International Review of Financial Analysis 81 (2022) 102069

Contents lists available at ScienceDirect

International Review of Financial Analysis

journal homepage: www.elsevier.com/locate/irfa

Risk transmissions between bitcoin and traditional financial assets during the COVID-19 era: The role of global uncertainties

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ARTICLE INFO

JEL codes:
C32
C50
G10
G11

Keywords:
Return connectedness
Risk transmissions
Bitcoin
Financial assets
Global uncertainty measures

ABSTRACT

This paper examines return and volatility connectedness between Bitcoin, traditional financial assets (Crude Oil, Gold, Stocks, Bonds, and the United States Dollar-USD), and major global uncertainty measures (the Economic Policy Uncertainty-EPU, the Twitter-based Economic Uncertainty-TEU, and the Volatility Index-VIX) from April 29, 2013, to June 30, 2020. To this end, the Time-Varying Parameter Vector Autoregression (TVP-VAR) model, dynamic connectedness approaches, and network analyses are used. The results indicate that total spillover indices reached unprecedented levels during COVID-19 and have remained high since then. The evidence also confirms the high return and volatility spillovers across markets during the COVID-19 era. Regarding the return spillovers, Gold is the centre of the system and demonstrates the safe heaven properties. Bitcoin is a net transmitter of volatility spillovers to other markets, particularly during the COVID-19 period. Furthermore, the causality-in-variance Lagrange Multiplier (LM) and the Fourier LM tests' results confirm a unidirectional volatility transmission from Bitcoin to Gold, Stocks, Bonds, the VIX and Crude Oil. Interestingly the EPU is the only global factor that causes higher volatility in Bitcoin. Several potential implications of the results are also discussed.

1. Introduction

Bitcoin is becoming more integrated into the global financial system every year. The market capitalisation of Bitcoin has exceeded the threshold of $1 T in March 2021, a year after the starting of the global COVID-19 pandemic. Although the market capitalisation of Bitcoin decreased around $600B in July 2021, Bitcoin still has a dominant role in the global cryptocurrency market, which has a market cap of around $1.3 T. It is also important to note that the dominance of Bitcoin has been steadily reducing with the introduction of Altcoins (Elsayed, Gozgor, & Lau, 2021; Ji, Bouri, Lau, & Roubaud, 2019; Shi, Tiwari, Gozgor, & Lu, 2020; Yi, Xu, & Wang, 2018), but Bitcoin still has almost three-folds higher market cap than the runner cryptocurrency (Ethereum).

On the other hand, tremendous price volatility in Bitcoin has been observed during the COVID-19 era. On March 11, 2020, the World Health Organization (WHO) announced that the COVID-19 had been a global pandemic and the closing price of Bitcoin was $7911. A day later, the price of Bitcoin plunged to $4970. However, Bitcoin's price had experienced a significant upward trend throughout the year, and its closing price has first exceeded $60 K on March 13, 2021 (Coindesk, 2021). However, it decreased to the level of around $30 K in July 2021. Accordingly, various research has been performed to analyse Bitcoin's returns and price volatility determinants during the COVID-19 crisis (see, e.g., Goodell & Goutte, 2021a; Jiang, Wu, Tian, & Nie, 2021).

Empirical literature examines different characteristics of cryptocurrencies including Bitcoin. For example, Caporale, Gil-Alana, and Plastun (2018), Tiwari, Jana, Das, and Roubaud (2018), and Urquhart (2016) investigate the inefficiency of cryptocurrency markets. Corbet, Lucey, and Yarovaya (2018) and Chowdhury, Damianov, and Elsayed (2021) examine the significance and behaviour of bubbles. Conlon, Corbet, and McGee (2020), Damianov and Elsayed (2020), Liu, Semeyutin, Lau, and Gozgor (2020), and Urquhart and Zhang (2019) show the significant hedging and safe haven features of cryptocurrency markets in general and Bitcoin in particular. Kajtazi and Moro (2019) observe the speculative characteristics of Bitcoin. Corbet and Katsiampa (2020) find a significant asymmetric reverting behaviour in Bitcoin returns. Bouri, Gupta, and Roubaud (2019) observe the significant

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https://doi.org/10.1016/j.irfa.2022.102069
Received 22 August 2021; Received in revised form 6 November 2021; Accepted 2 February 2022
Available online 6 February 2022

herding feature of cryptocurrencies including Bitcoin. Several studies also examine the drivers and the patterns of price volatility (see, e.g., Caporale & Zekokh, 2019; Elsayed et al., 2021; Katsiampa, 2019; Shi et al., 2020). Some other studies analyse investors' attention to Bitcoin (Dastgir, Demir, Downing, Gozgor, & Lau, 2019; Urquhart, 2018).

In light of these developments, this paper analyses return and price volatility connectedness between Bitcoin and traditional financial assets (Crude Oil, Gold, Stocks, Bonds, and the USD). We also include the role of global uncertainty measures (the EPU, the TEU, and the VIX) to address the catalyser impact of global uncertainty during the COVID-19 pandemic on the relationship between Bitcoin and traditional financial markets. This issue also links our empirical exercises to the previous empirical papers, which use the global uncertainty measures as the driver of the returns and the price volatility in Bitcoin and other cryptocurrency markets (see, e.g., the VIX in Bouri, Gupta, Tiwari, & Roubaud, 2017, the EPU in Demir, Gozgor, Lau, & Vigne, 2018, and the TEU in Wu, Tiwari, Gozgor, & Leping, 2021). Furthermore, Fang, Bouri, Gupta, and Roubaud (2019) extend the results of Demir et al. (2018) and find that the global EPU measure is a driving factor of the returns and the price volatility of Bitcoin. Wu, Tong, Yang, and Derbali (2019) demonstrate that Bitcoin has more hedging capacity than Gold during times of economic policy uncertainty shocks. Gozgor, Tiwari, Demir, and Akron (2019) observe the significant hedging feature of Bitcoin against trade policy uncertainty shocks in the United States. Following the spirit of Demir et al. (2018), Cheng and Yen (2020) show that the Chinese EPU has a significant capacity to predict Bitcoin returns, and the impact is negative. In a further study, Yen and Cheng (2021) demonstrate that the Chinese EPU can successfully predict the price volatility of Bitcoin. However, Wang, Li, Shen, and Zhang (2020) find an insignificant impact of the EPU on the price volatility of Bitcoin. Colon, Kim, Kim, and Kim (2021) also observe that cryptocurrencies have a weak hedging capacity against economic policy uncertainty shocks, especially during optimistic economic expectations.

Indeed, global uncertainty has a significant role in Bitcoin as monetary and fiscal policy implications have weakened the trust in traditional financial assets during the Global Financial Crisis in 2008. This issue has also led to the introduction of Bitcoin in 2008 as a decentralised alternative payment and investment asset (Aysan, Demir, Gozgor, & Lau, 2019). Particularly, during periods with higher economic policy uncertainty, as observed during the COVID-19 pandemic, Bitcoin can be an effective alternative to traditional assets and hedge risks against uncertainty shocks (Goodell, 2020). Nevertheless, the impact of economic policy uncertainty shocks on cryptocurrency markets during the COVID-19 crisis is still limited. For instance, Goodell and Goutte (2021a) show that the COVID-19 was positively related to the Bitcoin prices in April 2020. So, Chu, and Chan (2021) demonstrated that financial market connectedness in Hong Kong increased substantially during the 2020 COVID-19 outbreak. Wu et al. (2021) find that economic policy uncertainty during the COVID-19 pandemic has a limited effect on the returns of major cryptocurrencies. Given that our sample covers the data from April 29, 2013, to June 30, 2020 (capturing the COVID-19 crisis), we control the role of global uncertainty measures.

Following the previous papers, we also include traditional financial assets (Crude Oil, Gold, Stocks, Bonds, and the USD) to address safe haven properties of these assets during periods of higher uncertainty (see, e.g., Ji, Zhang, & Zhao, 2020 for commodities; Bredin, Conlon, & Potì, 2015 for Gold; Ashraf, 2020 for the stock markets; Ranaldo & Söderlind, 2010 for the USD; Flavin, Morley, & Panopoulou, 2014 for the bonds; Goodell & Goutte, 2021b; Conlon et al., 2020 for cryptocurrencies).[1]

Against this backdrop, this paper contributes to the literature in several ways. First, this paper analyses return connectedness and risk transmissions between Bitcoin and traditional financial assets during tranquil and turbulent episodes. To this end, the study strives to scrutinise this relationship over a relatively long period starting from April 29, 2013, to June 30, 2020 including the COVID-19 crisis period. Second, we examine the impact of global uncertainty shocks on Bitcoin and traditional financial assets during the COVID-19 crisis. Third, we examine the synchronization and spillover patterns among Bitcoin, and traditional financial assets, as well as how these are affected by and global uncertainty measures. In addition, we identify the main transmitters/receivers of shocks and their dynamic transmissions.

Unlike previous literature, our paper utilises several econometric methods (time-varying parameter vector autoregression model, causality-in-variance tests, dynamic connectedness approach, and network analyses) to examine the relationships among Bitcoin, traditional financial assets (Gold, Crude Oil, Stocks, Bonds, and the USD), and major global uncertainty measures (the EPU, the TEU, and the VIX), including the COVID-19 era. In particular, the spillover approach based on the TVP-VAR model has several advantages over the Diebold-Yilmaz framework. It provides a more accurate measurement of connectedness, it is not sensitive to outliers, no need to arbitrarily set a fixed rolling window to capture the dynamics of the connectedness across variables, no losses of observations as a result of the rolling window estimation approach (Antonakakis, Gabauer, & Gupta, 2019; Antonakakis, Gabauer, Gupta, & Plakandaras, 2018; Koop & Korobilis, 2014; Korobilis & Yilmaz, 2018).

Finally, we complement the spillover technique by applying the ForceAtlas2 algorithm developed by Jacomy, Venturini, Heymann, and Bastian (2014) to network analysis. In doing so, we are able to quantify and visualize the role played by global uncertainty factors in shaping the dynamics and transmission of spillovers between Bitcoin and traditional financial assets over the sample period.

The empirical results show that total spillover indices have reached unprecedented levels during the COVID-19 period and remained high since then, confirming high return and volatility spillovers across markets during the pandemic. Bitcoin is a net receiver of return spillovers from other markets; however, it transmits volatility spillovers to other markets. Therefore, Bitcoin plays a major role in volatility transmission during the COVID-19 period. Simultaneously, economic policy uncertainty is the only global uncertainty factor to increase volatility in Bitcoin. The directions of these relationships are robust to different econometric techniques. To the best of our knowledge, our study provides the first evidence in the empirical literature to show the pivotal role of Bitcoin in global financial markets and global uncertainty, including the COVID-19 era. Indeed, the EPU is the significant driver of the boom and bust cycle (price volatility) in Bitcoin.

The remaining structure of the paper is designed as follows. Section 2 explains the description of the data and the econometric methods. Section 3 discusses the empirical findings with their potential implications. Section 4 concludes.

2. Data and econometric methodology

2.1. Data sources and descriptive statistics

We consider the data for Bitcoin (closing price) and traditional financial assets: Stocks (S&P 500 index), Bonds (S&P 500 bond index), the United States Dollar (broad exchange rate), Gold (spot prices) and Crude Oil (West Texas Intermediate-WTI spot prices). These variables are calculated as the first logarithmic difference between two consecutive observations. Following the usual practice, the Volatility Index (VIX), the United States (US) Economic Policy Uncertainty (EPU) index, and Twitter-based Economic Uncertainty (TEU) index (US-based tweets) are calculated in logarithmic form. All data series are collected from the Thomson Reuters DataStream, except for the Economic Policy Uncertainty, and the Twitter-based Economic Uncertainty indices are collected from Baker, Bloom, and Davis (2016); and Baker, Bloom,

[1] See Corbet et al. (2019) for a review of the empirical literature in cryptocurrency markets.

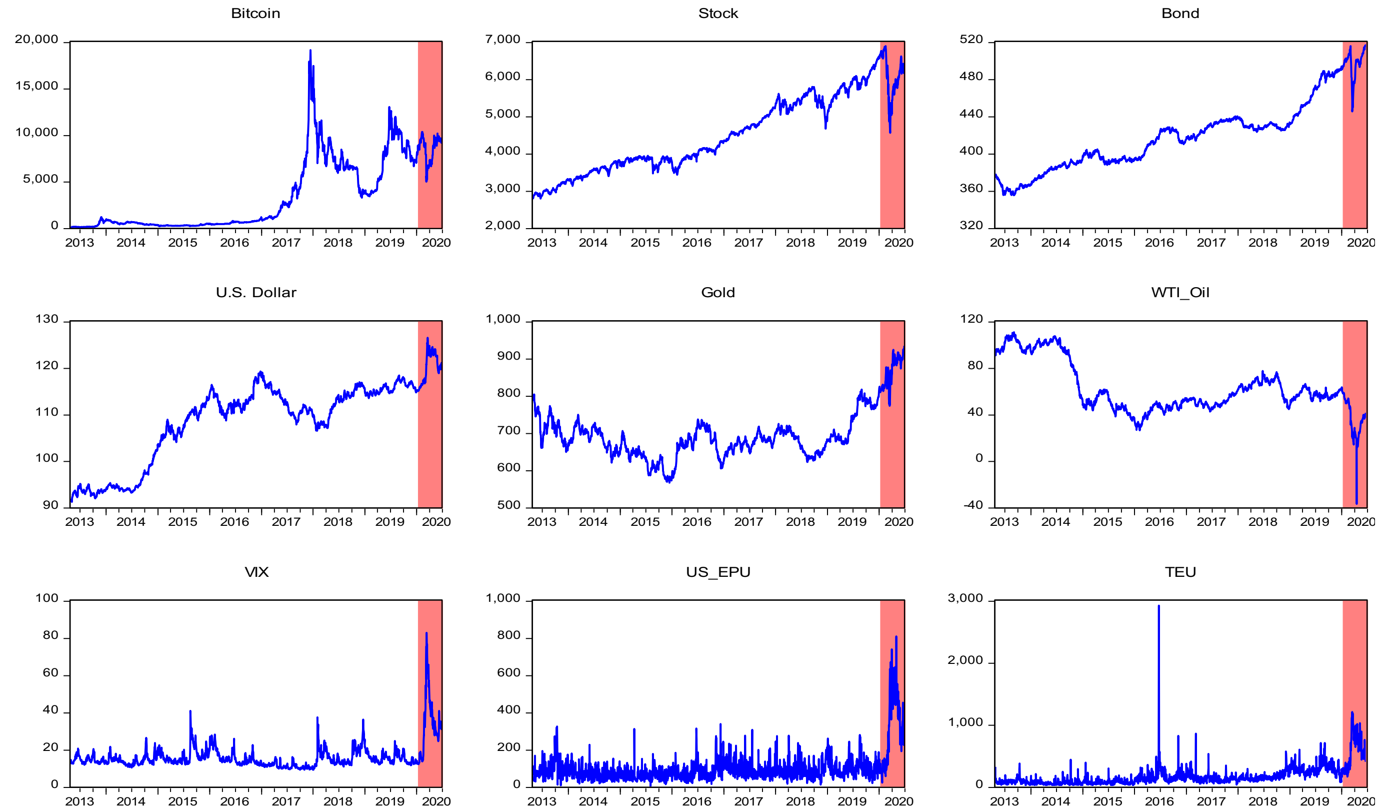

Fig. 1. Daily time evolution of bitcoin, traditional financial assets and major global uncertainty measures.
Notes: These figures portrait the variation of the daily data series for the Bitcoin price, the S&P 500 stock index, the S&P bond index, the USD Broad Exchange Rate, Gold price, the WTI Crude Oil price (WTI_Oil), the VIX, the US economic policy uncertainty index (US_EPU), and the Twitter-based economic uncertainty index (TEU) from April 29, 2013, to June 30, 2020. The red area captures the COVID-19 era.

Davis, & Renault, 2021.[2] We focus on the daily sample from April 29, 2013, to June 30, 2020, and the starting date is related to the data availability.

2.2. Econometric methodology: TVP-VAR dynamic connectedness approach

To answer the research questions, we utilise the Time-Varying Parameter Vector Autoregressive (TVP-VAR) model developed by Koop and Korobilis (2014) in conjunction with the dynamic connectedness approach introduced by Diebold and Yilmaz (2012); and Diebold & Yılmaz, 2014. Including the TVP-VAR model overcomes Diebold and Yilmaz's connectedness approach's limitations and significantly improves the estimation technique in several ways. Firstly, the TVP-VAR model provides a more accurate measurement of connectedness since the rolling window approach overestimates the connectedness measures by generating the "built-in persistence" and hence does not accurately capture the downward move in connectedness indices on time. Secondly, there is no need to arbitrarily set a fixed rolling window to capture the dynamics of the connectedness across variables as the VAR parameters are allowed to vary over time. Thirdly, no losses of observations as a result of the rolling window estimation approach. Finally, the TVP-VAR-based connectedness technique is not sensitive to outliers (Antonakakis et al., 2018; Antonakakis et al., 2019; Koop & Korobilis, 2014; Korobilis & Yilmaz, 2018).

A stationary TVP-VAR model of order one can be written as:

$$Y_t = \beta_t Y_{t-1} + \epsilon_t \; \epsilon_t|\Omega_t \sim N(0, S_t) \tag{1}$$

$$vec(\beta_t) = vec(\beta_{t-1}) + \upsilon_t \; \upsilon_t|\Omega_t \sim N(0, R_t) \tag{2}$$

Y_t is an $N \times 1$ vector of variables under consideration, while ϵ_t is an $N \times 1$ vector of the disturbance errors with $N \times N$ time-varying variance-covariance matrix (S_t). β_t is an $N \times Np$ dimensional time-varying coefficient matrix, whereas $vec(\beta_t)$ is the vectorisation of β_t which is an $N^2p \times 1$ dimensional vector. Finally, υ_t is an $N^2p \times 1$ vector of error terms with covariance matrix (R_t) of an $N^2p \times N^2p$ dimensional matrix. Consequently, based on the Wold representation theorem, the TVP-VAR model could be transferred into its Moving Average representation (VMA) in the form of:

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

With A_{it} is an $N \times N$ dimensional matrix. Following this, the TVP-VMA estimates are used to calculate the Generalised Impulse Response Functions (GIRF) and Generalised Forecast Error Variance Decomposition (GFEVD) of Koop, Pesaran, and Potter (1996) and Pesaran and Shin (1998) that form the basis of the dynamic connectedness approach. Accordingly, the H-step-ahead GFEVD function could be written as follows:

$$\tilde{\theta}_{ij}(H) = \frac{\sum_{t=1}^{H-1} \xi_{ij}^2}{\sum_{j=1}^{N}\sum_{t=1}^{H-1} \xi_{ij}^2} \tag{4}$$

where ξ_{ij} represents the response of all variables j to a shock in variable i. By construction, $\sum_{j=1}^{N}\tilde{\theta}_{ij}(H) = 1$ and $\sum_{i,j=1}^{N}\tilde{\theta}_{ij}(H) = N$. On that basis, the

[2] They are downloaded from the website (https://www.policyuncertainty.com).

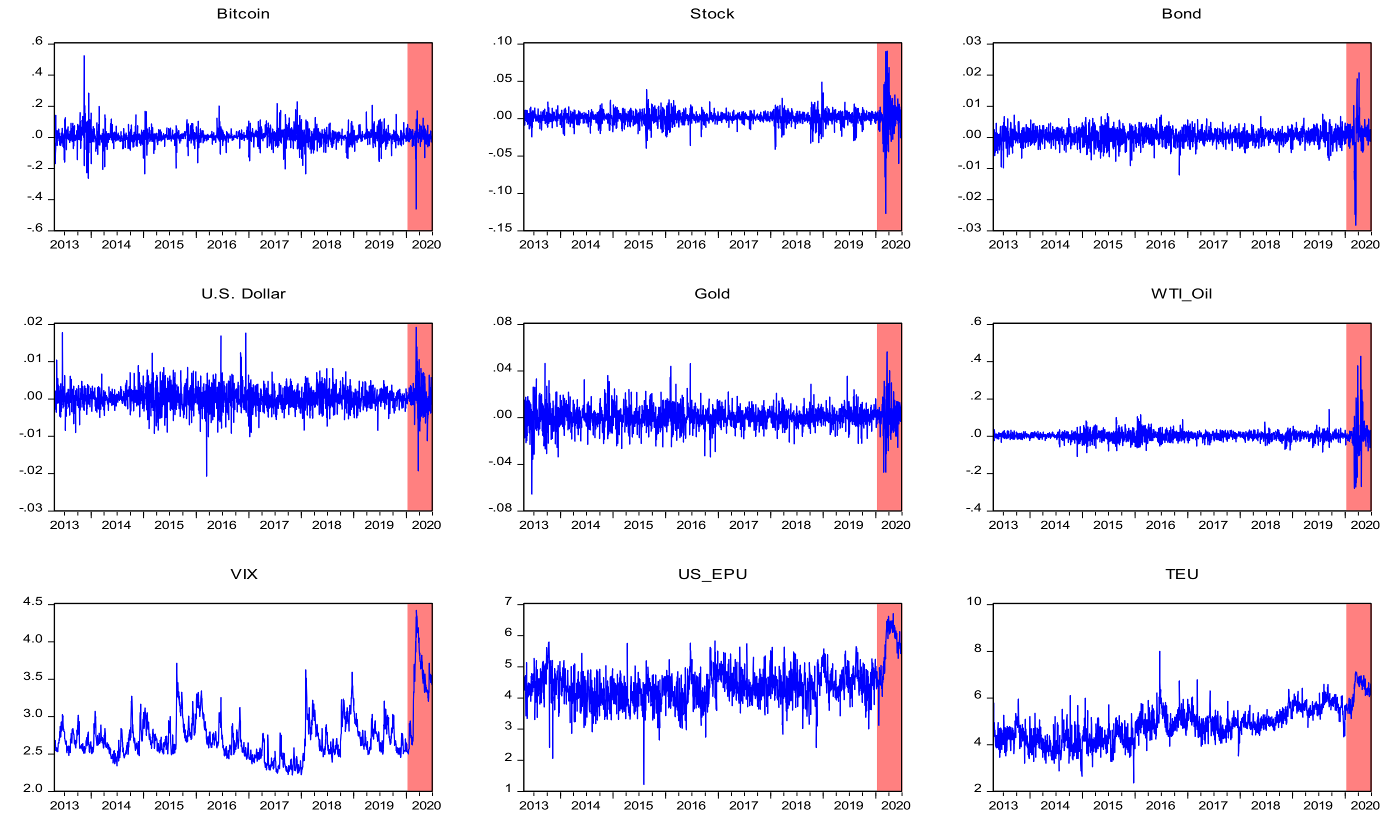

Fig. 2. Daily returns of bitcoin, traditional financial assets and major global uncertainty measures.
Notes: These figures portrait the returns of the daily data series for the Bitcoin price, the S&P 500 stock index, the S&P bond index, the USD Broad Exchange Rate, Gold price, the WTI Crude Oil price (WTI_Oil), the VIX, the US economic policy uncertainty index (US_EPU), and the Twitter-based economic uncertainty index (TEU) from April 29, 2013, to June 30, 2020. The red area captures the COVID-19 era.

Table 1
A summary of descriptive statistics.

	Bitcoin	Stock	Bond	U.S. Dollar	Gold	WTI-Oil	VIX	US_EPU	TEU
Mean	0.0022	0.0004	0.0002	0.0001	0.0001	−0.0001	2.721	4.381	4.831
Std. Dev.	0.0505	0.0108	0.0028	0.0031	0.0094	0.0324	0.3156	0.6125	0.7675
Max.	0.5207	0.0897	0.0206	0.0191	0.0560	0.4258	4.4151	6.6941	7.9791
Min.	−0.4647	−0.1276	−0.0284	−0.0208	−0.0660	−0.2813	2.2126	1.1999	2.3371
Skewness	−0.035	−1.085	−1.506	0.188	0.086	1.426	1.697	0.528	0.319
Kurtosis	13.494	24.867	19.368	5.009	5.092	41.738	4.297	1.661	0.06
J-B	14181***	48519***	29919***	1965***	2021***	136298***	2335***	301***	32***
ADF	−44.86***	−13.31***	−19.53***	−41.72***	−45.21***	−16.05***	−5.31***	−5.09***	−3.93***
PP	−45.25***	−51.48***	−36.77***	−41.73***	−45.17***	−47.41***	−4.86***	−32.95***	−16.83***
Q(20)	23.987***	258.570***	141.036***	14.952	16.518*	112.827***	13,210.218***	4750.260***	11,276.557***
$Q^2(20)$	1.764	510.707***	1001.681***	54.830***	83.718***	204.285***	13,370.530***	8453.823***	11,993.894***
ARCH(20)	56.032***	427.549***	256.992***	107.417***	106.676***	461.034***	82.36***	331.923***	413.959***

Notes: This table reports descriptive statistics for the daily data series. Daily Bitcoin, financial markets, USD, Gold and Crude Oil returns are calculated as the first logarithmic difference between two consecutive observations. Following the usual practice, the VIX, the U.S. economic uncertainty index, and Twitter-based economic uncertainty index are calculated in log form. All data series are collected from Thomson Reuters DataStream except for the Twitter-based economic uncertainty index collected from the Economic Policy Uncertainty website (https://www.policyuncertainty.com). J-B is the Jarque–Bera test for Normality. ADF and PP denote the empirical statistics of the Augmented Dickey-Fuller and Phillips-Perron unit root tests, respectively. Q(20) and $Q^2(20)$ are the Ljung–Box statistics for serial correlation in raw series and squared residuals. ARCH (20) testing Engle's ARCH effects up to 20 lags. Finally, ***, **, * indicate significance at 1%, 5%, and 10% levels.

Total Connectedness Index (TCI) is calculated as the ratio of the sum of all off-diagonal elements to the total variance. It, therefore, represents the average contribution of volatility spillovers across all variables to the total forecast error variance and hence is calculated as follows:

$$C_{TCI} = \frac{\sum_{i,j=1, i\neq j}^{N} \tilde{\theta}_{ij}(H)}{\sum_{i,j=1}^{N} \tilde{\theta}_{ij}(H)} \times 100 = \frac{\sum_{i,j=1, i\neq j}^{N} \tilde{\theta}_{ij}(H)}{N} \times 100 \tag{5}$$

The above representation of the generalised variance decomposition matrix is helpful as it allows the estimation of directional spillover indices among variables. The total directional connectedness from others is defined as the spillovers received by variable *i from* all other variables, *j*, which is measured as:

$$C_{i \leftarrow \bullet} = \frac{\sum_{j=1, j\neq i}^{N} \tilde{\theta}_{ij}(H)}{\sum_{i,j=1}^{N} \tilde{\theta}_{ij}(H)} \times 100 = \frac{\sum_{j=1, j\neq i}^{N} \tilde{\theta}_{ij}(H)}{N} \times 100 \tag{6}$$

Table 2
Returns connectedness.

	Bitcoin	Stock	Bond	U.S. $	Gold	WTI_Oil	VIX	US_EPU	TEU	FROM
Bitcoin	97.612	1.036	0.275	0.256	0.168	0.161	0.378	0.09	0.023	2.388
Stock	0.643	59.691	0.451	3.736	0.162	2.597	32.231	0.183	0.306	40.309
Bond	0.182	4.726	80.315	3.658	6.723	0.573	3.488	0.124	0.209	19.685
U.S. $	0.072	5.73	4.303	73.703	10.36	2.719	2.722	0.114	0.279	26.297
Gold	0.193	0.221	7.417	11.155	79.471	0.261	0.961	0.124	0.197	20.529
WTI_Oil	0.142	3.981	0.246	3.072	0.351	88.9	2.792	0.259	0.258	11.1
VIX	0.502	31.285	0.757	2.047	0.795	1.647	62.582	0.027	0.358	37.418
US_EPU	0.026	2.564	0.194	0.157	0.147	0.229	5.685	80.341	10.656	19.659
TEU	0.051	2.435	0.483	0.197	0.184	0.142	4.973	7.084	84.451	15.549
TO others	1.811	51.978	14.126	24.279	18.89	8.33	53.229	8.005	12.286	
Net spillovers	−0.577	11.669	−5.559	−2.019	−1.639	−2.771	15.811	−11.654	−3.263	TCI = 21.44%

Notes: This table summarises the empirical results of the total, directional and pairwise return spillovers between Bitcoin, financial markets and global uncertainty measures. These results are based on the generalised forecast error variance decomposition (GFEVD) obtained from a TVP-VAR model of order one and 10-step ahead forecasts. The lag length is selected by the Bayesian information criterion (BIC). 'TO others' signifies directional spillovers correspond to the off-diagonal column sums, i.e., spillovers from variable **i** to all variables j. 'FROM' represents the off-diagonal row sums of directional spillovers, i.e., spillovers from all variables j to the variable i. Net spillovers are simply the "TO others" minus "FROM others". Finally, TCI, the total spillover index, demonstrates that 21.4% of the forecast error variance comes from spillovers.

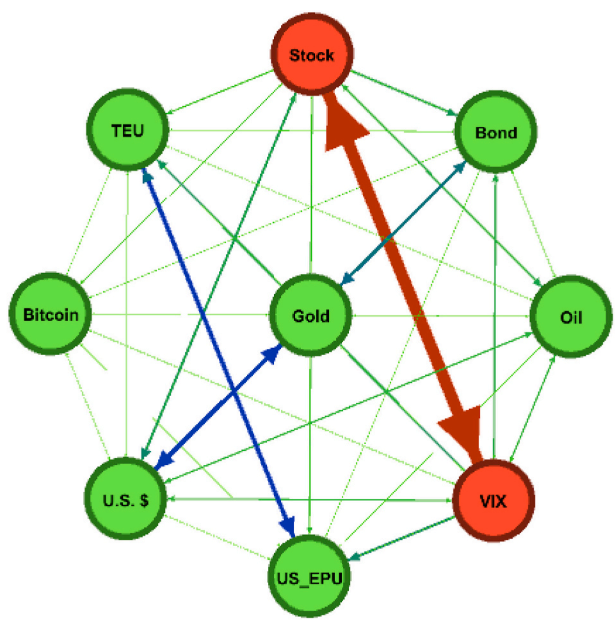

Fig. 3. Directional connectedness network of pairwise return spillovers.
Notes: This diagram shows the average pairwise directional return spillovers among all possible pairs of variables in the model. A node's colour implies whether a variable is a net transmitter/receiver of return spillovers. The red colour indicates a net transmitter, while the green colour shows a net receiver, respectively. Furthermore, the thickness and arrows' colour represents the average return spillover magnitude and strength between each pair. Red indicates strong, navy shows moderate, and green refers to weak return spillovers.

Likewise, the total directional connectedness to others demonstrates the informational outflow transmitted from variable *i to* all other variables, which is given by:

$$C_{i\rightarrow\bullet} = \frac{\sum_{j=1, j\neq i}^{N} \tilde{\theta}_{ji}(H)}{\sum_{i,j=1}^{N} \tilde{\theta}_{ji}(H)} \times 100 = \frac{\sum_{j=1, j\neq i}^{N} \tilde{\theta}_{ji}(H)}{N} \times 100 \quad (7)$$

Consequently, the net directional connectedness, the net spillovers transmitted/received by variable *i*, is measured as the difference between total directional spillovers "*to*" and "*from*" variable *i*:

The calculation of net spillover indices is very valuable as it allows us to determine whether a given variable is a net transmitter or receiver of shocks.

$$C_i = C_{i\rightarrow\bullet} - C_{i\leftarrow\bullet} \quad (8)$$

where positive (negative) values of the net pairwise connectedness index imply that the variable is a net transmitter (receiver) of shocks to (from) other variables. At last, the directional connectedness network is constructed based on the Net Pairwise Spillover (NPS) connectedness between *i* and *j* variables as follows:

$$NPS = C_{i\rightarrow j} - C_{i\leftarrow j} \quad (9)$$

where nodes represent components of a generalised variance decomposition matrix (variables), and edges demonstrate the direction and strength of the pairwise connectedness among each pair. Notably, the linkages between nodes are directed given that $\tilde{\theta}_{ij} \neq \tilde{\theta}_{ji}$, that is the volatility spillover transmitted from variable *j* to variable *i* is not necessarily equivalent to those received by *j* from *i*.

3. Empirical findings

3.1. Preliminary results

Fig. 1 presents the time series plot of raw data for the spot Bitcoin prices, the S&P 500 Stock Index, the S&P 500 Bond Index, the USD Broad Exchange Rate, Gold, the WTI Oil Price, the VIX, the US Economic Policy Uncertainty (US_EPU) index, and Twitter-based economic uncertainty (TEU) index from April 29, 2013, to June 30, 2020. We can see extreme movements starting from January 1, 2020. The gold price reached its historical high while the WTI Crude Oil price reached its lowest point (see the highlighted region in Fig. 1). We also notice that all uncertainty measures climbed up significantly during the first wave of the COVID-19 pandemic.

Fig. 2 portrays the transformed series under consideration, including returns on Bitcoin and other asset classes (i.e., the USD, Bonds, Stocks, Gold, and Crude Oil Returns), the VIX, the US EPU index, and Twitter-based economic uncertainty (TEU) index in log form.

Table 1 shows the descriptive statistics for daily variables. We observe the stationarity property of variables in interest following the results of Augmented Dickey-Fuller (ADF) and Phillips-Perron (PP) unit root tests (see Table 1).

3.2. Return spillovers

Table 2 presents the findings of the TVP-VAR model. As can be seen, the overall level of connectedness is 21.4%, which means that 21.4% of the forecast error variance comes from the connectedness between the

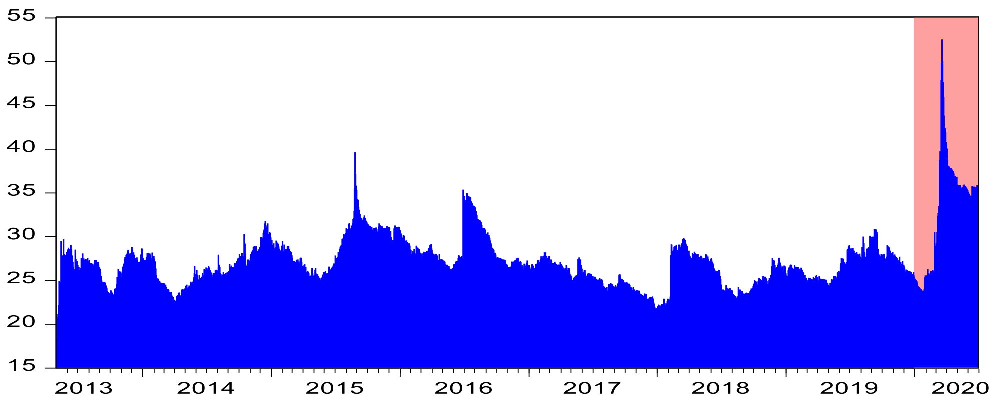

Fig. 4. Total return spillover index.
Notes: This graph portraits the time-varying behaviour of the total connectedness index across the Bitcoin, financial markets and major global uncertainty measures. It is based on the generalised forecast-error variance decomposition (GFEVD) obtained from estimating a TVP-VAR model of order one and 10-step ahead forecasts from April 29, 2013, to June 30, 2020. The red area captures the COVID-19 era.

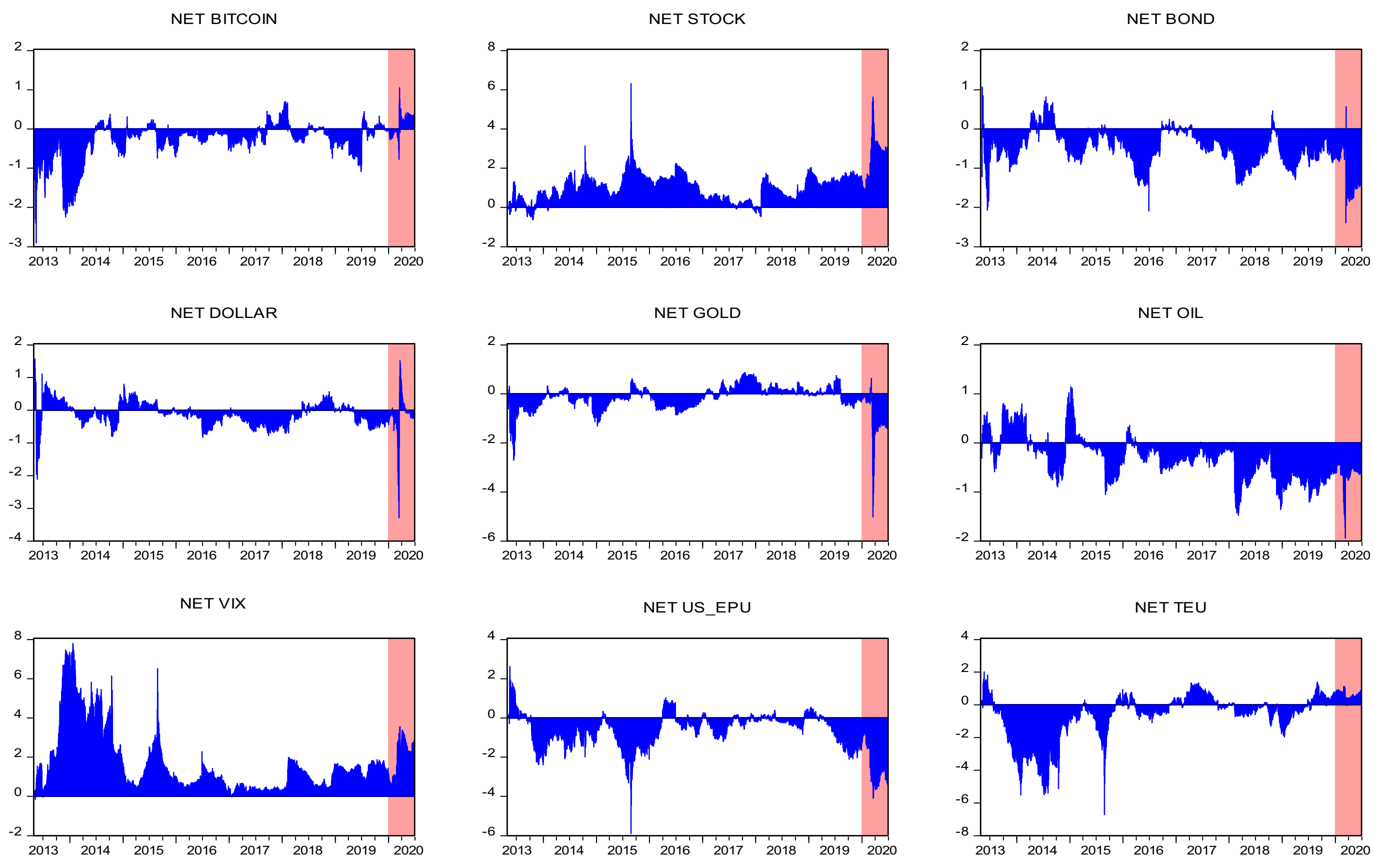

Fig. 5. Dynamic net directional return spillover indices.
Notes: This graph represents the net directional return spillovers time-varying behaviour for each variable under consideration. Positive (negative) values indicate that the variable is a net transmitter (receiver) of return spillover to (from) all other variables. Indices are estimated based on the generalised forecast-error variance decomposition (GFEVD) obtained from estimating a TVP-VAR model of order one and 10-step ahead forecasts. The red area captures the COVID-19 era.

underlying variables. Table 2 also summarises the empirical results of the directional and pairwise return spillovers between Bitcoin, financial markets, and global uncertainty measures. These results are based on the generalised forecast error variance decomposition (GFEVD) obtained from the TVP-VAR model of order one and 10-step ahead forecasts. The lag length is selected by the Bayesian information criterion (BIC). It is observed that the financial market volatility (VIX) contributes most of the spillover to the stock market (i.e., 32.23%), while its spillover to the Bitcoin market is minimal, with only 0.378%. The impact of the US EPU on financial markets is not significant, and it contributes the most to the Crude Oil market (0.259%) while contributing only 0.09% to the Bitcoin market.

Similarly, the impact of Twitter Based Economic Uncertainty (TEU) on financial markets is muted. It transmits spillover mostly to the stock market (0.306%) while contributing only 0.023% to the Bitcoin market. Table 2 shows that Bitcoin is a net return receiver from others.

It is worthy to note that the stock market is the main net transmitter of information in the financial markets, amounting to 11.67%. In contrast, the bond market is a primary net receiver of spillover (−5.56%).

Fig. 3 summarises the directional connectedness network of pairwise return spillovers, and it shows the average pairwise directional return spillovers among all possible pairs of variables in the model. A node's colour implies whether a variable is a net transmitter/receiver of return

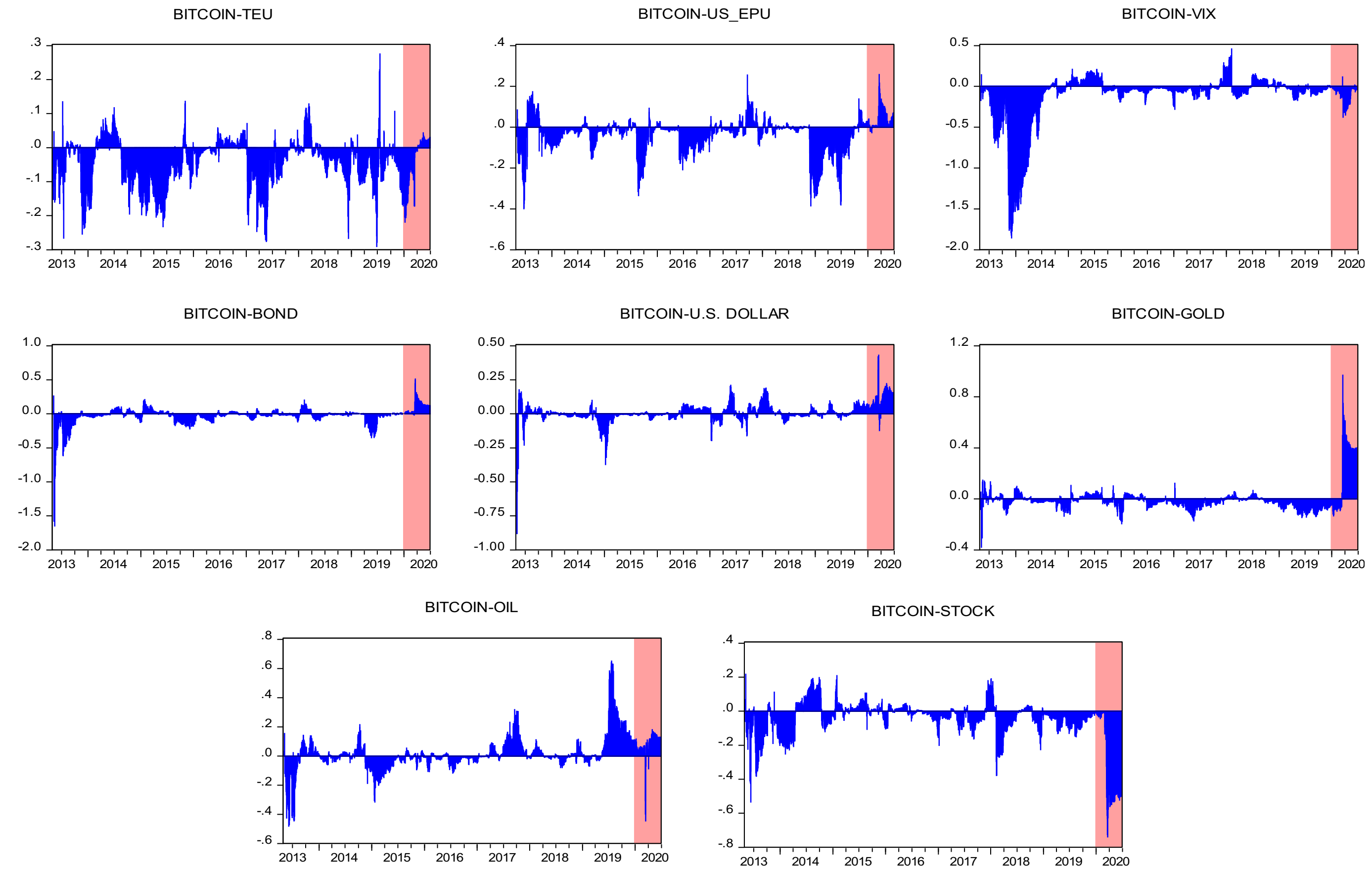

Fig. 6. Dynamic connectedness of pairwise return spillovers.
Notes: This graph represents the pairwise directional return spillovers time-varying behaviour between Bitcoin and each variable under consideration. Positive (negative) values indicate that Bitcoin is transmitting (receiving) return spillover to (from) the other variable. Indices are estimated based on the generalised forecast-error variance decomposition (GFEVD) obtained from estimating a TVP-VAR model of order one and 10-step ahead forecasts. The red area captures the COVID-19 era.

Table 3
Volatility connectedness.

	Bitcoin	Stock	Bond	U.S. $	Gold	WTI_Oil	VIX	US_EPU	TEU	FROM
Bitcoin	86.155	7.348	1.535	0.582	0.472	0.032	3.668	0.173	0.033	13.845
Stock	5.18	62.561	0.875	1.874	0.077	2.562	26.656	0.117	0.098	37.439
Bond	4.172	48.176	25.072	5.31	0.137	3.867	13.096	0.144	0.026	74.928
U.S. $	1.542	19.666	6.249	63.482	1.795	1.837	5.014	0.381	0.033	36.518
Gold	1.671	14.936	0.26	4.56	70.939	0.621	5.966	1.001	0.044	29.061
WTI_Oil	1.32	28.19	12.262	2.72	0.031	46.921	8.48	0.003	0.073	53.079
VIX	1.275	22.442	0.299	0.957	0.496	1.234	73.023	0.047	0.226	26.977
US_EPU	0.114	1.88	0.144	0.252	0.463	0.357	4.925	91.404	0.46	8.596
TEU	0.121	0.407	0.171	0.079	0.06	0.191	3.039	1	94.932	5.068
TO others	15.396	143.047	21.795	16.335	3.532	10.702	70.845	2.867	0.994	
Net spillovers	1.551	105.607	−53.134	−20.184	−25.529	−42.377	43.868	−5.729	−4.074	TCI = 31.72%

Notes: This Table summarises the empirical results of the total, directional and pairwise volatility spillovers between Bitcoin, financial markets and global uncertainty measures where volatilities are estimated based on ARMA-GARCH(1,1) process. These results are based on the generalised forecast error variance decomposition (GFEVD) obtained from a TVP-VAR model of order one and 10-step ahead forecasts. The lag length is selected by the Bayesian information criterion (BIC). 'TO others' signifies directional spillovers correspond to the off-diagonal column sums, i.e., spillovers from variable ***i*** to all variables *j*. 'FROM' represents the off-diagonal row sums of directional spillovers, i.e., spillovers from all variables *j* to the variable *i*. Net spillovers are simply the "TO others" minus "FROM others". Finally, TCI, the total spillover index, demonstrates that 31.7% of the forecast error variance comes from spillovers.

spillovers. The red colour indicates a net transmitter, while the green colour shows a net receiver, respectively. Furthermore, the thickness and arrows' colour represents the average return spillovers magnitude and strength between each pair. Red indicates strong, navy shows moderate, and green refers to weak return spillovers. The result highlights the central role of the VIX and stock markets, and they are the net transmitter with significant magnitude. The pairwise relationship between Gold and USD is interesting as they are significantly affecting each other. Moreover, the same pairwise relationship is found between the US EPU and the TEU, where the latter has a greater impact on the former.

Fig. 4 portrays the time-varying behaviour of the total connectedness index across the Bitcoin, financial markets and major global uncertainty measures from April 29, 2013, to June 30, 2020. The total

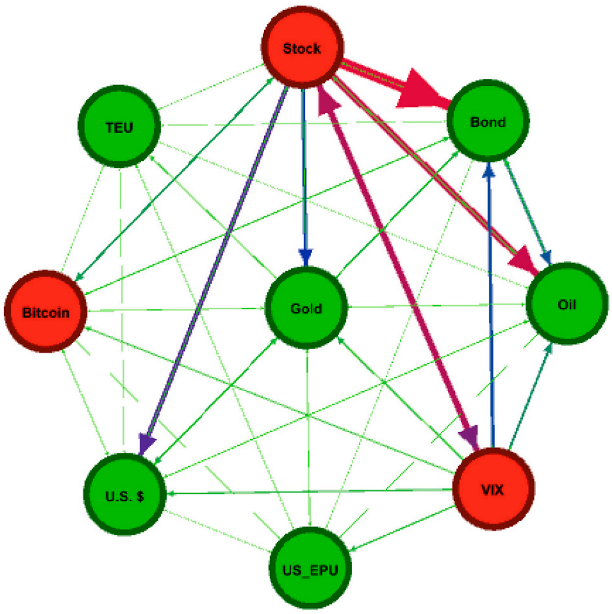

Fig. 7. Directional connectedness network of pairwise volatility spillovers.
Notes: This diagram shows the average pairwise directional volatility spillovers among all possible pairs of variables in the model. A node's colour implies whether a variable is a net transmitter/receiver of volatility spillovers. The red colour indicates a net transmitter, while the green colour shows a net receiver, respectively. Furthermore, the thickness and arrows' colour represents each pair's average volatility spillovers magnitude and strength. Red indicates strong, navy shows moderate, and green refers to weak volatility spillovers.

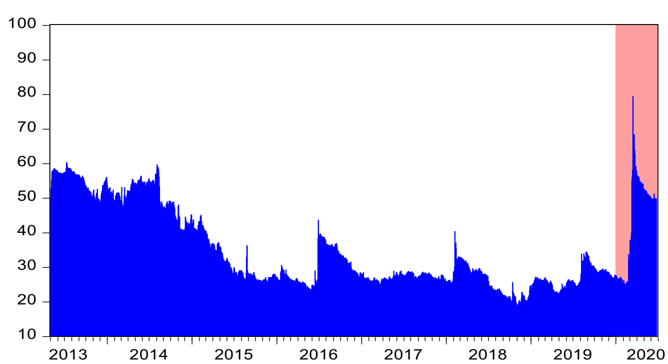

Fig. 8. Total volatility spillover index.
Notes: This graph shows the time-varying behaviour of the total volatility connectedness across the Bitcoin, financial markets and major global uncertainty measures. It is based on the generalised forecast-error variance decomposition (GFEVD) obtained from estimating a TVP-VAR model of order one and 10-step ahead forecasts from April 29, 2013, to June 30, 2020. The red area captures the COVID-19 era.

connectedness index is time-varying and very responsive to economic and financial turbulences. In line with the preliminary analysis, the total connectedness index peaked when the COVID-19 pandemic started in early 2020.

In addition, Fig. 5 portraits the dynamic net directional return spillover indices for each variable throughout the full sample period. Noteworthy, the net directional return spillovers are time-varying and behaviour differently over different periods. Positive (negative) values indicate that the variable is a net transmitter (receiver) of return spillover to (from) all other variables. The Stock market is the main net return transmitter to others, while Bitcoin, Bond, Crude Oil, Gold, and the USD markets are the net return receivers. Interestingly, Bitcoin is a return transmitter during the COVID-19 pandemic.

Fig. 6 provides the dynamic connectedness of pairwise return spillovers, and the graph represents the pairwise directional return spillovers time-varying behaviour between Bitcoin and each of the variables under consideration. Positive (negative) values indicate that Bitcoin is transmitting (receiving) return spillover to (from) the other variable. Bitcoin is receiving returns spillover from the TEU and the EPU before the COVID-19 pandemic. However, it is transmitting returns spillover to the TEU and the EPU during the second wave of the COVID-19 pandemic, while Bitcoin received returns spillover from the VIX for most of the time. Regarding other financial assets, we observe that Bitcoin is the returns transmitter of spillovers to all financial assets during the COVID-19 pandemic, except the stock market, where Bitcoin is the returns receiver. Interestingly, the directional spillover changed after the first wave of the COVID-19 pandemic (for example, Gold and Bond markets).

3.3. *Volatility spillovers and causality in-variance tests*

Now, let us turn our attention to the analysis of volatility spillovers among Bitcoin, financial assets and uncertainty measures. Table 3 reports the volatility connectedness where the total connectedness index accounts for 31.7% of the total forecast error variance. It is worth noting that the results for the VIX as a transmitter are the same as that of returns connectedness. Regarding the impact of the EPU on the USD is the largest volatility receiver, while Crude Oil is the least impacted market. For the TEU, the results are the same as that of the returns spillover analysis. Finally, similar to the returns spillover analysis, the stock market is the major net transmitter in the system (105.61%), followed by VIX (43.87%). In contrast, the bond market is the main net receiver of the spillover (−53.13%), followed by the oil market (−42.38%). According to Table 3, the net spillover of Bitcoin is 1.51%. This value is relatively small compared with spillovers of others. The volatility transmissions between Bitcoin and other asset is somehow weaker.

Figs. 7 to 10 presents the spillover patterns for volatility spillover among variables. These diagrams show the average pairwise directional volatility spillovers among all possible pairs of variables in the model. We observe that the stock market is in the centrality of the system, and it transmitted volatility to all financial assets, including Bitcoin. The biggest receiver of the volatility from the stock market is the bond market, and the VIX transmitted the biggest volatility to the stock market.

Fig. 8 shows the total volatility spillover index with time-varying behaviour of the total volatility connectedness across the Bitcoin, financial markets and major global uncertainty measures. Interestingly, the system has the highest volatility spillover during the first wave of the COVID-19 pandemic.

Fig. 9 displays the net directional volatility spillovers time-varying behaviour for each variable under consideration. It's worth noting that the stock and the VIX are the net contributors of volatility to other variables. Crude Oil and Bitcoin are also the net volatility transmitters during the COVID-19 pandemic. Bond, Gold, and Dollar are the net receiver of volatility during the COVID-19 pandemic. It is interesting to note that the directional spillover pattern of Bitcoin and Crude Oil is similar. They changed from net volatility receiver before the COVID-19 pandemic to net volatility transmitter during the first wave of the COVID-19 pandemic. This behaviour of changing directional spillover was observed for the USD, but it changed from net volatility transmitter before the COVID-19 pandemic to net volatility receiver during the first wave of the COVID-19 pandemic.

Finally, Fig. 10 indicates the time-varying behaviour of the pairwise directional volatility spillover between Bitcoin and each variable under consideration. We first observe that Bitcoin transmits volatility to all volatility indices and Gold during COVID-19 pandemics while it also transits volatility to the stock market in the second wave. At the same time, it receives volatility from the VIX and stock market before the COVID-19 pandemic. For bonds and the USD, Bitcoin is the receiver of

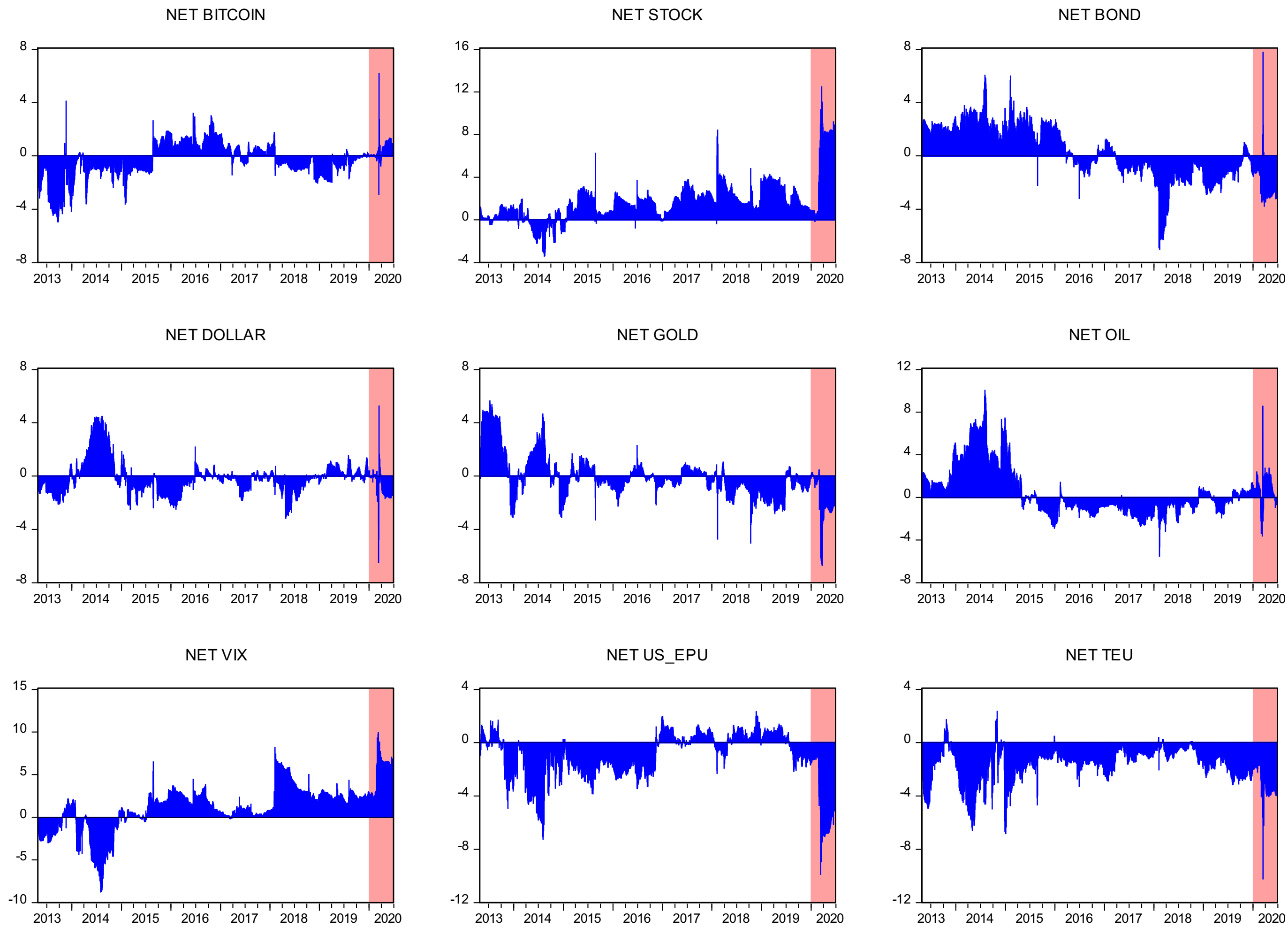

Fig. 9. Dynamic net directional volatility spillover indices.
Notes: This graph displays the net directional volatility spillovers time-varying behaviour for each variable under consideration. Positive (negative) values indicate that the variable is a net transmitter (receiver) of volatility spillover to (from) all other variables. Indices are estimated based on the generalised forecast-error variance decomposition (GFEVD) obtained from estimating a TVP-VAR model of order one and 10-step ahead forecasts. The red area captures the COVID-19 era.

volatility spillover during the COVID-19 pandemic. At the same time, we observed that Bitcoin was the net volatility transmitter before the COVID-19 pandemic.

Note that the EPU drives high volatility in Bitcoin and then transmits to other financial assets. However, the ratio of volatility spillover from EPU of Bitcoin is only 0.173%, according to Table 3. At this stage, it is important to emphasise that the connectedness of Bitcoin-EPU volatility spillover is more significant during the COVID-19 era (in Fig. 10) than the full sample.

As a robustness test, we conducted a causality-in-variance Lagrange Multiplier (LM) test of Hafner and Herwartz (2006) and the Fourier LM test introduced by Li and Enders (2018) to investigate the causality direction in-variance between Bitcoin, traditional financial assets, and major global uncertainty measures. Results are reported in Table 4, where the LM tests show a unidirectional risk transmission from Bitcoin to other markets, including Gold, Stock market, Bonds, the VIX, and the Crude Oil markets. Simultaneously, the EPU is the only global factor that causes higher volatility in Bitcoin. Note that Bitcoin is a volatility receiver from the stocks and the VIX in Table 3. However, it is a volatility transmitter to stocks and the VIX according to Table 4. Furthermore, other studies have also reported a bidirectional relationship between stocks, the VIX, and Bitcoin (see e. g., Dahir, Mahat, Amin Noordin, & Hisyam Ab Razak, 2020; Aktham & Hussein, 2021; Efthymia & Konstantinos, 2018). This highlighted the fact that the relationships between stocks, VIX, and Bitcoin are very sensitive to different econometric techniques.

3.4. Discussion and implications of the findings

The findings in this paper have several implications on portfolio allocations and diversification benefits. Specifically, if there is a well-diversified portfolio, there will be a decline in the return and the volatility spillovers among assets and uncertainty measures. Therefore, it can be suggested that efficient portfolio allocations can hedge the market risks related to uncertainty shocks. However, if there is a significant increase in the returns and volatility spillovers among financial markets and uncertainty measures, the spillover effects reduce diversification benefits. In this case, uncertainty shocks can create systematic risks, which are not subject to hedging features. Therefore, our findings on the *Bitcoin-Traditional Financial Assets-Uncertainty Measures* system have important implications for portfolio diversification benefits and effective risk management.

We observe that total spillover indices have reached unprecedented levels during the COVID-19 period. This evidence is in line with the hypothesis provided by previous papers (e.g., So et al., 2021) that there is a significant connectedness during the period of high-level uncertainty, such as observed during the COVID-19 era. Our results confirm this hypothesis since the high level and persistent return and volatility spillovers were observed across Bitcoin and financial markets during the COVID-19 era. This evidence implies decreasing diversification benefits,

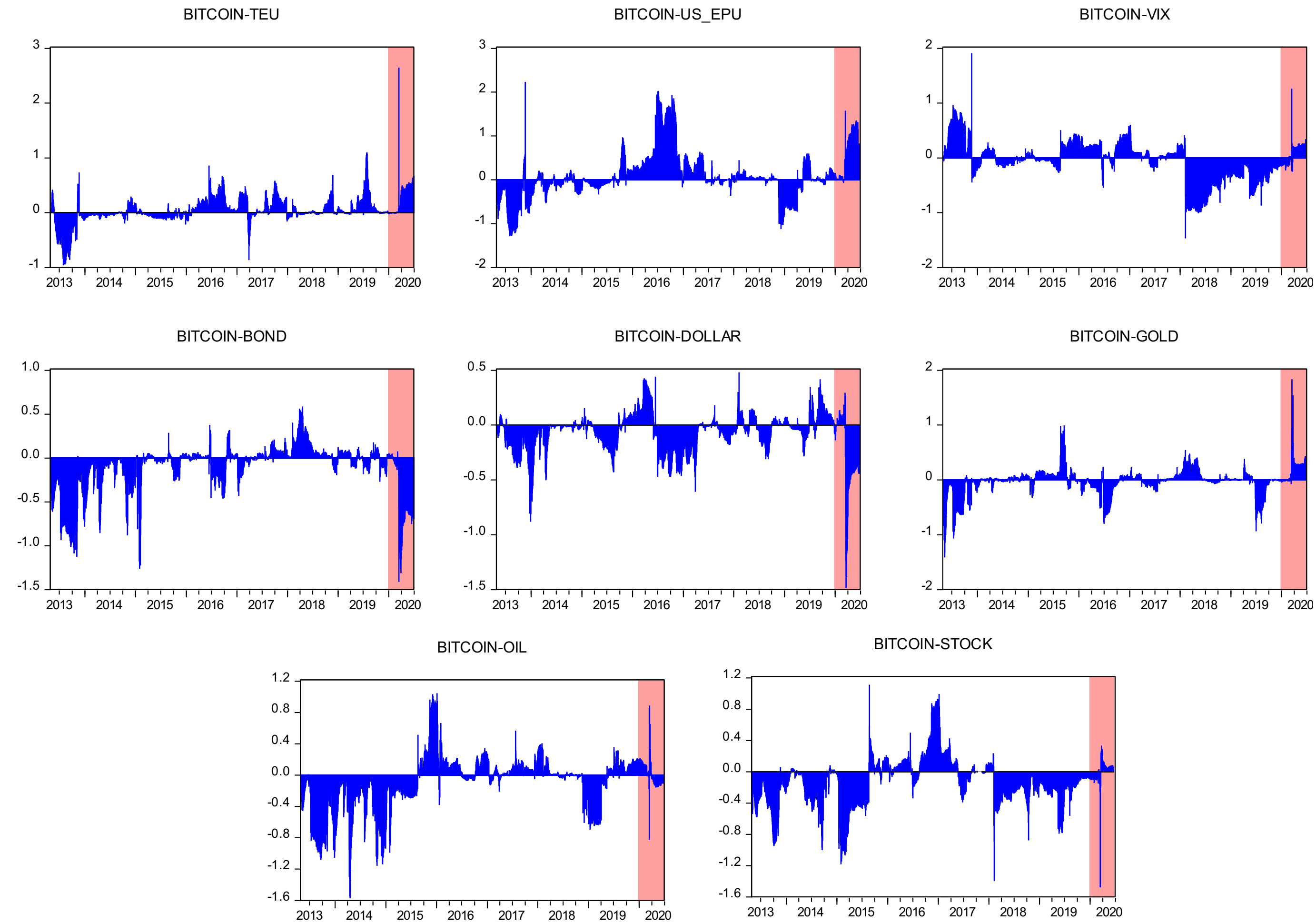

Fig. 10. Dynamic connectedness of pairwise volatility spillovers.
Notes: These graphs portrait the time-varying behaviour of the pairwise directional volatility spillover between Bitcoin and each of the variables under consideration. Positive (negative) values indicate that Bitcoin is transmitting (receiving) volatility spillover to (from) the other variable. Indices are estimated based on the generalised forecast-error variance decomposition (GFEVD) obtained from estimating a TVP-VAR model of order one and 10-step ahead forecasts. The red area captures the COVID-19 era.

Table 4
Causality in-variance tests.

	$Bitcoin \neq > Asset_i$					$Asset_i \neq > Bitcoin$				
	λ_{LM}	p-value	n	$F\lambda_{LM}$	p-value	λ_{LM}	p-value	n	$F\lambda_{LM}$	p-value
Stocks	8.715**	0.012	3	8.974**	0.011	3.232	0.198	3	1.813	0.403
Bonds	8.444**	0.014	3	13.287***	0.001	2.771	0.250	3	2.048	0.358
USD	1.897	0.387	3	2.784	0.248	2.569	0.276	3	0.648	0.723
Gold	8.291**	0.015	3	10.771***	0.004	1.398	0.497	3	1.384	0.500
WTI_Oil	5.478*	0.064	2	7.950**	0.018	1.699	0.427	3	1.035	0.595
VIX	7.399**	0.024	1	8.838**	0.012	0.668	0.715	3	0.458	0.795
US_EPU	0.671	0.714	0	0.671	0.714	11.205***	0.003	3	9.967***	0.006
TEU	1.011	0.603	3	1.534	0.464	0.951	0.621	3	0.735	0.692

Notes: This table is based on the Lagrange multiplier (LM) volatility spillover test developed by Hafner and Herwartz (2006) and the Fourier LM test introduced by Li and Enders (2018). λ_{LM} is the statistic from a Lagrange multiplier (LM) test for testing the null hypothesis of no-volatility spillover from asset j to asset i whereas $F\lambda_{LM}$ denotes the test statistic from a Fourier LM test that accounts for structural breaks. The maximum number of Fourier frequency (n) is set to 3, where the optimal frequency is determined by Akaike Information Criterion (AIC). Finally, ***, **, and * denotes 1%, 5%, and 10% statistical significance levels, respectively.

especially during the COVID-19 crisis.

On the other hand, Gold is the centre of the system regarding the return spillover and demonstrates the "safe heaven" properties against uncertainty shocks. This evidence aligns with previous findings on the pre-COVID-19 period (e.g., Wu et al., 2019) and the COVID-19 era (see, e.g., Ji et al., 2020). It is an interesting issue to emphasise the competitive role of Bitcoin for Gold investors. More specifically, this strike feature could be due to the distinct roles played by Bitcoin and Gold in the system (i.e., Bitcoin is the net transmitter while Gold is the net receiver) during the COVID-19 era. This evidence has a significant implication in terms of the safe-haven properties of Gold and portfolio diversification purposes.

There is a significant return spillover from the USD and bond markets to Gold Markets. This evidence can be related to the FED's monetary policy at the start of the pandemic in the United States in early 2020. When the FED decided to decrease policy interest rates with the start of the COVID-19 in the United States, this decision decreased the real value of the USD and Bond returns due to the inflation expectations. The decline in the USD and Bond returns causes investors to invest in the Gold market. Therefore, we observe that Gold is the dominant asset to alternate portfolio allocation. In addition, the VIX has significant return spillovers to stock returns implying that uncertainty shocks decrease the stock returns. Although there is a significant interaction between the EPU and the TEU indices, they seem to have an insignificant role in determining the returns of Bitcoin and traditional financial assets. Here, the only significant return connectedness observed between the VIX and the S&P 500 stock returns.

Regarding the volatility spillover analyses, Bitcoin is a net transmitter of volatility spillovers to other markets, particularly during COVID-19. This evidence is consistent with the findings in Goodell and Goutte (2021a). Also, there is a significant price volatility connectedness between the VIX and the S&P 500 stocks. Further results from the causality-in-variance LM and the Fourier LM tests indicate a unidirectional volatility transmission from Bitcoin to other markets, including Gold, Stocks, Bonds, VIX, and Crude Oil. This evidence is in line with previous papers (e.g., Goodell & Goutte, 2021b; Yi et al., 2018). Bitcoin price volatility also increases the volatility of the VIX. Therefore, Bitcoin is the leading asset to provide diversification benefits against volatility shocks (see Corbet, Lucey, Urquhart, & Yarovaya, 2019 and the related references therein).

Interestingly, the EPU is the only factor that causes higher volatility in Bitcoin. While the EPU drives volatility spillover of Bitcoin, the TEU does not affect Bitcoin's volatility. This evidence could be related to the fact that the EPU is a news-based index and measures economic policy uncertainty, whereas the TEU index measures investor sentiment. Therefore, there can be a distinction between these two uncertainty measures. This evidence also means that the EPU shocks increase the price volatility of Bitcoin, and this transmits to Gold, Stocks, Bonds, and Crude Oil markets. Other studies have shown the catalyser effect of the EPU on the price volatility in Bitcoin (see, e.g., Fang et al., 2019; Wang et al., 2020; Yen & Cheng, 2021), and our results are in line with the results of these papers.

4. Conclusion

This paper analyses the return connectedness and the price volatility connectedness between Bitcoin, traditional financial assets (Crude Oil, Gold, Stocks, Bonds, and the USD), and major global uncertainty measures (the EPU, the TEU, and the VIX) from April 29, 2013, to June 30, 2020. For this purpose, we utilise the time-varying parameter vector autoregression model, dynamic connectedness approach, and network analyses. Furthermore, we applied the causality-in-variance LM, and the Fourier LM tests to detect the causality direction in-variance. We observe that total spillover indices reached unprecedented levels during the COVID-19 period and remain high. Since then, we confirmed the high return and volatility spillovers across markets during the COVID-19 pandemic. During the COVID-19 era, Bitcoin has been a net receiver of return spillovers from other markets, and it has been a net transmitter of volatility spillovers to other markets. However, Bitcoin has been weakly connected over the full sample period. Therefore, we concluded that Bitcoin plays a major role in the volatility transmission during the COVID-19 period.

On the other hand, the LM-type tests show a unidirectional risk transmission from Bitcoin to other markets, including Gold, Stock market, Bonds, the VIX, and to some extent, to the Crude Oil market. Simultaneously, the EPU is the only global factor that causes higher volatility in Bitcoin. Therefore, we observed that the EPU is positively related to the price volatility of Bitcoin. In short, we concluded that Bitcoin has a significant price volatility transmission to traditional financial markets during the COVID-19 period, and its price volatility has been driven by economic policy uncertainty. Policymakers should realise that their decisions can significantly increase the price volatility of Bitcoin. Investors and traders should also realise that the high price volatility in Bitcoin can transmit to traditional financial markets (most significantly to stock and bond markets).

Future studies on this subject can focus on other cryptocurrencies to examine their relationships between traditional financial markets. At this stage, future papers can include emerging and global exchange rates. Another research plan is that to focus on new measures of global uncertainty. For instance, we have limited knowledge of the effects of Twitter-based uncertainty measures on the relationship between cryptocurrencies and traditional financial markets. These research topics can be examined by utilising new econometric techniques.

CRediT authorship contribution statement

Ahmed H. Elsayed: Conceptualization, Data, Methodology, Formal analysis, Visualization, Writing – review & editing, Project administration. **Giray Gozgor:** Conceptualization, Writing – original draft, Writing – review & editing, Project administration. **Chi Keung Marco Lau:** Conceptualization, Writing – original draft, Writing – review & editing, Project administration.

Data availability

Data will be made available on request.

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