.3	10.3	79.8
ESGLI	1.7	1.1	11.7	6.1	7.2	22.2	16.8	22.2	2.1	9.1	77.8
GBI	4.1	2.7	10.3	7.1	7.1	6.5	9.6	6.2	36.2	10.3	63.8
GCEI	2.9	2.6	13.7	7.4	7.4	10.3	12.3	9.7	3.9	29.8	70.2
TO	33.1	24.4	97.1	64.3	54.2	91.7	109.7	88.3	28.5	80.0	671.3
NTS	−13.2	−8.5	20.9	−7.6	−20.1	13.6	29.9	10.4	−35.3	9.8	TS
NPS	7.0	7.0	2.0	5.0	6.0	3.0	1.0	4.0	8.0	3.0	67.1
Transmitter											

Note: This table describes the time-average connectedness of cryprocurrency-financial asset markets based on the whole sample period. Interpretations of abbreviations of incorporated variables and different terms depicting various connectedness are from Section 3 and Section 5.1, respectively.

Table 4
Volatility spillovers in the pre-COVID-19 period.

	DI	CI	TSX	FTSE	ASX	SP500	SWI	ESGLI	GBI	GCEI	FROM
DI	82.5	14.3	0.5	0.3	0.2	0.6	0.4	0.6	0.1	0.5	17.5
CI	14.1	81.3	1.4	0.2	0.4	0.7	0.5	0.7	0.4	0.4	18.7
TSX	0.2	0.9	35.4	7.1	5.8	11.5	14.0	11.0	0.5	13.7	64.6
FTSE	0.1	0.3	11.6	43.5	4.6	7.2	14.5	7.1	0.9	10.2	56.5
ASX	0.3	0.3	9.3	4.4	33.7	14.1	14.1	13.9	0.9	9.0	66.3
SP500	0.2	0.2	9.2	4.1	3.8	26.7	18.0	26.5	0.6	10.6	73.3
SWI	0.2	0.2	11.8	8.0	5.6	17.6	25.2	17.4	0.9	13.1	74.8
ESGLI	0.3	0.3	8.9	4.0	3.8	26.9	18.1	27.0	0.6	10.2	73.0
GBI	0.5	0.8	5.9	3.4	4.2	3.7	5.5	3.6	67.1	5.3	32.9
GCEI	0.3	0.2	13.5	6.4	5.8	12.3	16.0	11.8	0.6	33.0	67.0
TO	16.2	17.5	72.1	37.9	34.3	94.7	100.9	92.6	5.5	72.9	544.5
NTS	−1.4	−1.2	7.5	−18.7	−31.9	21.4	26.1	19.6	−27.4	6.0	TS
NPS	6.0	5.0	3.0	6.0	6.0	2.0	1.0	3.0	8.0	4.0	54.5
Transmitter											

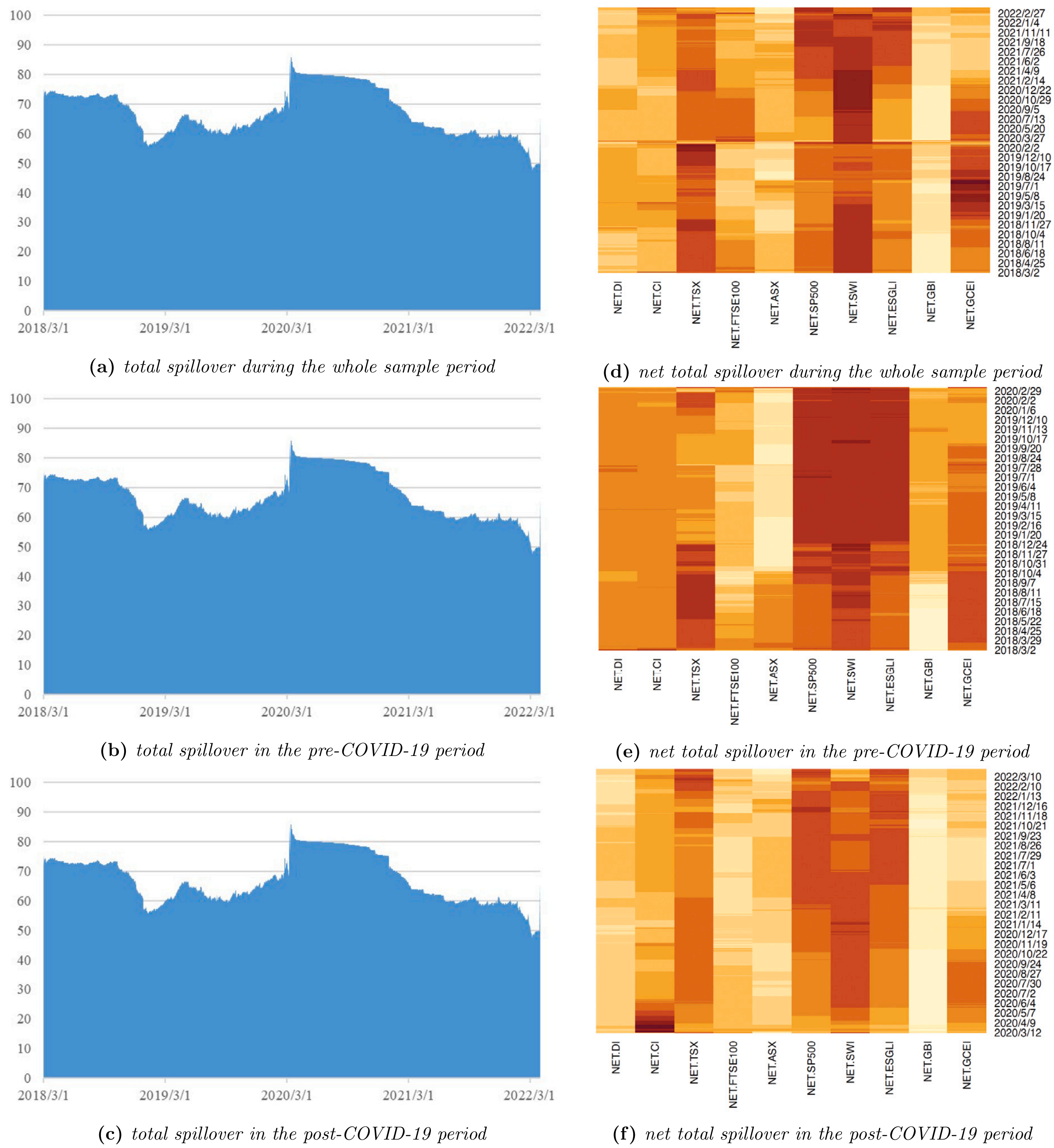
Note: This table describes the time-average connectedness of cryprocurrency-financial asset markets during the pre-pandemic periods. Interpretations of abbreviations of incorporated variables and different terms depicting various connectedness are from Section 3 and Section 5.1, respectively.

whole system with 109.7%, involving that of ESGLI (16.8%) and followed by SP500 (16.7%), Toronto Stock Exchange Index (TSX, 15.3%), FTSE (15.3%), Australian Securities Exchange Index (ASX, 13.2%), S&P Global Clean Energy Index (GCEI, 12.3%), S&P Green Bond Index (GBI, 9.6%), DI (7.0%), and CI (3.4%). The green asset, i.e., SWI, is ranked as the largest information receiver that contributes to the innovation dynamics of the whole system with 79.8%, involving that of SP500 (15.1%) followed by ESGLI (14.8%), TSX (14.1%), FTSE (10.3%), GCEI (10.3%), ASX (7.1%), GBI (3.3%), DI (3.2%), and CI (1.4%).

Overall, the dynamics of cryptocurrencies are shown to be weakly connected with that of both traditional and green assets with CI ranked as the most isolated type of cryptocurrencies to the financial system. Thus, it is concluded that the cryptocurrency (with both types of clean and dirty) can help with diversification and risk mitigation against both traditional and green assets, and vice versa. Moreover, regarding the net total spillovers (NTS), cryptocurrencies (DI and CI), traditional stock assets in the UK and Australian stock markets (FTSE and ASX), and green asset GBI are found to act as net receivers of shocks in the whole system with negative values of NTS with GBI is ranked as the largest net receiver (−35.3%). In contrast, SWI is shown to be the largest net information giver with about 29.9% of the shocks in the system. These findings can be further confirmed by the graphical analysis of NTS for each incorporated variables shown in Fig. 2.

To further study whether and how the COVID-19 pandemic alters the market networks of cryptocurrencies with financial assets, we decompose the whole sample into sub-samples of pre- and post-COVID-19 periods with the dynamic spillover results shown in Tables 4 and 5. Overall, the total connectedness of the market system before and after the pandemic is 54.5% and 62.4%, respectively, which is slightly lower than that of the whole sample. Moreover, although the market network remains weak irrespective of the pandemic, the extent of the network slightly raise in the post-pandemic era. Generally, the finding of the weak market connection of dirty and clean cryptocurrencies with traditional and green assets in the whole sample keeps being consistent after the sample split, implying that the sheltering role of the dirty and clean cryptocurrencies for financial assets holds irrespective of the pandemic onset. It is also worth noting that the connection of clean cryptocurrencies (CI) with the financial system is found to be even weaker compared to that of dirty cryptocurrencies (DI) after the pandemic as shown by the fact that the information received by CI is only around one third by DI. The above finding corroborate the existing findings on the connectedness between cryptocurrencies and financial markets (see, Ji et al., 2019; Naeem and Karim, 2021; Ren and Lucey, 2022), and further indicates that the sheltering role of CI appears to be more effective than that of DI since the pandemic onset.

In specific, our results regarding the market network of cryptocurrencies with financial assets connect with existing literature in various aspects. First, existing research has found a weak dependence between cryptocurrency and financial assets, whereas that within the financial system tends to be relatively strong. This is in line with our findings that connection within the ecosystem of finance is closer than the financial-cryptocurrency linkage. For example, Bouri et al. (2020) employ the wavelet coherency approach to ascertain that the dependence between Bitcoin/gold/other commodities and the stock market is not very strong, with Bitcoin being the most isolated type. Mensi et al. (2019) examine the asymmetric volatility connectedness between Bitcoin and major precious metals, and suggest that the majority of the information received by precious metals is from sources within the



(a) *total spillover during the whole sample period*

(b) *total spillover in the pre-COVID-19 period*

(c) *total spillover in the post-COVID-19 period*

(d) *net total spillover during the whole sample period*

(e) *net total spillover in the pre-COVID-19 period*

(f) *net total spillover in the post-COVID-19 period*

Fig. 2. Plots of total spillover and net total spillover.
Note: The left-hand-side plots illustrate the dynamic degree of the overall spillover of the cryprocurrency-financial asset linkages over time; the right-hand-side plots depict the degree of the net total spillover from each target market to others being considered over time.

same group instead of Bitcoin. Moreover, the findings hold valid and are supported by Ren and Lucey (2022) and Gil-Alana et al. (2020) after division of cryptocurrencies are into clean and dirty groups. Ren and Lucey (2022) find the return and volatility connectedness between clean energy and both clean and dirty cryptocurrencies is much lower than that between clean energy and other equity markets, suggesting that both types of cryptocurrencies are more isolated and act as a separate asset class. Gil-Alana et al. (2020) find evidence that the two clean and four dirty cryptocurrencies under research can provide diversification gains for investors since there is no cointegration between cryptocurrencies and mainstream financial assets. Our findings are consistent with the above literature that the market linkage between dirty/clean cryptocurrencies and financial traditional/green assets is weak, and main sources of the spillover is found within the system of financial assets.

Second, our findings are supported by the literature that both dirty and clean cryptocurrencies act as the investment sheltering role for financial assets, and such the role remains consistent irrespective of the pandemic outbreak. Among related applications, Hsu et al. (2021) apply a Diagonal BEKK model to investigate the risk spillovers of Bitcoin (dirty), Ethereum (dirty), and Ripple (clean) to traditional currencies and gold prices, and document that cryptocurrencies can act as a diversifier for most traditional currencies and gold during both the whole research sample and the financial turmoil associated with

Table 5
Volatility spillovers in the post-COVID-19 period.

	DI	CI	TSX	FTSE	ASX	SP500	SWI	ESGLI	GBI	GCEI	FROM
DI	68.6	5.6	3.6	3.3	2.4	2.9	4.0	2.9	3.0	3.7	31.4
CI	6.4	88.1	0.5	0.6	0.5	0.4	0.5	0.4	0.3	2.5	11.9
TSX	1.0	1.0	23.0	10.4	8.2	14.4	16.5	13.8	2.7	9.0	77.0
FTSE	1.3	1.2	15.9	28.7	7.3	10.4	15.6	9.8	2.5	7.3	71.3
ASX	0.6	2.7	12.4	6.4	25.5	14.8	13.2	14.7	2.4	7.4	74.5
SP500	0.6	0.9	12.7	5.8	9.5	21.9	18.1	21.6	1.3	7.5	78.1
SWI	0.9	1.2	14.5	9.2	8.5	18.0	20.7	17.7	1.8	7.7	79.3
ESGLI	0.7	0.9	12.4	5.6	9.6	22.0	18.2	22.0	1.4	7.3	78.0
GBI	2.2	1.0	8.9	5.3	7.6	8.2	8.5	8.2	44.2	5.9	55.8
GCEI	1.6	1.7	12.2	6.6	6.5	12.1	12.0	11.6	2.3	33.5	66.5
TO	15.1	16.2	93.1	53.1	60.2	103.0	106.6	100.8	17.6	58.3	623.9
NTS	−16.3	4.3	16.1	−18.2	−14.4	24.9	27.2	22.8	−38.2	−8.2	TS
NPS Transmitter	8.0	5.0	3.0	5.0	6.0	1.0	1.0	3.0	8.0	5.0	62.4

Note: This table describes the time-average connectedness of cryprocurrency-financial asset markets during the post-pandemic periods. Interpretations of abbreviations of incorporated variables and different terms depicting various connectedness are from Section 3 and Section 5.1, respectively.

the COVID-19 pandemic. In contrast, Pham et al. (2021) only include dirty cryptocurrencies (Bitcoin and Ethereum) with fossil fuel and green investments in the market network. They find that the spillover of cryptocurrencies with assets an is weak during non-crisis periods but increases significantly during crisis periods. Thus, it is clear that there exists no consensus on the sensitivity of the market dependence of cryptocurrencies and financial assets to the COVID-19 pandemic, possibly due to the fact that the types of cryptocurrencies considered are not comprehensive enough. Our paper conducts a comprehensive analysis that distinguishes between clean and dirty cryptocurrencies, and studies the linkage of both types of cryptocurrencies with financial assets and its dynamics before/after the pandemic, extending the related literature in this regard.

Noteworthy, our research adds to the existing literature by focusing on the potentially different effectiveness of the sheltering role of clean and dirty cryptocurrencies. By far, there exists limited literature discussing the different linkage of dirty and clean cryptocurrencies with financial assets. Ren and Lucey (2022) find that clean energy is a more effective safe haven for dirty cryptocurrencies than for clean cryptocurrencies during the period with increasing uncertainty. Although existing literature finds the sheltering role of clean cryptocurrencies for financial assets (Gil-Alana et al., 2020; Hsu et al., 2021), it fails to provide an in-depth comparison of its effectiveness with dirty cryptocurrencies for different types of financial assets. Our paper therefore analyzes whether and how dirty and clean cryptocurrencies connect with green/traditional assets differently by pointing out that clean cryptocurrencies tend to transmit less information than dirty cryptocurrencies to financial assets, especially during the COVID-19 pandemic period.

5.2. The role of uncertainty in a non-linear setting

Whether and how does evolution of the uncertainty level in the economy alter the cross-market networks between cryptocurrencies and financial assets? Correspondingly, what is the underlying difference in the network response when the target agent (either cryptocurrencies or financial assets) is eco-friendly or carbon-intensive? Since the non-linearity of our data sample, we further employ a causality-in-quantiles test to study the nonlinear causal effects of the economic policy uncertainty (EPU) on the net pairwise spillovers (NPS_{ij}) between cryptocurrency and financial assets as gauged in the last section. The corresponding results based on the whole sample, pre-, and post-COVID-19 sub-samples are depicted in Tables 6–8, respectively. Generally, the lower, middle and higher quantiles respectively corroborate the periods of bearish, normal and bullish market conditions. For intuitive illustration, we have further plotted the non-linear causality test results that present in Appendix A.

Intuitively, some important patterns emerge as follows. First, the EPU dynamics tend to exert an enhanced causal impact on the market network after the COVID-19 pandemic as evinced by increasing significance of the causality from EPU to the market linkage. It can be seen that causal relations between EPU and pairwise market spillovers appear to be insignificant at many quantiles in the pre-COVID-19 period, while majority of the quantiles turns to become significant during the COVID-19 period. Specifically, the EPU has causal effects on twelve market networks such as that between dirty cryptocurrency (DI) / clean cryptocurrency (CI) and the Australian stock market (ASX) / Dow Jones Sustainability World Index (SWI) in the period after the pandemic onset. In contrast, before the COVID-19 pandemic, only six causalities from EPU to pair-wise market spillovers are found to be significant and only at few quantiles, including market spillovers between DI/CI and the US stock market (SP500) / S&P ESG Leader Index (ESGLI), as well as DI and Canadian stock market (TSX) / S&P Global Clean Energy Index (GCEI). Interestingly, it is worth noting that while in the post-COVID-19 period there exist causalities in most quantiles between EPU and most of the pairwise market spillovers, the spillover between CI and ASX is found to have no response when facing an uncertainty shock over the data distribution.

Overall, there exists an enhancement of the significance of causalities between EPU and cryptocurrency-financial asset market spillovers after the pandemic. An underlying reason may be that EPU captures the dynamics of economic fundamentals including alternations in policy-making, and it tends to attract more attention during the post-pandemic period when the economy witnesses marked fluctuations in uncertainty (Adekoya and Oliyide, 2021). Moreover, given that trading of cryptocurrency has had an increasing popularity over time, it makes the crypto market dynamics gradually closer to the financial system, further leading to the cross-market linkages being more vulnerable to uncertainty. Specifically, the total market capitalization of crypto assets has increased dramatically from less than $20 billion in January 2017 to more than $3 trillion in November 2021 (Iyer, 2022). As increases in market capitalization and trading volume of cryptocurrencies, their widespread adoption could result in financial stability risks given their highly volatile prices, rising use of leverage in their trading, and increasing exposures of financial institutions to cryptocurrency-related assets (Iyer, 2022). Some literature has confirmed the increasing market network between cryptocurrencies and financial assets during the market stress (Conlon and McGee, 2020; Elsayed et al., 2022); however, the literature that discusses whether the uncertainty level alters the cross-market network is rather limited. Among limited applications, Pham et al. (2022) find that EPU significantly impacts the full-distributional connectedness among carbon, green and non-green cryptocurrency markets on extreme lower (5th) and extreme upper (95th) quantiles, but they do not analyze the potential differences

Table 6
Causality tests in quantiles during the whole sample period.

Ho: EPU does not Granger-cause:	Nonlinear causality		0.3	0.4	0.5	0.6	0.7	0.8	0.9
	0.1	0.2							
Net volatility spillover between DI and TSX	2.719***	2.293**	1.955	2.830***	4.446***	5.982***	6.372***	4.886***	2.078**
Net volatility spillover between DI and FTSE	2.260**	3.402***	3.526***	3.774***	4.156***	4.149***	4.033***	3.211***	1.744
Net volatility spillover between DI and ASX	2.062**	5.663***	9.073***	7.016***	2.811***	1.459	2.512**	3.666***	1.267
Net volatility spillover between DI and SP500	0.944	0.636	0.914	1.090	0.757	1.044	0.922	1.035	0.855
Net volatility spillover between DI and SWI	3.553***	4.562***	2.546**	1.335	2.868***	4.515***	6.348***	5.679***	2.457**
Net volatility spillover between DI and ESGLI	0.688	0.530	1.048	1.003	0.756	0.629	0.925	1.128	0.790
Net volatility spillover between DI and GBI	1.659	2.716***	4.217***	4.128***	2.924***	2.468**	1.929	1.724	1.592
Net volatility spillover between DI and GCEI	2.019**	3.170***	4.569***	2.993***	2.019**	4.295***	5.223***	5.290***	2.103**
Net volatility spillover between CI and TSX	1.519	3.381***	2.586***	1.174	1.287	2.349**	3.514***	2.151**	1.243
Net volatility spillover between CI and FTSE	1.275	2.123**	2.455***	2.612***	3.040***	1.820	1.906	1.964**	1.407
Net volatility spillover between CI and ASX	1.509	2.583***	1.996**	1.680	0.541	0.745	1.630	2.676***	1.569
Net volatility spillover between CI and SP500	0.374	1.577	1.350	1.309	0.683	1.062	1.285	1.261	0.538
Net volatility spillover between CI and SWI	3.044***	3.724***	4.131**	4.269***	4.730***	4.709***	4.903***	4.782***	3.502***
Net volatility spillover between CI and ESGLI	0.278	1.050	1.415	1.468	0.798	0.898	1.187	1.472	0.506
Net volatility spillover between CI and GBI	2.608***	3.821***	3.797***	2.596***	1.551	1.164	1.798	2.488**	2.039**
Net volatility spillover between CI and GCEI	0.758	1.428	1.479	0.896	1.525	2.802***	2.699***	2.745***	1.267

Note: This table reports the causality from economic policy uncertainty (EPU) to various linkages between cryptocurrency and financial asset markets based on the whole sample.
*** Represents the significance at 1%.
** Represents the significance at 5%.

Table 7
Causality tests in quantiles during the pre-pandemic period.

Ho: EPU does not Granger-cause:	Nonlinear causality		0.3	0.4	0.5	0.6	0.7	0.8	0.9
	0.1	0.2							
Net volatility spillover between DI and TSX	0.639	1.170	1.646	3.350***	2.117**	2.501**	2.492**	1.400	0.662
Net volatility spillover between DI and FTSE	1.176	1.746	1.757	1.559	1.182	1.124	1.682	1.542	1.067
Net volatility spillover between DI and ASX	0.546	1.165	1.402	1.287	1.394	1.553	1.648	1.193	1.200
Net volatility spillover between DI and SP500	1.707	2.722***	2.808***	2.865***	2.426**	2.279**	2.570**	1.840	1.391
Net volatility spillover between DI and SWI	0.738	1.103	1.411	1.543	1.679	1.204	1.535	1.079	0.804
Net volatility spillover between DI and ESGLI	1.898	2.557**	2.853***	2.869***	2.759***	2.499**	2.225**	1.891	1.270
Net volatility spillover between DI and GBI	0.930	1.457	1.468	1.908	1.909	1.514	1.573	1.252	1.155
Net volatility spillover between DI and GCEI	4.064***	4.801***	5.294***	5.570***	6.071***	5.459***	4.529***	3.847***	2.335**
Net volatility spillover between CI and TSX	0.429	0.477	1.005	0.901	0.638	0.630	1.013	0.912	0.565
Net volatility spillover between CI and FTSE	0.965	0.982	1.169	1.432	1.289	1.217	1.082	1.042	0.894
Net volatility spillover between CI and ASX	1.071	0.906	1.046	0.838	0.478	0.716	0.813	0.851	0.841
Net volatility spillover between CI and SP500	0.687	1.420	1.677	2.480**	1.886	1.935	1.810	1.355	0.901
Net volatility spillover between CI and SWI	0.587	1.114	1.467	1.889	1.317	0.990	1.120	1.002	0.745
Net volatility spillover between CI and ESGLI	0.897	1.992	1.788	2.793***	2.644***	2.214**	1.881	0.974	1.087
Net volatility spillover between CI and GBI	1.071	1.352	1.475	1.830	1.747	1.649	1.687	1.558	0.916
Net volatility spillover between CI and GCEI	0.842	0.936	0.795	0.565	0.821	0.804	1.319	1.420	1.146

Note: This table reports the causality from economic policy uncertainty (EPU) to various linkages between cryptocurrency and financial asset markets during the pre-pandemic periods.
*** Represents the significance at 1%.
** Represents the significance at 5%.

of the market connection before and after the COVID-19 pandemic. Our findings of underlying changes in the causal impacts due to the pandemic onset extends the extant literature that studies the effects of EPU on cross-market spillovers (e.g., Albulescu et al., 2019 for the oil and commodity currency market; Das et al., 2019 for the stock markets; Fasanya et al., 2021 for the precious metals markets).

Second, the causal effect from EPU to cross-market linkages depicts idiosyncratic features depending on whether cryptocurrencies/financial assets are eco-friendly or carbon-intensive. The causality degree tends to be relatively stronger between DI and financial assets, especially after the pandemic onset. It is clear that numbers of quantiles where the DI-asset linkages are significant are relatively greater than the case of the CI-asset linkages. In specific, before the pandemic, the spillover between CI and financial assets mostly remains unchanged in the face of EPU, while the DI-related spillover tends to have a closer relation with EPU. While the cross-market spillovers tend to be more vulnerable to the uncertainty shock after the pandemic, the spillovers related to different types of cryptocurrencies (i.e., CI and DI) and asset types (i.e., traditional and green) behave clearly different patterns. Therefore, the spillover (in volatility) of the two types of cryptos (i.e., CI and DI) with financial assets has different response in the face of the uncertainty shock. In addition, we further find that most of the causalities turns to be insignificant at extreme low quantiles, i.e., 10% quantile, in both sub-samples before and after the COVID-19 pandemic. This implies the sheltering role of the cryptocurrency-financial asset linkages against the uncertainty level irrespective of whether the cryptocurrencies/financial assets are carbon-intensive or -friendly.

Existing literature has studied the hedging role of financial assets against EPU, while little has studied how EPU impacts the market linkages between cryptocurrencies and financial assets. More-so, far little has distinguished different types of cryptocurrencies and financial assets according to whether the asset is eco-friendly. Haq and Bouri (2022) examine co-movements between conventional and sustainable cryptocurrencies by considering two cryptocurrency uncertainty indices (i.e., UCRY price and UCRY policy), and find a weak co-movement. Cheema et al. (2020) investigate the predictability of EPU for cryptocurrency returns over different time horizons and conclude that cryptocurrencies might not act as a safe haven against financial

Table 8
Causality tests in quantiles during the post-pandemic period.

Ho: EPU does not Granger-cause:	Nonlinear causality		0.3	0.4	0.5	0.6	0.7	0.8	0.9
	0.1	0.2							
Net volatility spillover between DI and TSX	1.010	1.232	1.266	4.188***	8.661***	15.651***	13.360***	8.656***	2.933***
Net volatility spillover between DI and FTSE	3.189***	4.037***	4.394***	4.394***	4.767***	4.870***	4.422***	3.869***	2.230**
Net volatility spillover between DI and ASX	1.710	2.535**	1.946**	2.479**	6.339***	11.788***	8.491***	4.336***	1.090
Net volatility spillover between DI and SP500	0.768	1.714	2.066**	2.369**	3.179***	3.802***	3.901***	2.530**	1.018
Net volatility spillover between DI and SWI	0.749	0.997	0.696	1.893	6.095***	11.895***	12.226***	7.983***	2.890***
Net volatility spillover between DI and ESGLI	0.909	1.503	2.014**	2.443**	3.354***	3.775***	4.305***	3.633***	1.449
Net volatility spillover between DI and GBI	0.497	0.637	1.081	1.633	3.318***	3.407***	2.715***	1.977**	0.842
Net volatility spillover between DI and GCEI	1.302	2.087**	2.057**	1.507	1.635	2.694***	4.837***	5.486***	2.086**
Net volatility spillover between CI and TSX	0.862	2.837***	3.744***	2.500**	3.159***	3.952***	1.477	0.907	0.752
Net volatility spillover between CI and FTSE	0.169	1.026	2.300**	0.782	0.745	0.375	1.121	0.686	0.619
Net volatility spillover between CI and ASX	0.778	1.040	1.568	1.580	1.765	1.641	1.135	1.075	0.494
Net volatility spillover between CI and SP500	1.931	2.367**	2.696***	2.612***	3.261***	2.999***	2.351**	1.820	1.383
Net volatility spillover between CI and SWI	0.319	1.777	4.499***	3.154***	1.310	1.026	0.748	1.199	0.479
Net volatility spillover between CI and ESGLI	2.017**	2.222**	2.394**	2.564**	3.463***	3.108***	2.451**	1.844	1.267
Net volatility spillover between CI and GBI	1.939	3.458***	2.754***	1.933	1.722	1.812	2.547**	5.401***	3.088***
Net volatility spillover between CI and GCEI	0.531	2.865***	6.159***	7.905***	6.094***	3.757***	1.014	0.644	0.978

Note: This table reports the causality from economic policy uncertainty (EPU) to various linkages between cryptocurrency and financial asset markets during the post-pandemic periods.

*** Represents the significance at 1%.

** Represents the significance at 5%.

assets when facing a high degree of uncertainty. Recently, Fasanya et al. (2021) analyze how EPU connects with the cross-market spillover. They include Bitcoin and precious metals in their built market networks and argue that the cross-market connectedness might lack a hedging effect for EPU, especially around the median and higher quantiles.

Our paper adds to the literature by revealing that the spillovers of the dirty and clean cryptocurrencies with financial assets act differently under the uncertainty shock. It is found that the causality from EPU to DI-asset linkages tends to be stronger than CI-asset linkages. An underlying reason may be that dirty cryptocurrencies appear to be more strongly connected within the network of cryptocurrencies than clean cryptocurrencies, making dirty cryptocurrencies relatively more vulnerable to information transmission from one of them Milunovich (2022). Specifically, Milunovich (2022) observes that dirty cryptocurrencies import price volatility from the same group and export future price volatility to both dirty and clean cryptocurrencies, while clean cryptocurrencies transmit some uncertainty amongst themselves and export less price risk to dirty cryptocurrencies. Accordingly, if one of the DI-asset linkages exhibits a strong connection with EPU, other DI-asset linkages under consideration might be also affected, further increasing the degree of causality from EPU to each pair of the DI-asset linkage.

5.3. Hedge ratios and portfolio weights

To further explore the implications of our obtained results for portfolio diversification and risk management, we evaluate the merits of involving dirty and clean cryptocurrencies in portfolio risk analysis by employing optimal hedge ratios and portfolio weights. Specifically, the optimal hedge ratios are constructed by the proportion of long position in volatility of dirty/clean cryptocurrencies i that can be hedged with a short position in one of the green and traditional assets' price volatility j, so as to minimize the variance of portfolio. Following Antonakakisa et al. (2018) and Maghyereh et al. (2017), the hedge ratio between the volatility of asset i (i.e., DI/CI volatility) and that of asset j (i.e., financial asset volatility) is calculated as

$$\beta^*_{ij,t} = \frac{Cov(Y_{it}, Y_{jt})}{var(Y_{jt})} = \frac{H_{ij,t}}{H_{jj,t}} \tag{17}$$

where $H_{ij,t}$ denotes the conditional covariance of DI/CI volatility i and financial asset volatility j at time t, and $H_{jj,t}$ refers to the conditional variance of financial asset's price volatility j at time t, which is estimated from the DCC-GARCH model following Engle (2002). The optimal portfolio weights are then given by

$$w^*_{ij,t} = \frac{H_{jj,t} - H_{ij,t}}{H_{ii,t} - 2H_{ij,t} + H_{jj,t}}, \text{ with } w^*_{ij,t} = \begin{cases} 0, & if \quad w^*_{ij,t} < 0 \\ w^*_{ij,t}, & if \quad 0 \le w^*_{ij,t} \le 1 \\ 1, & if \quad w^*_{ij,t} > 1 \end{cases} \tag{18}$$

where $w^*_{ij,t}$ is the weight of DI/CI volatility i in a one-dollar portfolio at time t, while the weight of financial asset volatility j is computed as $1 - w^*_{ij,t}$.

The time-varying evolutions of hedge ratios and portfolio weights are shown in Figs. 3 and 4. Overall, hedge ratios and portfolio weights between dirty/clean cryptocurrencies and green/traditional assets are widely volatile over time, suggesting the necessary of active portfolio diversification and risk management when considering the DI/CI volatility. Specifically, it can be seen from Fig. 3 that the hedge ratios is relatively low when dirty/clean cryptocurrencies is taken as a long position. This is consistent with our findings shown in Section 5.1, which suggests that dirty and clean cryptocurrencies tend to transmit little information to green and traditional assets while are mainly impacted by these financial asset volatilities. Moreover, the hedge ratios reach a peak after the announcement of COVID-19 as a pandemic, i.e., 11 March 2020, indicating an increased hedging cost after the pandemic onset. According to Fig. 4, the optimal portfolio weights in most case show a one dollar investment in the volatility of dirty/clean cryptocurrencies, suggesting that the minimum-variance portfolio is constructed by a single-asset portfolio of dirty or clean cryptocurrency volatility. Interestingly, the optimal weights have witnessed a severe turbulence after pandemic oneset, with almost all of the weights drop sharply, except for the weight of green asset of GBI with clean cryptocurrency. This shows that dirty and clean cryptocurrencies can provide diversification gains for investors, especially during the COVID-19 pandemic period, being in line with the existing literature (e.g., Gil-Alana et al., 2020; Hsu et al., 2021).

To further study the impact of COVID-19 pandemic shock, we estimate the hedge ratios and portfolio weights during the whole sample, pre-COVID-19, and post-COVID-19 period, and report the summary statistics of three sample periods in Table 9. From Table 9 panel A, on average, both dirty and clean cryptocurrencies are cheap hedge for green and traditional asset volatilities with their associated hedge

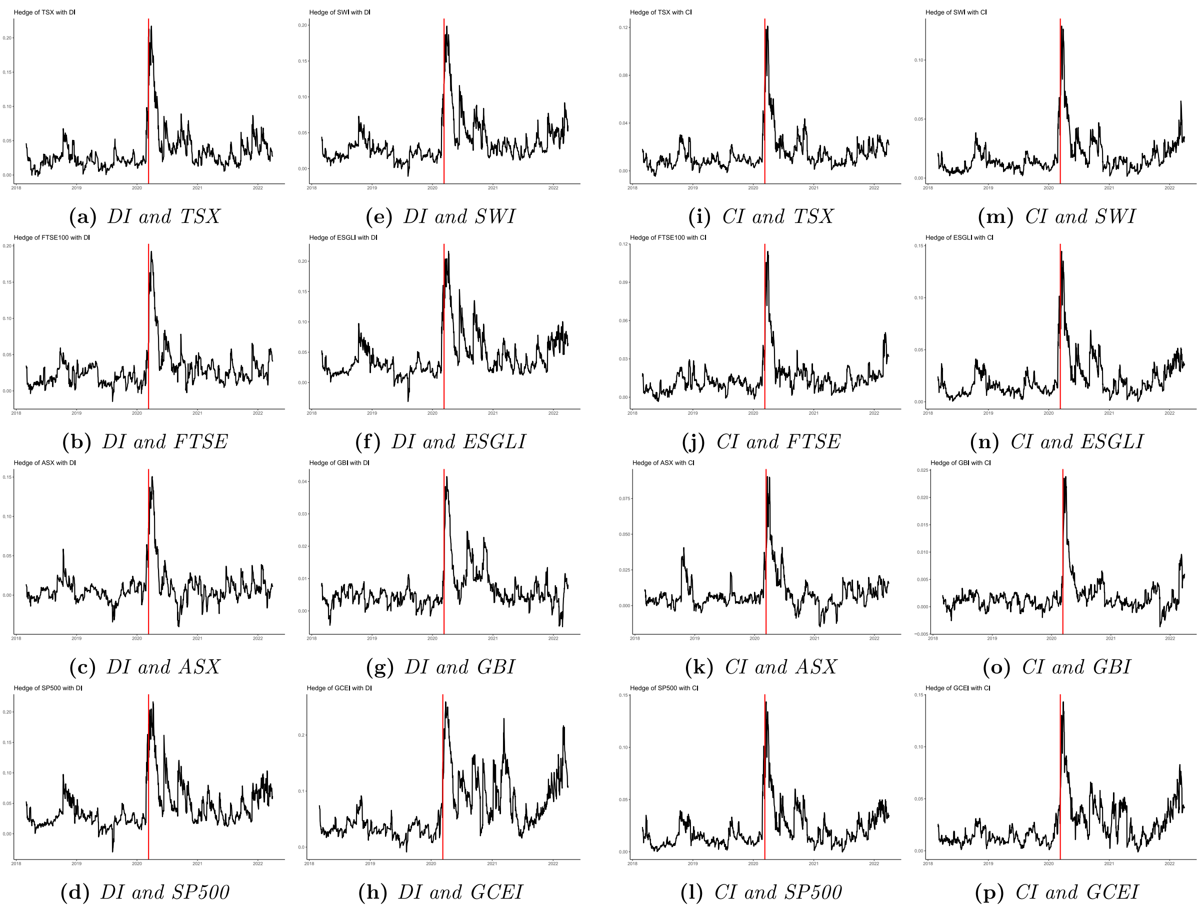


Fig. 3. Dynamic hedge ratios.
Note: Red line denotes the first day of the COVID-19 being announced as a pandemic by the WHO, which is 11 March 2020. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

ratios being close to zero, wherein clean cryptocurrency provides the cheaper hedging opportunities compared to the dirty one for three sample periods. For example, the most expensive hedge for a $1 long position in dirty cryptocurrency is obtained by take a short position of only 7 cents on green asset of GCEI in the whole sample period. This suggests that GCEI is the least useful asset to hedge against DI volatility. Moreover, it is noticed that the average hedge ratios during the post-COVID-19 period is higher than that during the pre-COVID-19 period, showing the critical role of the COVID-19 pandemic shock on the hedging strategy of dirty/clean cryptocurrencies for the market volatility interactions. Turning to Table 9 panel B, the majority of portfolios shows high weights of dirty/clean cryptocurrencies with values close to one, indicating that for $1 portfolio, nearly all cents are invested in dirty or clean cryptocurrency volatility. We also observe that there are higher average weights after the COVID-19 period compared to that before the pandemic. Therefore, these findings also support that dirty and clean cryptocurrencies can act as a diversifier for most green and traditional assets during the financial turmoil associated with the COVID-19 pandemic.

5.4. Robustness check

How sensitive are our main results to changes in the research design? In this section, we conduct the robustness analyses in the face of alternative estimation strategy, i.e., changes in forecast horizon and lag length, replacement of key green assets, and inclusion of commodities, respectively.

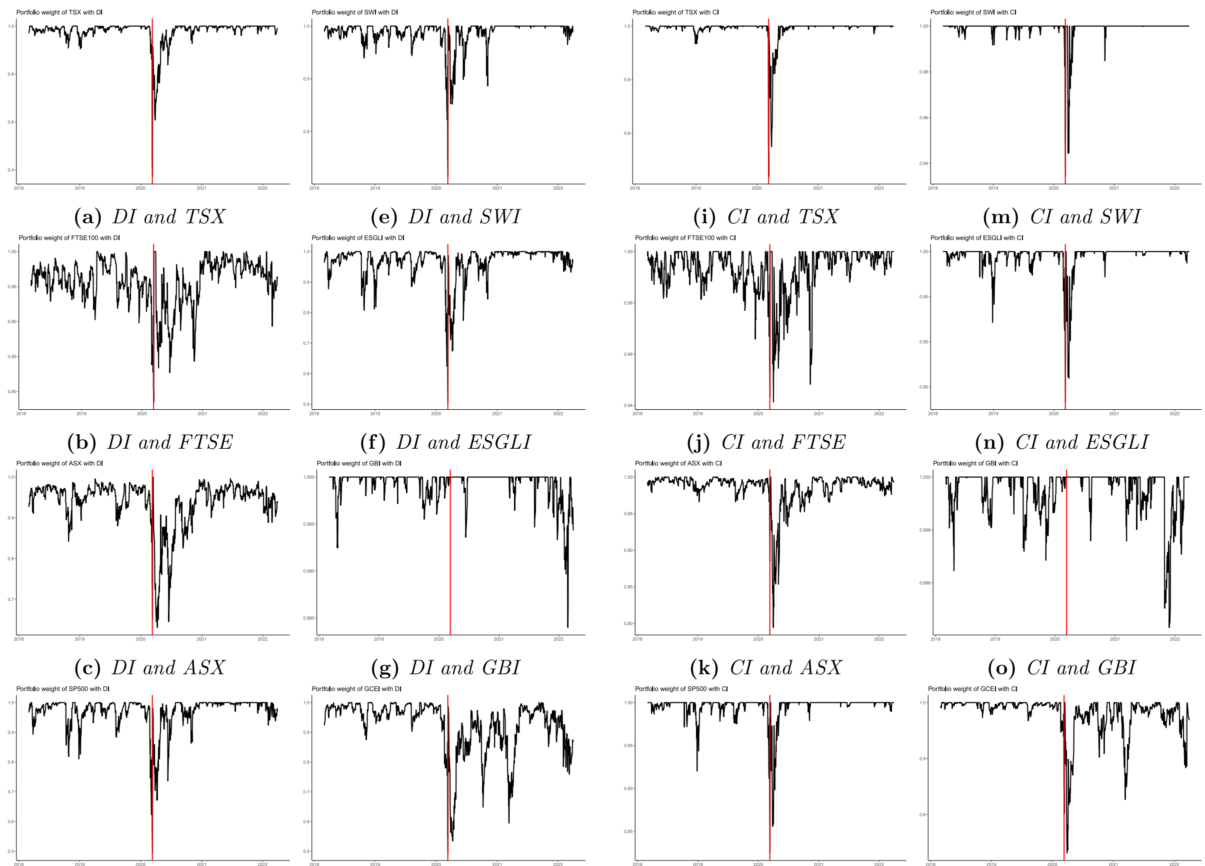
5.4.1. Changes in forecast horizon and lag-length

To test the robustness of our findings regarding the volatility spillover networks of dirty and clean cryptocurrencies with green and traditional assets, we start by changing estimation strategy of forecast horizon and lag-length. In specific, following the extant literature (e.g., Diebold and Yılmaz, 2012; Fasanya et al., 2021; Iyer, 2022), we have updated the forecast horizon of 12-step ahead forecast and lag length of 2 in the TVP-VAR model, respectively, when re-estimating the volatility spillover dynamics of dirty and clean cryptocurrencies with green and traditional assets.

Overall, as an intuitive illustration through the dynamic connectedness approach, it is observed that the results tend to be in line with the estimations without changing forecast horizon and lag order. In particular, the volatility spillover networks when using alternative forecast horizon and lag length for the whole sample period are presented in Tables 10 and 11, respectively, which results are similar to the corresponding counterparts in the main analysis shown in Table 3. The weak interactions between dirty/clean cryptocurrencies and green/traditional assets is broadly consistent when the forecast horizon and lag length is modified, further showing that our results remain robust in the face of changes in estimation strategy.

5.4.2. Replacement of green assets with alternative ones

As an additional robustness check, we follow Ren and Lucey (2022) and Huang et al. (2023) by considering the WilderHill Clean Energy Index (CEI) that measures the overall performance of clean energy sector, and conduct a re-estimation of our volatility spillover and causality test by replacing the S&P Global Clean Energy Index (GCEI). Our obtained results after the replacement of GCEI by CEI have been



(a) *DI and TSX* (e) *DI and SWI* (i) *CI and TSX* (m) *CI and SWI*
(b) *DI and FTSE* (f) *DI and ESGLI* (j) *CI and FTSE* (n) *CI and ESGLI*
(c) *DI and ASX* (g) *DI and GBI* (k) *CI and ASX* (o) *CI and GBI*
(d) *DI and SP500* (h) *DI and GCEI* (l) *CI and SP500* (p) *CI and GCEI*

Fig. 4. Dynamic portfolio weights.
Note: Red line denotes the first day of the COVID-19 being announced as a pandemic by the WHO, which is 11 March 2020. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

visually exhibited by the volatility spillover of the whole sample period depicted in Table 12 and the impact of economic policy uncertainty on these spillover dynamics shown in Table 13. The dynamic volatility interaction of clean and dirty cryptocurrencies with green and traditional assets, and the impact of uncertainty shock on the above networks generally mimic that obtained in our main findings shown in Tables 3 and 6, although there are more significant Granger causalities of the economic policy uncertainty on market linkages between dirty/clean cryptocurrencies and green assets. This therefore indicates that our results are not sensitive to the replacement of the green assets.

5.4.3. Inclusion of commodities

To further examine the robustness of our main results, following the existing literature (Bouri et al., 2020; Mensi et al., 2019; Ren and Lucey, 2022), we include commodities in our empirical analysis. Specifically, we re-estimate the market interaction of clean and dirty cryptocurrencies with green and traditional assets by using dynamic connectedness approach and the role of uncertainty shocks on above-obtained market networks, while considering the commodities of gold and oil. The corresponding results are reported in Tables 14 and 15, respectively. Particularly, the volatility spillovers for the dirty/clean cryptocurrencies and financial assets and the asymmetry of the dynamic networks in the face of uncertainty shocks with the inclusion of commodities are found to be not much different from the main results respectively depicted in Tables 3 and 6. Importantly, the market linkages between dirty/clean cryptocurrencies and gold/oil is not very strong, although there are significant impacts of uncertainty shocks on the above volatility spillovers. The above speaks in favor of the weak sheltering role of clean and dirty cryptocurrencies in the market dynamics, further demonstrating that our results are not sensitive to inclusion of additional commodities.

6. Conclusion

In the era of the digital economy, widespread attention has been recently raised on the market nexus between digital currencies and the financial ecosystem for various purposes such as studying the cross-market information transmission, and sheltering the financial investment, etc., while in-depth research in this regard remains to be explore further. This paper therefore investigates dynamic and possibly bidirectional volatility linkages of energy-intensive (i.e., dirty) cryptocurrencies and energy-efficient (i.e., clean) cryptocurrencies with financial assets over time in a TVP-VAR framework. For the latter, both traditional and recently-emerging green assets are considered. The causal effects of the uncertainty level in the economy on the above-obtained market linkages are further studied in a setting of asymmetry and non-linearity by using a non-parametric causality test.

Our results generally demonstrate a limited market connection between cryptocurrencies and the system of financial assets, and the information transmission from clean cryptocurrencies (CI) to the financial system is even relatively weaker compared to that from dirty cryptocurrencies (DI) especially after the pandemic onset. Within the financial system, there exist a close connection instead between traditional and green assets, indicating the investment sheltering role of cryptocurrencies. We further examine the portfolio diversification and risk management of our obtained market connection with the use of optimal hedge ratios and portfolio weights, and find that dirty and clean cryptocurrencies can act as a diversifiers for investors, especially

Table 9
Hedge ratios and portfolio weights.

	Full sample			Min	Pre-COVID 19			Min	Post-COVID-19			Min
	Mean	St.Dev	Max		Mean	St.Dev	Max		Mean	St.Dev	Max	
Panel A: Hedge ratios												
DI/TSX	0.03	0.03	0.22	0.00	0.01	0.01	0.12	−0.03	0.08	0.05	0.36	0.03
DI/FTSE	0.03	0.03	0.19	−0.01	0.00	0.01	0.04	−0.05	0.07	0.03	0.17	0.03
DI/ASX	0.01	0.02	0.15	−0.04	0.00	0.01	0.06	−0.05	0.03	0.03	0.16	0.00
DI/SP500	0.04	0.03	0.22	−0.03	0.00	0.02	0.09	−0.10	0.10	0.05	0.36	0.04
DI/SWI	0.04	0.03	0.20	−0.01	0.00	0.01	0.05	−0.05	0.08	0.04	0.29	0.03
DI/ESGLI	0.04	0.04	0.22	−0.03	0.00	0.02	0.09	−0.10	0.10	0.05	0.35	0.04
DI/GBI	0.01	0.01	0.04	0.00	0.00	0.00	0.01	−0.01	0.01	0.00	0.03	0.01
DI/GCEI	0.07	0.05	0.26	−0.01	0.01	0.01	0.07	−0.05	0.16	0.05	0.33	0.07
CI/TSX	0.01	0.02	0.12	0.00	0.00	0.01	0.05	−0.02	0.03	0.02	0.18	0.01
CI/FTSE	0.01	0.01	0.11	0.00	0.00	0.01	0.04	−0.02	0.03	0.01	0.08	0.01
CI/ASX	0.01	0.01	0.09	−0.01	0.01	0.01	0.05	−0.01	0.01	0.01	0.09	0.00
CI/SP500	0.02	0.02	0.14	0.00	0.00	0.01	0.09	−0.02	0.04	0.03	0.21	0.01
CI/SWI	0.02	0.02	0.13	0.00	0.00	0.01	0.06	−0.01	0.03	0.02	0.15	0.01
CI/ESGLI	0.02	0.02	0.14	0.00	0.01	0.01	0.09	−0.02	0.04	0.03	0.20	0.01
CI/GBI	0.00	0.00	0.02	0.00	0.00	0.00	0.01	−0.01	0.00	0.00	0.02	0.00
CI/GCEI	0.02	0.02	0.14	0.00	0.01	0.01	0.04	−0.01	0.05	0.02	0.16	0.02
Panel B: Portfolio weights												
DI/TSX	0.98	0.05	1.00	0.37	0.97	0.04	1.00	0.41	1.00	0.01	1.00	0.89
DI/FTSE	0.96	0.03	1.00	0.79	0.93	0.03	1.00	0.76	0.98	0.03	1.00	0.90
DI/ASX	0.94	0.06	1.00	0.63	0.94	0.03	1.00	0.71	0.93	0.05	1.00	0.68
DI/SP500	0.97	0.05	1.00	0.49	0.94	0.06	1.00	0.52	1.00	0.02	1.00	0.80
DI/SWI	0.99	0.03	1.00	0.71	0.96	0.03	1.00	0.70	1.00	0.00	1.00	0.96
DI/ESGLI	0.97	0.05	1.00	0.51	0.93	0.07	1.00	0.51	1.00	0.02	1.00	0.85
DI/GBI	1.00	0.00	1.00	0.98	1.00	0.00	1.00	0.99	1.00	0.00	1.00	1.00
DI/GCEI	0.93	0.09	1.00	0.49	0.94	0.05	1.00	0.51	0.93	0.06	1.00	0.71
CI/TSX	0.99	0.02	1.00	0.72	0.99	0.02	1.00	0.67	1.00	0.01	1.00	0.89
CI/FTSE	0.99	0.01	1.00	0.94	0.98	0.01	1.00	0.91	0.98	0.03	1.00	0.90
CI/ASX	0.99	0.02	1.00	0.79	0.99	0.01	1.00	0.88	0.93	0.05	1.00	0.68
CI/SP500	1.00	0.02	1.00	0.82	0.98	0.02	1.00	0.77	1.00	0.02	1.00	0.80
CI/SWI	1.00	0.00	1.00	0.93	0.99	0.01	1.00	0.88	1.00	0.00	1.00	0.96
CI/ESGLI	1.00	0.02	1.00	0.83	0.98	0.03	1.00	0.77	1.00	0.02	1.00	0.85
CI/GBI	1.00	0.00	1.00	0.99	1.00	0.00	1.00	0.99	1.00	0.00	1.00	1.00
CI/GCEI	0.98	0.04	1.00	0.73	0.99	0.02	1.00	0.76	0.93	0.06	1.00	0.71

Table 10
Robustness: Volatility spillovers during the whole sample period with the change in forecast horizon.

	DI	CI	TSX	FTSE	ASX	SP500	SWI	ESGLI	GBI	GCEI	FROM
DI	53.7	9.7	6.1	6.9	2.3	2.9	7.0	2.7	4.2	4.5	46.3
CI	10.6	67.0	3.7	3.4	1.9	1.6	3.4	1.4	2.1	4.9	33.0
TSX	3.0	1.9	23.7	9.9	7.4	11.9	15.3	11.3	3.6	11.9	76.3
FTSE	4.2	2.2	13.9	28.0	6.7	8.3	15.3	7.9	4.1	9.4	72.0
ASX	1.7	1.5	11.9	7.1	25.6	12.9	13.2	12.5	3.1	10.4	74.4
SP500	1.7	1.1	12.0	6.2	7.3	21.9	16.7	21.7	2.1	9.4	78.1
SWI	3.2	1.7	14.2	10.3	7.1	15.1	20.1	14.7	3.3	10.3	79.9
ESGLI	1.7	1.1	11.7	6.1	7.2	22.1	16.8	22.1	2.1	9.1	77.9
GBI	4.1	2.7	10.3	7.1	7.1	6.5	9.6	6.2	36.0	10.3	64.0
GCEI	2.9	2.6	13.7	7.4	7.4	10.3	12.3	9.7	4.0	29.8	70.2
To	33.1	24.4	97.5	64.3	54.3	91.7	109.7	88.3	28.5	80.3	672.1
NTS	−13.2	−8.6	21.1	−7.7	−20.1	13.6	29.8	10.4	−35.5	10.0	TS
NPS Transmitter	7.0	7.0	2.0	5.0	6.0	3.0	1.0	4.0	8.0	3.0	67.2

Note: This table describes the time-average connectedness of cryprocurrency-financial asset markets based on the whole sample period. Interpretations of abbreviations of incorporated variables and different terms depicting various connectedness are from Section 3 and Section 5.1, respectively.

when suffering from financial turmoil associated with the COVID-19 pandemic. Moreover, the causal relationship between uncertainty and the above-obtained market nexus is shown to be enhanced in the post-pandemic period, and the causality from uncertainty to the market nexus with DI is relatively stronger than that with CI. In addition, the majority of the market linkages are shown to be negligible at extremely low quantiles, further indicating effectiveness of the hedge and safe haven role of cryptocurrencies especially CI for the financial system as well as the uncertainty in depression.

Our results possess important implications to various stakeholders. As for market investors, the obtained weak market linkages between cryptocurrencies and the financial system demonstrate the investment sheltering role of cryptocurrencies for adverse fluctuations in the portfolio built by traditional and/or green assets. In particular, since that eco-friendly clean cryptocurrencies (CI) behave a more weakened linkage with financial assets than energy-intensive dirty cryptocurrencies (DI) and the CI related asset linkage further demonstrates a weak relationship with uncertainty, these findings indicate the presence of an effective clean and green safe haven. Cryptocurrencies especially the clean ones are therefore known to contribute to not only diversification and risk mitigation in the financial investment portfolio but also sheltering against uncertainty. As for policymakers, the aforementioned sheltering role of clean cryptocurrencies contributes to achievement of the important dual goal of risk management and green market transition, enhancing the financial stability of the system in a low-carbon manner.

Given that the current research scope lies in the relation of cryptocurrencies with financial assets, future research could extend the

Table 11
Robustness: Volatility spillovers during the whole sample period with the change in lag length.

	DI	CI	TSX	FTSE	ASX	SP500	SWI	ESGLI	GBI	GCEI	FROM
DI	54.1	9.9	6.0	7.1	2.4	2.7	6.8	2.6	3.9	4.5	45.9
CI	10.8	68.4	3.5	3.6	1.8	1.2	3.1	1.1	1.8	4.6	31.6
TSX	3.0	1.9	25.4	9.9	7.3	11.2	15.3	10.6	3.1	12.3	74.6
FTSE	4.4	2.4	13.3	29.1	6.1	8.4	15.5	8.1	3.5	9.2	70.9
ASX	1.7	1.5	11.9	6.8	26.9	12.7	13.1	12.2	2.7	10.5	73.1
SP500	1.3	0.7	11.2	5.8	6.1	23.7	17.3	23.4	1.3	9.3	76.3
SWI	3.0	1.5	13.8	10.3	6.3	15.7	21.0	15.3	2.6	10.4	79.0
ESGLI	1.3	0.7	10.9	5.7	5.9	23.9	17.4	23.9	1.3	9.0	76.1
GBI	3.8	2.3	10.3	6.5	7.3	6.5	9.1	6.2	37.6	10.4	62.4
GCEI	2.8	2.4	13.8	7.3	7.2	10.3	12.3	9.8	3.2	30.9	69.1
To	32.4	23.4	94.6	63.1	50.3	92.5	109.8	89.3	23.3	80.1	658.9
NTS	−13.5	−8.2	20.1	−7.8	−22.8	16.2	30.8	13.2	−39.0	11.0	TS
NPS Transmitter	7.0	8.0	2.0	5.0	6.0	2.0	1.0	4.0	8.0	3.0	65.9

Note: This table describes the time-average connectedness of cryprocurrency-financial asset markets based on the whole sample period. Interpretations of abbreviations of incorporated variables and different terms depicting various connectedness are from Section 3 and Section 5.1, respectively.

Table 12
Robustness: Volatility spillovers during the whole sample period with the replacement of green assets.

	DI	CI	TSX	FTSE	ASX	SP500	SWI	ESGLI	GBI	CEI	FROM
DI	54.0	9.7	6.1	7.0	2.4	3.1	7.2	2.9	4.3	3.3	46.0
CI	10.6	67.0	3.7	3.5	1.8	1.8	3.6	1.6	2.2	4.2	33.0
TSX	3.1	2.0	24.0	10.1	7.4	12.5	15.8	11.9	3.6	9.6	76.0
FTSE	4.3	2.3	14.0	28.8	6.7	8.6	15.7	8.2	4.1	7.3	71.2
ASX	1.6	1.5	11.6	7.1	25.6	13.0	13.3	12.6	3.2	10.5	74.4
SP500	1.7	1.1	11.7	6.0	7.1	21.6	16.4	21.4	2.1	11.0	78.4
SWI	3.2	1.8	14.1	10.3	7.0	15.4	20.3	15.0	3.4	9.5	79.7
ESGLI	1.7	1.1	11.5	6.0	7.0	21.8	16.5	21.8	2.1	10.7	78.2
GBI	4.1	2.7	9.8	7.0	7.1	6.7	9.8	6.3	37.8	8.8	62.2
CEI	2.2	2.1	10.9	5.8	7.2	12.7	11.6	12.1	3.3	32.1	67.9
To	32.4	24.4	93.4	62.9	53.7	95.4	109.9	92.0	28.1	74.9	667.0
NTS	−13.6	−8.6	17.4	−8.3	−20.7	17.0	30.3	13.7	−34.2	7.0	TS
NPS Transmitter	7.0	7.0	2.0	5.0	6.0	2.0	1.0	4.0	8.0	4.0	66.7

Note: This table describes the time-average connectedness of cryprocurrency-financial asset markets based on the whole sample period. Interpretations of abbreviations of incorporated variables and different terms depicting various connectedness are from Section 3 and Section 5.1, respectively.

Table 13
Robustness: Causality tests in quantiles during the whole sample period with the replacement of green assets.

Ho: EPU does not Granger-cause:	Nonlinear causality		0.3	0.4	0.5	0.6	0.7	0.8	0.9
	0.1	0.2							
Net volatility spillover between DI and TSX	2.873***	2.728***	2.317**	2.502**	4.326***	6.548***	6.594***	4.877***	2.674***
Net volatility spillover between DI and FTSE	1.448	2.266**	2.390**	1.258	1.884	3.361***	4.549***	3.391***	1.407
Net volatility spillover between DI and ASX	1.818**	4.082***	5.514***	2.946***	1.288	2.962***	3.492**	3.524***	1.384
Net volatility spillover between DI and SP500	1.011	0.720	1.006	2.048**	2.197**	1.837	1.602	1.793	0.920
Net volatility spillover between DI and SWI	3.392***	4.538***	2.331**	2.301**	3.827***	6.144***	6.784***	5.929***	2.840***
Net volatility spillover between DI and ESGLI	0.851	0.520	0.698	1.174	1.683	1.443	1.006	1.098	0.909
Net volatility spillover between DI and GBI	1.480	2.982***	3.769***	3.380***	2.259**	2.235**	1.525	1.857	1.166
Net volatility spillover between DI and CEI	1.426	2.299**	3.228***	2.149**	3.630***	6.917***	6.534***	4.615***	2.205**
Net volatility spillover between CI and TSX	2.199**	3.619***	3.698***	2.843***	2.395**	3.463**	4.011***	3.559***	1.953**
Net volatility spillover between CI and FTSE	1.210	2.04**	2.424**	2.621***	2.904***	1.833	1.917	1.886	1.447
Net volatility spillover between CI and ASX	1.521	2.864***	2.739***	2.018**	1.684	1.482	1.719	1.994**	1.696
Net volatility spillover between CI and SP500	0.468	1.255	1.627	1.790	1.354	1.414	2.247**	1.837	0.840
Net volatility spillover between CI and SWI	1.614	1.835	1.879	2.399**	2.807***	4.472***	5.511***	5.724***	3.672***
Net volatility spillover between CI and ESGLI	0.539	1.211	1.716	1.700	1.396	2.010**	2.358**	2.007**	1.013
Net volatility spillover between CI and GBI	2.573***	3.806***	3.674***	2.739***	1.494	1.120	1.781	2.574***	1.893
Net volatility spillover between CI and CEI	1.494	2.743***	2.029**	1.706	0.994	1.395	1.988**	2.887***	1.010

Note: This table reports the causality from economic policy uncertainty (EPU) to various linkages between cryptocurrency and financial asset markets based on the whole sample.
*** Represents the significance at 1%.
** Represents the significance at 5%.

Table 14
Robustness: Volatility spillovers during the whole sample period with the inclusion of commodities.

	DI	CI	GOLD	OIL	TSX	FTSE	ASX	SP500	SWI	ESGLI	GBI	GCEI	FROM
DI	51.0	9.3	2.0	1.8	5.9	6.7	2.4	2.8	6.8	2.6	4.3	4.4	49.0
CI	10.3	65.5	1.5	0.8	3.7	3.5	1.9	1.5	3.3	1.4	2.1	4.6	34.5
GOLD	1.8	2.4	36.9	2.9	7.4	6.9	5.8	5.8	8.0	5.5	8.3	8.4	63.1
OIL	1.1	0.9	1.3	48.0	9.2	5.2	6.7	6.0	7.1	5.8	2.0	6.8	52.0
TSX	2.8	2.0	2.9	3.5	22.1	9.4	6.9	11.1	14.5	10.6	3.3	10.9	77.9
FTSE	3.9	2.2	4.6	3.2	13.0	25.8	6.3	7.5	14.2	7.2	3.7	8.6	74.2
ASX	1.6	1.4	3.4	3.5	11.1	6.8	24.3	11.8	12.3	11.4	2.9	9.4	75.7
SP500	1.5	0.9	2.6	2.7	11.4	5.8	6.9	21.0	16.0	20.8	1.9	8.6	79.0
SWI	2.9	1.6	3.4	2.9	13.4	9.7	6.7	14.1	18.9	13.8	3.1	9.5	81.1
ESGLI	1.5	1.0	2.5	2.7	11.1	5.7	6.8	21.2	16.0	21.2	1.9	8.3	78.8
GBI	3.9	2.8	7.4	3.3	9.5	6.4	6.6	5.6	8.7	5.3	31.4	9.2	68.6
GCEI	2.6	2.5	3.8	3.6	12.9	6.8	6.9	9.3	11.3	8.8	3.7	28.0	72.0
To	33.7	27.1	35.4	30.8	108.6	72.9	63.8	96.7	118.0	93.1	37.2	88.7	806.0
NTS	−15.3	−7.4	−27.7	−21.2	30.7	−1.3	−11.9	17.7	36.9	14.3	−31.4	16.7	TS
NPS Transmitter	8.3	7.7	9.2	8.4	1.9	5.0	6.0	2.8	0.8	3.9	8.9	3.2	67.2

Note: This table describes the time-average connectedness of cryprocurrency-financial asset markets based on the whole sample period. Interpretations of abbreviations of incorporated variables and different terms depicting various connectedness are from Section 3 and Section 5.1, respectively.

Table 15
Robustness: Causality tests in quantiles during the whole sample period with the inclusion of commodities.

Ho: EPU does not Granger-cause:	Nonlinear causality		0.3	0.4	0.5	0.6	0.7	0.8	0.9
	0.1	0.2							
Net volatility spillover between DI and Gold	1.641	2.588***	2.787***	3.017***	3.593***	4.316***	4.126***	2.906***	1.572
Net volatility spillover between DI and Oil	1.217	2.732***	2.712***	3.268***	3.018***	1.496	2.373**	1.849	1.033
Net volatility spillover between DI and TSX	2.042**	2.687***	2.136**	2.681***	4.805***	7.417***	9.340***	6.243***	1.750
Net volatility spillover between DI and FTSE	1.783	3.277***	2.796***	1.624	1.706	2.525***	2.473**	3.436***	1.772
Net volatility spillover between DI and ASX	3.714***	4.515***	2.504**	1.300	2.886***	4.595***	6.238***	5.732***	2.403**
Net volatility spillover between DI and SP500	0.887	1.200	1.530	1.582	1.607	1.761	1.526	0.876	0.822
Net volatility spillover between DI and SWI	3.333***	4.522***	3.049***	2.191**	4.537***	7.492***	8.122***	6.617***	2.716***
Net volatility spillover between DI and ESGLI	1.215	1.473	1.846	1.839	2.100**	2.626***	2.330**	1.298	1.140
Net volatility spillover between DI and GBI	1.802	4.152***	3.027***	1.222	1.484	2.385**	3.078***	2.050**	1.139
Net volatility spillover between DI and GCEI	1.615	3.478***	3.118***	0.741	2.353**	6.270***	6.171***	4.781***	1.863
Net volatility spillover between CI and Gold	1.085	2.414**	2.320**	2.107**	1.666	1.964**	1.560	1.684	0.906
Net volatility spillover between CI and Oil	2.397**	5.489***	7.000***	7.837***	4.724***	1.345	1.349	1.812	1.451
Net volatility spillover between CI and TSX	1.410	1.990**	1.184	0.821	1.293	3.040***	2.192**	1.771	1.169
Net volatility spillover between CI and FTSE	1.339	2.204**	2.468**	2.549**	2.111**	1.765	2.312**	2.636***	1.483
Net volatility spillover between CI and ASX	1.002	1.923	2.088**	1.219	1.287	2.936***	3.369***	3.303***	2.932***
Net volatility spillover between CI and SP500	0.600	1.390	1.757	1.009	0.875	1.426	1.707	1.723	0.936
Net volatility spillover between CI and SWI	1.923	2.778***	1.815	1.886	2.137**	3.864***	4.489***	4.782***	2.123**
Net volatility spillover between CI and ESGLI	0.797	1.511	1.273	0.764	0.683	1.497	2.820***	2.161**	1.219
Net volatility spillover between CI and GBI	3.522***	7.322***	10.822***	12.071***	7.270***	2.342**	2.514**	3.279***	2.423**
Net volatility spillover between CI and GCEI	1.229	2.847***	1.859	1.371	3.225***	4.717***	6.385***	4.920***	2.180**

Note: This table reports the causality from economic policy uncertainty (EPU) to various linkages between cryptocurrency and financial asset markets based on the whole sample.
*** Represents the significance at 1%.
** Represents the significance at 5%.

scope by further studying the linkage of (clean and dirty) cryptocurrencies with a broad financial system that not only includes different (traditional and green) assets but also various commodities. Moreover, as another promising research directions, future research could move a step further by focusing on determinants of the cross-market network, and the potential dynamics of the determination process over time.

CRediT authorship contribution statement

Kun Duan: Conceptualization, Methodology, Investigation, Writing – original draft. **Yanqi Zhao:** Investigation, Writing – original draft, Writing – review & editing. **Andrew Urquhart:** Conceptualization, Writing – review & editing, Supervision. **Yingying Huang:** Conceptualization, Methodology, Software, Formal analysis, Writing – original draft.

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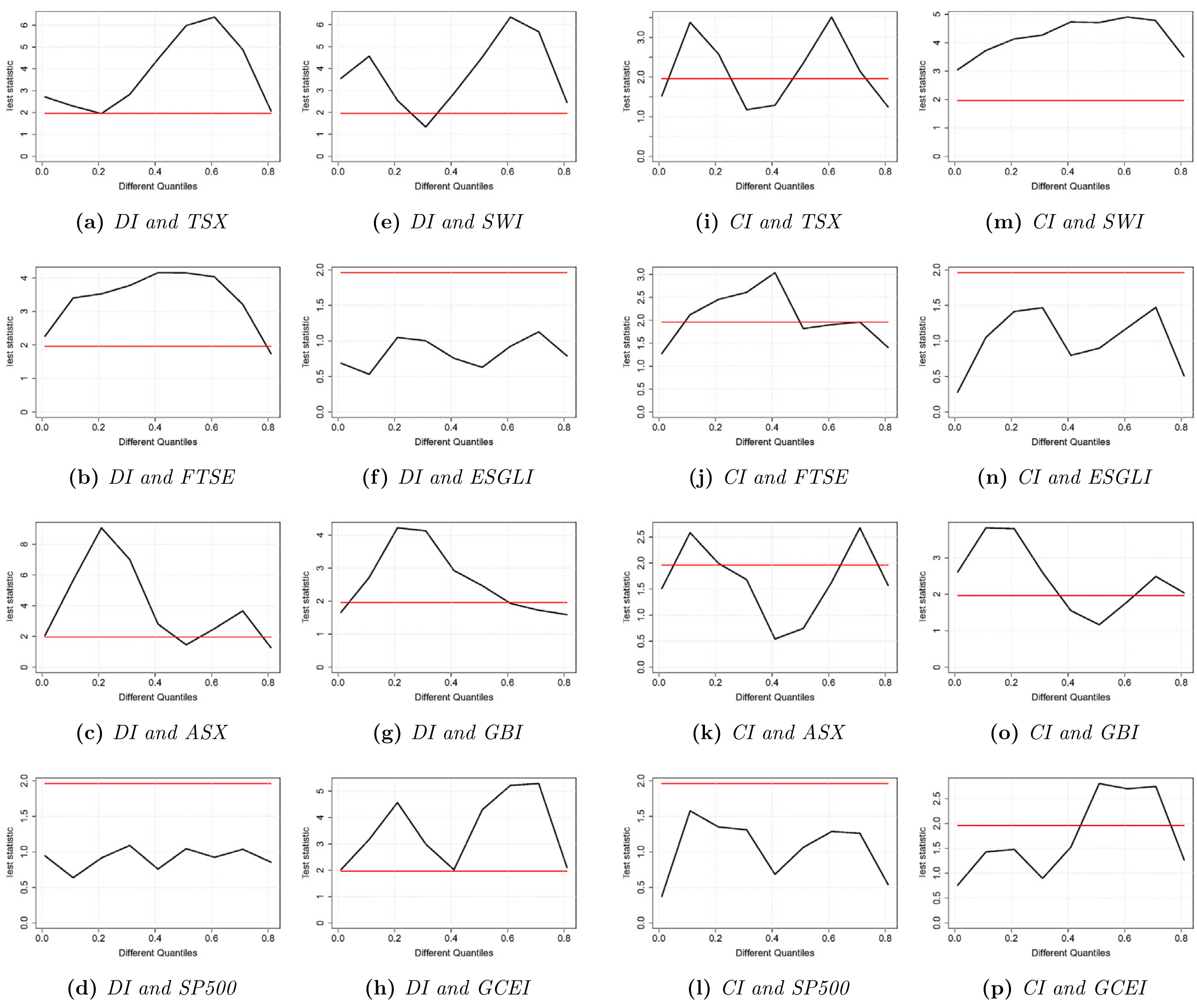
Appendix A. Plots of causality test in quantiles

See Figs. A.1–A.3.

Appendix B. Summary of the key literature on the market linkages of cryptocurrencies with financial assets

See Table B.1.



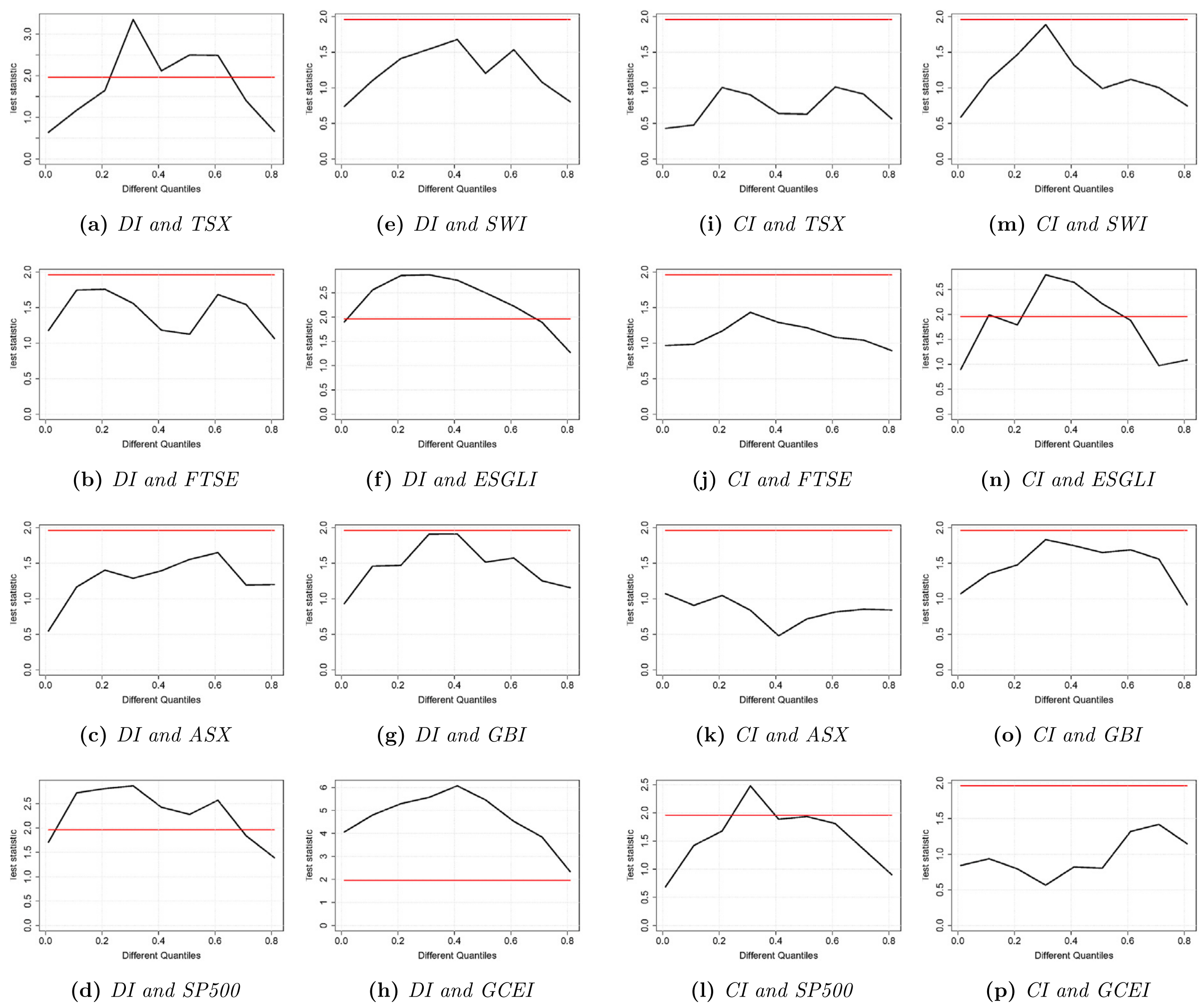
(a) *DI and TSX* (e) *DI and SWI* (i) *CI and TSX* (m) *CI and SWI*

(b) *DI and FTSE* (f) *DI and ESGLI* (j) *CI and FTSE* (n) *CI and ESGLI*

(c) *DI and ASX* (g) *DI and GBI* (k) *CI and ASX* (o) *CI and GBI*

(d) *DI and SP500* (h) *DI and GCEI* (l) *CI and SP500* (p) *CI and GCEI*

Fig. A.1. Plots for the causality-in-quantiles from EPU to cross-market interactions during the whole sample period.
Note: Each of the sub-figures illustrates the causal response of the cross-market interaction in the face of a shock in EPU based on the whole data sample. X-axis stands for different quantiles of the level of the cross-market connectedness. The red-color horizontal line is the 5% significance level. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)



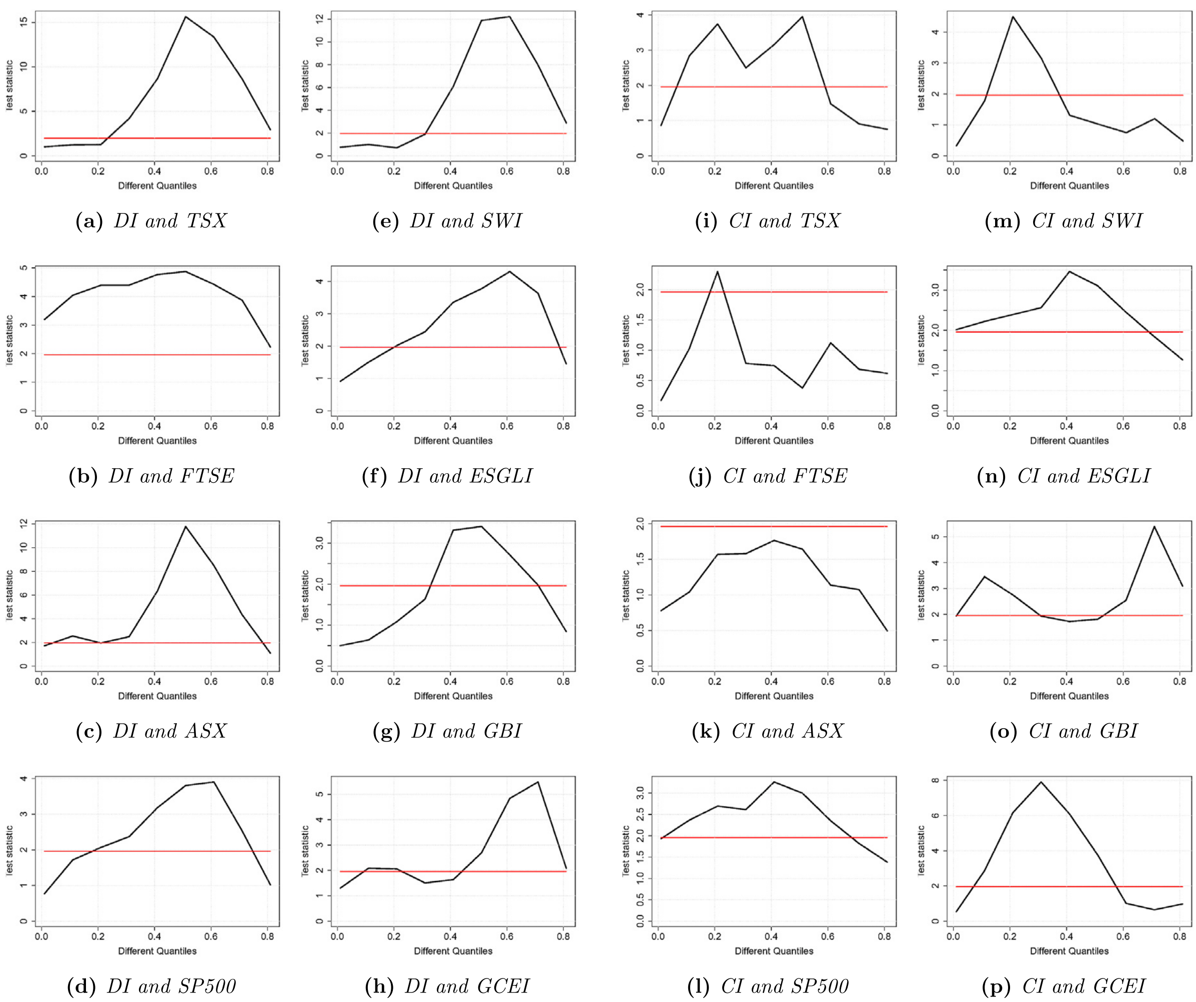
(a) *DI and TSX* (e) *DI and SWI* (i) *CI and TSX* (m) *CI and SWI*

(b) *DI and FTSE* (f) *DI and ESGLI* (j) *CI and FTSE* (n) *CI and ESGLI*

(c) *DI and ASX* (g) *DI and GBI* (k) *CI and ASX* (o) *CI and GBI*

(d) *DI and SP500* (h) *DI and GCEI* (l) *CI and SP500* (p) *CI and GCEI*

Fig. A.2. Plots for the causality-in-quantiles from EPU to cross-market interactions in the pre-COVID-19 period.
Note: Each of the sub-figures illustrates the causal response of the cross-market interaction in the face of a shock in the pre-COVID-19 period. X-axis stands for different quantiles of the level of the cross-market connectedness. The red-color horizontal line is the 5% significance level. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)



(a) *DI and TSX* (e) *DI and SWI* (i) *CI and TSX* (m) *CI and SWI*

(b) *DI and FTSE* (f) *DI and ESGLI* (j) *CI and FTSE* (n) *CI and ESGLI*

(c) *DI and ASX* (g) *DI and GBI* (k) *CI and ASX* (o) *CI and GBI*

(d) *DI and SP500* (h) *DI and GCEI* (l) *CI and SP500* (p) *CI and GCEI*

Fig. A.3. Plots for the causality-in-quantiles from EPU to cross-market interactions in the post-COVID-19 period.
Note: Each of the sub-figures illustrates the causal response of the cross-market interaction in the face of a shock in the post-COVID-19 period. X-axis stands for different quantiles of the level of the cross-market connectedness. The red-color horizontal line is the 5% significance level. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

Table B.1
Summary of the key literature on the market linkages of cryptocurrencies with financial assets.

Authors	Method	Period	Cryptocurrency	Main finding
Bouri et al. (2020)	Wavelet coherence and wavelet VaR	2010.07.20-2018.02.22	Bitcoin (dirty)	Compared to gold and commodities, Bitcoin is the most promising safe haven asset with diversification benefits.
Charfeddine et al. (2020)	ARFIMA-FIAPARCH models	2010.07.18-2018.10.01 (Bitcoin) 2015.09.01-2018.10.01 (Ethereum)	Bitcoin and Ethereum (dirty)	Cryptocurrencies can be applied for investment diversification.
Conlon et al. (2020)	VaR and CVaR method	2010.01–2020.04 (Bitcoin) 2015.08–2020.04 (Ethereum) 2014.10–2020.04 (Tether)	Bitcoin, Ethereum, and Tether (dirty)	Bitcoin and Ethereum are not safe havens for the majority of international equity markets examined, while Tether acts as a safe haven investment for all of the international indices examined.
Dutta et al. (2020)	DCC-GARCH approach	2014.12–2020.03	Bitcoin (dirty)	Gold is a safe haven asset for global crude oil markets, while Bitcoin acts only as a diversifier for crude oil.
Ghorbel and Jeribi (2021)	Multivariate BEKK-GARCH model and DCC-GARCH model	2016.01.01-2020.04.01	Bitcoin, Ethereum, and Monero (dirty); Dash and Ripple (clean)	Ripple, Ethereum, and Monero are more volatile than Bitcoin and Dash concerning the dynamic correlations with Cboe Volatility Index (VIX).
Gil-Alana et al. (2020)	Fractional integration and cointegration	2015.05.07-2018.10.05	Bitcoin, Ethereum, Litecoin, and Tether (dirty); Ripple and Stellar (clean)	Both clean and dirty cryptocurrencies are decoupled from mainstream financial and economic assets, which implies the role of cryptocurrencies as a diversifier.
Hsu et al. (2021)	Diagonal BEKK model	2015.08.07-2020.06.15	Bitcoin and Ethereum (dirty); Ripple (clean)	While the two types of cryptocurrencies display different co-volatility spillovers with various financial assets, both have hedging or safe-haven opportunities for the traditional currency market.
Le et al. (2021)	Time domain VAR model and frequency domain spillover method	2018.11.28-2020.06.29	Bitcoin (dirty)	Bitcoin acts as a net contributor of volatility shocks among Fintech, green bonds, and itself.
Naeem and Karim (2021)	Time-varying optimal copula approach, AGDCC-GARCH models	2013.05.01-2021.07.19	Bitcoin (dirty)	There is an asymmetric and time-varying dependence structure between Bitcoin and green financial assets.
Pham et al. (2021)	TVP-VAR network connectedness model	2015.08–2021.08	Bitcoin and Ethereum (dirty)	The spillovers between cryptocurrencies and green/fossil fuel investment are small during non-crisis periods but increase during crisis periods.
Rehman and Kang (2021)	Partial wavelet coherence and multiple wavelet coherence	2012.01.01-2018.10.12	Bitcoin (dirty)	There is a lead–lag price connection exists between oil and gas with Bitcoin.
Ren and Lucey (2022)	DCC-GARCH model and VAR model	2018.01.01-2021.09.17	Bitcoin, Ethereum, Bitcoin Cash, Ethereum Classic, and Litcoin (dirty); Cardano, Ripple, IOTA, Stellar, and Nano (clean)	Clean energy is more likely to be a safe haven for dirty cryptocurrencies than that for clean cryptocurrencies, especially in periods of high uncertainty.

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