Information spillovers across traditional hedging assets, cryptocurrencies and uncertainty measures:

Evidence from an entropy-based network analysis

Abstract

In this paper, we regard various traditional hedging assets, including oil, gold, silver, other commodities and the US dollar, five leading cryptocurrencies, and four uncertainty measures (namely, Geopolitical Risk Index(GPR) , Economic Policy Uncertainty Index(EPU), CBOE Volatility Index(VIX) and Equity Market Uncertainty Index(EMU)) as a system and analyze their information spillovers. We use effective transfer entropy to measure their return spillovers and construct an information spillover network to exhibit the dominant direction of the information flow. The results show that compared to the traditional hedging asset, the cryptocurrency is less affected by uncertainty. EPU index affects the least hedging assets, while VIX index affects the most hedging assets, especially affecting gold and crude oil significantly. Additionally, we construct an information integration network to examine the integration of the system and centrality of the vertexes. The results show that oil and gold play central roles. Furthermore, we use rolling windows to capture the time-varying, and discover that the values of the nature of the network fluctuate with no significant trends.

Key words： Traditional hedging asset; Cryptocurrency; Uncertainty; Information spillover; Effective transfer entropy; Complex network

1. Introduction

In order to hedge against the financial risk and reduce the negative effect from uncertainties, investors often select hedging assets to form a portfolio diversification. Uncertainties are important factors for such investment decisions and, thus, likely to affect the prices of hedging assets.

Many studies assert the impact of uncertainty shocks on traditional hedging assets. Balcilar et al. (2016) analyze the causality between two news-based indexes, which are EPU and equity market uncertainty, and gold returns and volatility, and find the evidence of causality in daily and monthly data. More comprehensively, Bilgin et al. (2018) and Gozgor et al. (2019a) examine the impact of the EPU, VIX, GPR, the US real effective exchange rate, crude oil prices, Partisan Conflict index, and SKEW indexes on the returns and the price volatility of gold, and they conclude that GPR and the US real effective exchange rate significantly explain gold returns and that the rise of EPU contributes to increases of the gold price. Besides gold, commodities can also be used as hedging assets. Bakas and Triantafyllou (2018) research the impact of uncertainty shocks on the volatility of commodity prices. The results show that compared to observable measures of economic uncertainty, the unobserved ones have the more significant impact, which is long-lasting positive effect, on commodity price volatility and that the impact is stronger on prices of energy commodities when comparison with those of agricultural and metals. After that, focusing on volatility of commodity price, they do further researches about forecast using macro uncertainty and the impact of pandemics uncertainty (Bakas and Triantafyllou, 2019, 2020). Razmi et al. (2020) discover that US monetary policy uncertainties affect oil return volatility. However, most studies focus on gold and commodities. The impact of uncertainty on other hedging assets, such as the US dollar and crude oil, is also worth researching.

After Bitcoin emerged in 2008, cryptocurrencies were accepted gradually and became new hedging assets(Bouri et al., 2020a; Tiwari et al., 2019; Urquhart and Zhang, 2019; Wang et al., 2019b; Wang et al., 2019c), even called digital gold. As digital cash, they can be sent directly to other parties online, without passing any financial institution. The value of cryptocurrencies is not based on other tangible assets or the economy of any country, which is a significant difference from cryptocurrency and other assets(Urquhart and Zhang, 2019). In view of the great attractiveness of cryptocurrencies to investors during periods with high various uncertainty, there is an ongoing interest in investigating the impact of uncertainty on this kind of hedging assets. Many studies explore the relationship between Bitcoin and EPU and reveal the hedging or safe haven property of Bitcoin against EPU (Demir et al., 2018; Fang et al., 2019; Wang et al., 2019a; Wu et al., 2019). However, such literature has a limitation of categories of cryptocurrencies and of uncertainties. Other leading cryptocurrencies also attract investors, and other uncertainties are also worth studying. Some literature extends the objects of cryptocurrencies. Yen and Cheng (2020) and Cheng and Yen (2020) research the relationship between EPU of different countries and three and four varieties of cryptocurrencies respectively. They find that only Chinese EPU can predict the volatility of cryptocurrencies and that Bitcoin and Litecoin can be chosen to hedge against EPU. There are also some studies that extend the objects of uncertainties. The study of Wang et al. (2019a) includes EPU, EMU and VIX, and the results show that the risk spillovers from uncertainties to Bitcoin is not significant. Gozgor et al. (2019b) examine the relationship between Bitcoin and trade policy uncertainty trade uncertainty. Moreover, Al Mamun et al. (2020) add GPR to the study, and claim that GPR influences the volatility and risk premia of Bitcoin significantly and that the effects of GPR and EPU are much more significant when under severe economic conditions. More comprehensive, Colon et al. (2020) widen this discussion on Bitcoin to the whole cryptocurrency market by analyzing 25 cryptocurrencies, covering 95% of the aggregate cryptocurrency capitalization. They claim that the cryptocurrency can be a weak hedge and safe haven against EPU during a bull market and that it can be a strong hedge but not a safe haven against GPR. Furthermore, taking both the traditional hedging asset and the cryptocurrency into consideration, Wu et al. (2019) compare gold and Bitcoin on hedging EPU and discover that the reaction to EPU shocks of gold is steadier, while Bitcoin is more responsive and that neither of them can act as a strong hedge. Nevertheless, the conclusions of former literature are not totally consistent. As the previous studies demonstrated, the relationship between hedging assets and uncertainties is not static so that the time variant is demanded to be considered. However, much literature fails to do so.

Furthermore, the existing literature mainly focuses on the pairwise relationship between hedging assets and uncertainties instead of the complex relationship of the whole system, lacking the systemic perspective and the holistic perspective. There are also information spillovers between hedging assets so that the impact of uncertainties may be transferred to the whole system. Although the ample studies have analyzed the relationships between cryptocurrencies and between traditional hedging assets and cryptocurrencies (Bouri et al., 2020b; Ji et al., 2019b; Jin et al., 2019; Moratis, 2020; Okorie and Lin, 2020; Papadimitriou et al., 2020; Qureshi et al., 2020; Yaya et al., 2019; Zeng et al., 2019), the literature has remained comparatively silent on the impact of uncertainty on this system or this network. In this paper, different from the existing literature, we regard traditional hedging assets, cryptocurrencies and uncertainty as a system and focus on the information spillovers among them based on the complex network to research their complex connections and integration. Complex network is widely employed to investigate the connection between different financial markets (Bekiros et al., 2017; Cao et al., 2017; Gong et al., 2019; Han et al., 2019; Sun et al., 2019; Wu et al., 2020). To be specific, we use a directed network to examine the direction of the information flow among assets and uncertainties and a minimum spanning trees (Ji et al., 2019b; khoojine and Han, 2019; Kristoufek et al., 2012; Mantegna, 1999a, b; You et al., 2015) to exhibit the centrality of them and the integration of the system.

In this paper, we extend the research objects of both cryptocurrencies and uncertainties. Our data set covers five traditional hedging assets (crude oil, gold, silver, US dollar(USD) and Commodity), five leading cryptocurrencies (Bitcoin, Ethereum, Ripple, USDT, Litecoin) and four uncertainty measures (Geopolitical Risk Index(GPR) , Economic Policy Uncertainty Index(EPU), CBOE Volatility Index(VIX) and Equity Market Uncertainty Index(EMU)).

With regard to the methodology of measuring information spillovers, we use effective transfer entropy (ETE). In available literature, several approaches are used to measure relationships. Correlation coefficient is a simple and widely used approach. Besides, based on information theory, many scholars use Mutual Information. However, those are symmetric and therefore contains no directional sense. A significant number of studies use the spillover index approach developed by Diebold and Yilmaz (2012); Diebold and Yılmaz (2014) based on VAR model and forecast error variance decomposition (Antonakakis et al., 2014; Balli et al., 2019; Ji et al., 2019a; Jiang et al., 2019; Nishimura and Sun, 2018; Nishimura et al., 2018; Sun et al., 2019). However, it cannot analyze a large multivariate system. Moreover, developed by Schreiber (2000) and based on the theory of information, transfer entropy (TE) is also a useful approach (Bekiros et al., 2017; Gong et al., 2019; Ji et al., 2019b). Compared to Mutual Information, transfer entropy better describes the direction of information flow. Besides, Dimpfl and Peter (2018) show in the empirical analysis that the VAR approach only accounts for linear dependencies, but the transfer entropy can detect the nonlinear dependencies. Furthermore, Gong et al. (2019) also compare the two approaches, and discover that the VAR model is not stable enough because of the difficulty explaining the jumping points. However, transfer entropy suffers from bias caused by finite sample effects or other possible factors. In order to solve this problem, Marschinski and Kantz (2002) propose effective transfer entropy (ETE), an extended concept about TE, to provide improved estimation. However, it is rarely applied in finance research (Bekiros et al., 2017; Sensoy et al., 2014; Yang et al., 2017) and never used to construct an information spillover network.

There are two main contributions of this paper. First, our study is the first attempt to investigate the information spillovers across traditional hedging assets, cryptocurrencies and uncertainty measures, considering them as a system, by constructing complex networks in both static perspective and dynamic perspective. Second, we employ effective transfer entropy, which can capture both linear and nonlinear dependencies and provide an improved estimation than transfer entropy, to quantify the connection and used to measure the edges of the complex network. This method is mentioned in the future avenues of Ji et al. (2019b) to modify the entropy-based network, and we achieve the improvement that they want.

The remainder of the paper is organized as follows. Section 2 presents the methods that we utilize to analyze the connection, with the use of ETE, dynamic complex network, MST and diverse topology characteristics measures and centrality measures. Section 3 provides and discusses the empirical results. Section 4 offers concluding remarks.

2. Methods

2.1. Effective transfer entropy

Originally developed by Schreiber (2000) and based on the theory of information proposed by Shannon (1948), transfer entropy can quantify the information flow of variables and detect its asymmetry. When we predict a variable X by using the information from itself, using additional information from another variable Y may decrease the uncertainty of prediction. Transfer entropy measures this possible decrease.

Shannon (1948) proposes Shannon entropy

$$H_X = -\sum_i p(i) \log_2 p(i) \quad (1)$$

, where $p(i)$ is the prior probability of state i. And it is used to measure how much information is needed to optimally encode an independent variable X from a given discrete distribution. We will drop the base of the logarithm hereafter, because it just determines the units for information quantification.

For a variable set with two variables X and Y, the joint entropy is defined as:

$$H(X,Y) = -\sum_{x,y} p(x,y) \log p(x,y) \quad (2)$$

, where $p(x,y)$ is the joint probability.

Relative entropy proposed by Kullback and Leibler (1951) measures the excess coded number of bits if we use a different distribution $q(i)$.

$$KL_X = \sum_i p(i) \log p(i)/q(i) \quad (3)$$

Conditional entropy measures the average amount of information transmitted by the latest observation $X(t+1)$ after the last t observations of X are known, and their information has been completely exploited. It is defined as:

$$\begin{aligned} h_{X(t)} &= H_{X(t+1)} - H_{X(t)} \\ &= -\sum p(i_1, \cdots, i_{t+1}) \log p(i_{t+1}|i_1, \cdots, i_t) \end{aligned} \quad (4)$$

, where $p(i_{t+1}|i_1, i_2, \cdots, i_t) = p(i_1, \cdots, i_t, i_{t+1})/p(i_1, \cdots, i_t)$

When we already know the information about the variable Y, the uncertainty of X can be measured as conditional entropy:

$$H(X|Y) = H(X,Y) - H(X)$$

$$= -\sum_{x,y} p(x,y) \log p(x|y) \tag{5}$$

To measure the dependence of two variables, we want to measure the excess number of coded bits caused by the false hypothesis that two variables are independent. We use the mutual information (MI):

$$M_{XY} = H\ (X) - H\ (X \mid Y) = H\ (Y) - \ H\ (Y \mid X)$$
$$= \sum_{ij} p(i,j) \log \frac{p(i,j)}{p(i)p(j)} \tag{6}$$

However, MI is symmetric, and cannot provide any directional sense of information flow. In order to measure the predominating direction of asymmetric information flow, we use transfer entropy. Let time series of variable X be a stationary Markov process of order k, and the state i_{t+1} is conditional on the k previous states.

$$p(i_{t+1}|i_t, i_{t-1}, \cdots, i_0) = p(i_{t+1}|i_t, i_{t-1}, \cdots, i_{t-k+1}) \tag{7}$$

When we measure the information flow from another variable Y, we presume that the state i_{t+1} of X is influenced by the l previous states of variable Y. Quantified by a relative entropy, the deviation from $p(i_{t+1}|i_t^{(k)}) = \ p(i_{t+1}|i_t^{(k)}, j_t^{(l)})$ gives the information flow from Y to X. This conception can be explained as (Marschinski and Kantz, 2002):

Transfer Entropy = + information about future observations X(t + 1)

gained from past joint observations of X and Y

− information about future observations X(t + 1)

gained from past observations of X only

Therefore, transfer entropy from Y to X is defined as:

$$TE_{Y\to X}(k,l) = \sum_{ij}\ p(i_{t+1}, i_t^{(k)}, j_t^{(l)}) \log \frac{p(i_{t+1}|i_t^{(k)}, j_t^{(l)})}{p(i_{t+1}|i_t^{(k)})} \tag{8}$$

Transfer entropy is asymmetric for X to Y and Y to X, and it provides a directional causality relationship between two variables. Referring to Bekiros et al. (2017), we assume that k=l=1, based on the efficient market hypothesis and random walk behavior of stock prices.

The calculation of transfer entropy demands processes consisting of discrete states, but the processes of financial data consisting of continuous states. Therefore, in order to realize the method, we need to discretize the state spaces of the processes. We divide each state space into four bins. Considering the importance of tail observation of financial data, we set 15th, 50th and 85th percentile to be the break point (Dimpfl and Peter, 2018).

When we calculate transfer entropy, we use empirical frequencies to estimate the probabilities and use Bayes' law to get the conditional probabilities.

However, TE suffers from bias caused by finite sample effects or other possible factors. In order to solve this problem, we use effective transfer entropy (ETE).

For the two time series X and Y, we shuffle Y randomly to destroy all causal relations and re-calculate the TE from Y to X, and use this re-calculated TE to estimate the bias. To make it more accurate, we perform the shuffling for 100 times and calculate the average of 100 re-calculated TE for each pair of series. ETE from Y to X is defined as the difference of the usual TE from Y to X and this average of the re-calculated TE.

$$ETE_{Y\to X} = TE_{Y\to X} - TE_{Y_{shuffled}\to X} \tag{9}$$

The result of Eq 9 may be negative and close to 0. In this situation, we consider that there is no information flow in this direction and use 0 to replace the original ETE.

2.2. Networks based on entropy

In this research, we built two networks: the information spillover network which focuses on the direction of the information flow between assets or between assets and uncertainty measures and the information integration network which focuses on the centrality of them and the integration of the system.

2.2.1. Information spillover network

First, using the ETE calculated by methods in 2.1., we construct an effective transfer entropy spillover matrix $\boldsymbol{T} = [T_{ij}]$, where T_{ij} denotes the $ETE_{j\to i}$. We make an analogy between ETE and the Diebold and Yilmaz (2012); Diebold and Yılmaz (2014) dynamic spillover index and use their framework to analyze the ETE. Pairwise net ETE is calculated by

$$N(T_{ij}) = T_{ij} - T_{ji}. \tag{10}$$

'From' ETE is calculated by the row sum of the matrix T

$$T_{i\leftarrow\cdot} = \sum_{j=1}^{N} T_{ij}\ ,\ j \neq i\ . \tag{11}$$

And 'To' ETE is calculated by the column sum

$$T_{\cdot\leftarrow i} = \sum_{j=1}^{N} T_{ji}\ ,\ j \neq i\ . \tag{12}$$

The system total spillover index is calculated by

$$T_{total} = \frac{1}{N} \sum_{i,j=1}^{N} T_{ij}\ ,\ j \neq i\ . \tag{13}$$

Next, we use the net ETE to construct the information spillover network. If and only if $N(T_{ij}) > 0$, a directional edge from j to i is constructed, and the $N(T_{ij})$ is the weight of the edge. Then a weighted directed network is constructed.

There are three measures to describe the topology characteristics of the network.

Graph density (GD) is the ratio of the number of edges and the maximum number of possible edges.

$$GD = \frac{E}{C_N^2} \tag{14}$$

, where E is the number of the existing edges in the network.

Clustering coefficient (CC) measures the probability that the adjacent vertexes of a vertex are connected. The CC of a vertex is defined as the ratio of the real number of edges between node i and neighbor nodes and the maximum possible number of edges. And the CC of a network is the average of the CC of all vertexes.

$$CC = \frac{1}{N} \sum_{i=1}^{N} CC_i \tag{15}$$

, where N is the number of vertexes in the network.

Average shortest path length (APL) is the average length of the shortest paths between any two nodes on the graph.

$$APL = \frac{1}{\frac{1}{2}N(N+1)} \sum_{i \geq j} l_{ij} \tag{16}$$

, where l_{ij} is the shortest path length between i and j, and the length is defined as the number of the edges.

Besides, we use in-degree and out-degree to measure the influence and the roles of the vertexes in the system. They are respectively defined as the number of edges to the vertex and the number of edges from the vertex.

$$D_i^{in} = \sum_{j=1}^{N} a_{ij}^{in} \quad (17)$$

$$D_i^{out} = \sum_{j=1}^{N} a_{ij}^{out} \quad (18)$$

, where $a_{ij}^{in} = 1$ if and only if $T_{ij} - T_{ji} > 0$, and $a_{ij}^{out} = 1$ if and only if $T_{ij} - T_{ji} < 0$.

2.2.2. Information integration network

We also construct the information integration network of the system to measure the centrality of the assets and uncertainty measures. In this section, we focus on the intensity of their interaction instead of the direction. Therefore, we construct a symmetric ETE intensity matrix $\widetilde{\boldsymbol{T}} = [\widetilde{T_{ij}}]$ to be the adjacency matrix. Its diagonal elements are 0, and the other elements are

$$\widetilde{T_{ij}} = \widetilde{T_{ji}} = T_{ij} + T_{ji}, i \neq j \quad (19)$$

However, there are abundant edges in the network structured by the adjacency matrix $\tilde{T}$, but we want to find the important edges to analyze. Therefore, we use minimum spanning tree (MST) to filter unimportant information of the network. Before that, with reference to Mantegna (1999b), we transform the adjacency matrix from the ETE intensity matrix into the distance matrix $\boldsymbol{D} = [d_{ij}]$,

$$d_{ij} = 1 - \widetilde{T_{ij}}, i \neq j \quad (20)$$

, and its diagonal elements are 0. In this specific research case, $0 < \widetilde{T_{ij}} < 0.23$ holds in both static results and dynamic results. Therefore, d_{ij} numerically fulfills the three axioms of a Euclidean metric: (i) $d_{ij} = 0$ if and only if $i = j$; (ii) $d_{ij} = d_{ji}$ and (iii) $d_{ij} \leqslant d_{ik} + d_{kj}$ (Mantegna, 1999a).

Then, we use Prim's algorithm (Prim, 1957) to build an MST. And there are only N-1 edges with the closest distance in the MST.

We use three centrality measures to identify the importance of vertexes in the system.

Degree centrality measures the number of adjacent edges of a given vertex.

$$D_i = \sum_{j=1}^{N} a_{ij} \quad (21)$$

where $a_{ij} = 1$ if and only if there is an edge between vertex i and j in the MST.

Closeness centrality measures how many steps is required to access every other vertex from a given vertex.

$$C_i = 1 \Big/ \sum_{j=1}^{N} l_{ij} \qquad (22)$$

Betweenness centrality measures the number of shortest paths going through a given vertex.

$$B_i = \sum_{j \neq k \neq i \in V} \frac{\sigma(j,k|i)}{\sigma(j,k)} \qquad (23)$$

, where $\sigma(j,k|i)$ is the number of shortest paths between j and k going through i and $\sigma(j,k)$ is the number of shortest paths between j and k.

Moreover, we use system integration index to measure the degree of the integration of the whole system, and it is defined as:

$$I = \frac{1}{N-1} \sum_{e_{ij} \in MST} (1 - d_{ij}) = \frac{1}{N-1} \sum_{e_{ij} \in MST} (T_{ij} + T_{ji}) \qquad (24)$$

, where e_{ij} is the edges in the MST.

3. Empirical Results

3.1. Data

We use the daily observations of fourteen prices of assets or values of indices, and we divide them into three groups. The first group is about traditional hedging assets, including prices of crude oil (WTI), gold, silver, US dollar index (USD) and Commodity Research Bureau Index (CRB). The second group includes the prices of five leading cryptocurrencies (Bitcoin, Ethereum, Ripple, USDT, Litecoin), which represent new hedging assets. The third group is about uncertainty measures, including the daily date of Geopolitical Risk Index (GPR), Economic Policy Uncertainty Index (EPU), CBOE Volatility Index (VIX) and Equity Market Uncertainty Index (EMU).

We get the price data of cryptocurrencies from https://coinmarketcap.com/ and the gold price from https://www.gold.org/goldhub/data/gold-prices. The date of VIX is from https://www.cboe.com/products/vix-index-volatility. The date of remaining uncertainty measures is from https://www.policyuncertainty.com/. And the other data all comes from the Wind.

Table 1

Summary statistics of returns.

	Mean	Stdev	Skewness	Kurtosis	Jarque-Bera	ADF test	PP test
Oil	0.000113	0.024	0.336	3.085	453.503***	-10.376***	-1063.280***
USD	0.000012	0.004	-0.076	2.620	313.555***	-11.185***	-1037.034***
Silver	0.000173	0.014	-0.082	2.936	393.440***	-10.966***	-1051.822***
Gold	0.000336	0.008	0.421	2.383	290.673***	-10.327***	-1101.999***
CRB	-0.000012	0.003	-0.021	3.363	514.490***	-8.769***	-1088.465***
Bitcoin	0.003287	0.046	-0.162	4.616	973.160***	-8.926***	-1112.399***
Ethereum	0.004050	0.089	-2.834	54.443	135856.083***	-8.065***	-1148.966***
Ripple	0.003243	0.077	2.400	17.953	15663.381***	-8.381***	-1125.703***
USDT	0.000000	0.006	-0.514	26.837	32712.114***	-13.093***	-1149.622***
Litecoin	0.002649	0.066	1.529	11.822	6765.573***	-8.521***	-990.369***
EPU	0.000859	0.703	0.126	1.110	59.300***	-15.191***	-1311.307***
GPR	0.003245	0.523	0.299	1.558	127.050***	-15.194***	-1208.220***
VIX	0.000107	0.085	1.474	8.968	4044.259***	-13.061***	-1023.065***
EMU	0.001809	1.047	0.080	0.903	38.557***	-14.187***	-1195.157***

*** denotes significance at 1% level.

The sample period, including 1089 observations after deleted the date in which there is a missing value, is from 7 August 2015 to 10 February 2020. The decision of the start day of the sample is due to the data availability for the Ethereum. We conduct our analysis with the daily returns computed by taking the difference in the logarithm of two consecutive values. We show the summary statistics of the daily returns in Table 1. Ethereum exhibits the highest mean return, whereas the lowest number is from CRB, which is the only negative one. Additionally, the means and standard deviations of the returns of the cryptocurrencies, except the USDT, are significantly higher than traditional hedging assets. And the series of USD and CRB exhibit the least standard deviations. Furthermore, all the series depart from normality. Moreover, all the series are stationary according to ADF test and Phillips–Perron (PP) tests.

3.2. Result of effective transfer entropy

In this section, we use ETE to measure the information spillover among the variables and analysis indices about information spillover. We first calculate the transfer entropy (TE). The Fig. 1 is the heat map of the TE matrix, where brighter tones represent higher value of the transfer entropy while darker tones represent lower value. After shuffling 100 times for each pair and subtracting the average randomized TE matrix from the original TE matrix, we get the effective transfer entropy (ETE) matrix, as showed in the Table 2. Additionally, we also get the heatmap Fig. 2.

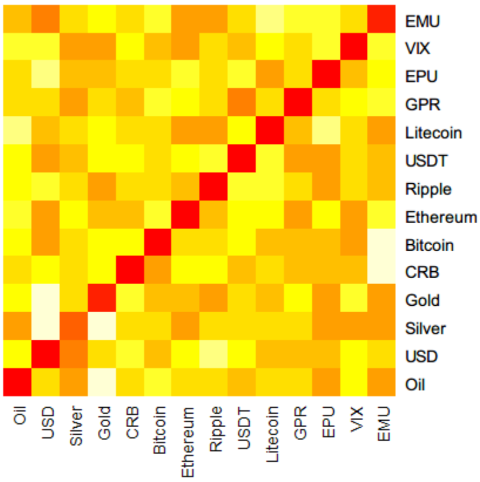

Fig. 1. Heat map of TE.

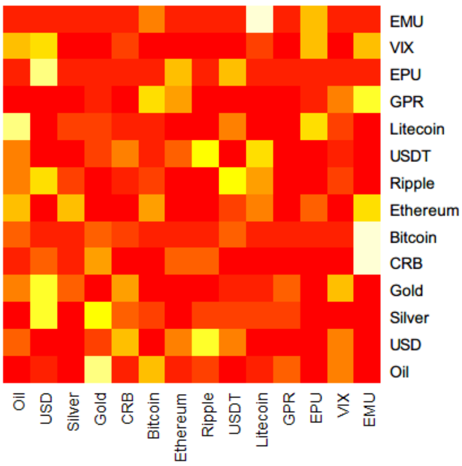

Fig. 2. Heat map of ETE.

As can be seen in the Table 2, the biggest effective transfer entropy is from the gold to the silver (0.0524) and from the USD to the silver (0.0502). 88.5% of effective transfer entropy is less than 0.01, and 43.4% is equal to 0. All assets and uncertainty measures are generally well integrated in the system, and there is information flow among them. Focusing on the uncertainty measures, GPR mainly affects silver (0.0124) and gold (0.0110), which is in accordance with the common sense. Interestingly, EPU affects the least hedging assets, only two cryptocurrencies, Ethereum (0.0040) and Litecoin (0.0114). For instance, Wang et al. (2019a) also conclude that risk spillover effect from EPU to Bitcoin is negligible in most conditions. VIX affects the most hedging assets, especially the gold (0.0187) and oil (0.0092). The information flow from EMU to CRB, Bitcoin and Ethereum are all more than 0.01, which is a relatively high value. The information flow from these uncertainty measures to USD, Ripple and USDT are comparatively less. They might be good choices to hedge against the uncertainty.

Table 2

Information spillover among hedging assets and uncertainty measures.

	Oil	USD	Silver	Gold	CRB	Bitcoin	Ethereum	Ripple	USDT	Litecoin	GPR	EPU	VIX	EMU	**From**
Oil	0.0000	0.0037	0.0000	0.0215	0.0031	0.0135	0.0034	0.0059	0.0016	0.0036	0.0065	0.0000	0.0092	0.0000	0.0719
USD	0.0061	0.0000	0.0000	0.0044	0.0095	0.0000	0.0068	0.0138	0.0063	0.0014	0.0000	0.0000	0.0067	0.0001	0.0550
Silver	0.0000	0.0524	0.0000	0.0502	0.0161	0.0125	0.0000	0.0143	0.0103	0.0145	0.0124	0.0000	0.0000	0.0000	0.1826
Gold	0.0120	0.0270	0.0088	0.0000	0.0153	0.0000	0.0011	0.0000	0.0047	0.0029	0.0110	0.0000	0.0187	0.0000	0.1015
CRB	0.0013	0.0041	0.0008	0.0058	0.0000	0.0000	0.0036	0.0036	0.0000	0.0001	0.0000	0.0000	0.0000	0.0147	0.0341
Bitcoin	0.0031	0.0000	0.0000	0.0033	0.0017	0.0000	0.0010	0.0002	0.0032	0.0000	0.0000	0.0000	0.0000	0.0137	0.0261
Ethereum	0.0084	0.0000	0.0078	0.0000	0.0000	0.0076	0.0000	0.0000	0.0030	0.0055	0.0000	0.0040	0.0000	0.0100	0.0463
Ripple	0.0054	0.0097	0.0031	0.0000	0.0015	0.0035	0.0000	0.0000	0.0105	0.0076	0.0012	0.0000	0.0031	0.0000	0.0455
USDT	0.0050	0.0000	0.0000	0.0026	0.0053	0.0017	0.0037	0.0090	0.0000	0.0086	0.0000	0.0000	0.0020	0.0000	0.0379
Litecoin	0.0167	0.0000	0.0028	0.0041	0.0023	0.0018	0.0000	0.0000	0.0066	0.0000	0.0000	0.0114	0.0031	0.0000	0.0488
GPR	0.0000	0.0000	0.0000	0.0012	0.0000	0.0064	0.0048	0.0000	0.0000	0.0000	0.0000	0.0008	0.0040	0.0081	0.0253
EPU	0.0000	0.0062	0.0000	0.0000	0.0000	0.0000	0.0040	0.0000	0.0034	0.0000	0.0000	0.0000	0.0000	0.0001	0.0138
VIX	0.0041	0.0047	0.0000	0.0000	0.0014	0.0000	0.0000	0.0000	0.0000	0.0014	0.0000	0.0043	0.0000	0.0045	0.0203
EMU	0.0000	0.0000	0.0000	0.0000	0.0000	0.0014	0.0000	0.0000	0.0000	0.0047	0.0000	0.0024	0.0000	0.0000	0.0084
To	0.0621	0.1078	0.0234	0.0929	0.0561	0.0484	0.0284	0.0468	0.0496	0.0502	0.0310	0.0228	0.0468	0.0512	**Total**
Net	-0.0098	0.0528	-0.1593	-0.0086	0.0221	0.0222	-0.0180	0.0013	0.0118	0.0014	0.0057	0.0090	0.0265	0.0428	0.7174

There are three indices to measure the information spillovers of each hedging asset and of each uncertainty measure in the system sight : ‘To’ ETE, ‘From’ ETE and net ETE. As it was shown in the Table 2 and Fig. 3, ‘To’ ETE indicates the sum of the information spillovers from the given asset (or uncertainty measure) to all of other assets (or uncertainty measures). For the hedging assets, the USD and the gold contribute the most, with the values of 0.1078 and 0.0929 respectively, whereas the silver and Ethereum contribute the least, with the values of 0.0234 and 0.0284. USD and gold are two of the most popular traditional hedging assets, and the price fluctuation of them influences the decisions of a wide range of investors, because their return is useful to predict the return of other assets. For uncertainty measures, EMU contributes the most, with the values of 0.0512, whereas EPU contributes the least, with the values of 0.0228.

'From' ETE indicates the sum of the information spillovers which the given asset receives from all of other assets (or uncertainty measures). For the hedging assets, the silver receives the most, with the value of 0.1826, whereas the Bitcoin receives the least, with the value of 0.0261. This result is expected and shows the hedge and safe haven property of Bitcoin. As for the net ETE, it is the difference between the 'To' ETE and 'From' ETE, 'To' ETE minus 'From' ETE. The net ETE of oil, silver, gold, Ethereum are negative, while the net ETE of the remaining assets are positive. All the cryptocurrencies, except Ethereum, act as net transmitters in the system. Not only the Bitcoin but also the other leading cryptocurrencies play important roles in the information flow of the whole system, which is in accordance with the result of Ji et al. (2019b). The USD has the biggest net ETE with the value of 0.0528, while silver has the least with the value of -0.1593. Last but not least, the system total spillover is 0.7174.

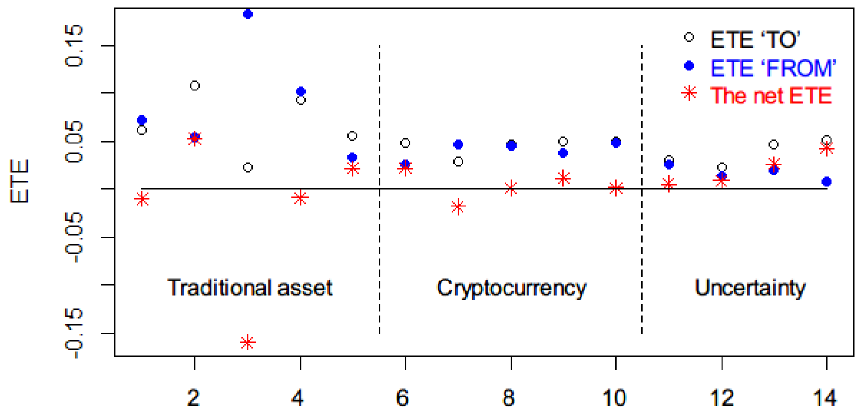

Fig. 3. 'To' ETE, 'From' ETE and net ETE of each variable

Table 3

Information spillover among different groups.

	Traditional hedging asset	Cryptocurrency	Uncertainty	From
Traditional hedging asset	0.0121	0.0050	0.0040	0.0210
Cryptocurrency	0.0033	0.0037	0.0024	0.0094
Uncertainty	0.0009	0.0013	0.0020	0.0042
To	0.0163	0.0099	0.0084	
Net	-0.0047	0.0005	0.0042	

Table 4

Net pairwise spillover among different groups.

	Traditional hedging asset	Cryptocurrency	Uncertainty
Traditional hedging asset	0.0000	0.0016	0.0031
Cryptocurrency		0.0000	0.0011
Uncertainty			0.0000

As it is showed in Table 3, we calculate the group ETE, which is the average of the value of pairwise ETE between a vertex in the one group to another vertex in the other group (or the one group itself). The largest group ETE is from the traditional hedging asset to itself, and this group is the main information transmitter of the system, with the 'To' ETE value 0.0163. However, this group is also the main receiver of the system, with the 'From' ETE value 0.0210, which leads to its net ETE being negative, and all of the groups transmit the most information to this group. This result shows that the traditional hedging asset is affected much by other assets or uncertainty measures, although it strongly affects other assets. As for the cryptocurrency, this group receives most information from itself, with the ETE value 0.0037, and it receives similar value of information from the traditional hedging asset. In addition, the 'To' ETE of the uncertainty is the least. Although the most information from it is transmitted to the traditional hedging asset, this pairwise ETE is less than the pairwise ETE from other groups to traditional hedging asset. Last but not least, we provide the net ETE among three groups in the Table 4. We discover that the direction of net ETE is from the cryptocurrency to the traditional hedging asset and from the uncertainty to other groups. Compare to the traditional hedging asset, the cryptocurrency is less affected by uncertainty.

3.3. Information spillover network analysis

We use the net ETE as the weight of the edge to construct a weighted directed network to measure the direction of the information spillovers between hedging assets and between hedging assets and uncertainty measures. And we do the analysis in both static perspective and dynamic perspective.

3.3.1. Static result

Fig. 4 shows the information spillover network of variables. The edge from USD to silver and the edge from gold to silver are the weightiest. Focusing on the topology structure of the network, we calculate the graph density (GD), clustering coefficient (CC), and average shortest path length (APL) of the network. The value of GD is 0.76, which means the information flow between assets and between assets and uncertainty measures is common. The value of CC is 0.75, and the value of APL is 1.73. The high CC value and small APL value indicate that assets or uncertainty measures are closely linked, and the information transfers quickly in the system.

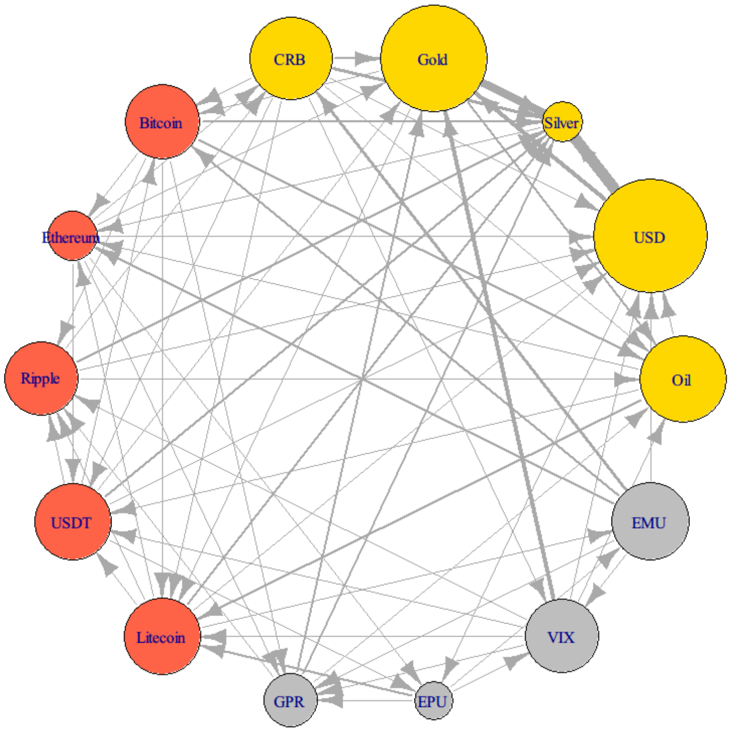

Fig. 4. The information spillover network.

To research the role of each asset and uncertainty measure in the information transfer, we calculate the out degree and in degree of each vertex, showing in the Fig. 5. For the out degree, CRB has the highest, with the value of 8, which means that the information of CRB spillover to the most other vertexes, and the effect of the commodity return is the widest. However, other traditional hedging assets don't have high value, and silver has the least, with the value of 1. Cryptocurrencies, except the Ripple, have a high value of 6, and they play important transmitters in the network. For the uncertainty measures, the VIX and EMU have high values. Interestingly, although USD and gold have high 'To' ETE because of their weighty edges to silver, the out degree of them is just 3 and 4, respectively. For the in degree, USD and silver have the highest value, which is 8. CRB has the least value, which is 3, in the group of the traditional hedging asset and the group of the cryptocurrency. Other traditional hedging assets have the value of 6. Compared to the traditional assets, the cryptocurrency has a lesser in degree in general. Therefore, the vertexes which can affect it are fewer than the traditional asset.

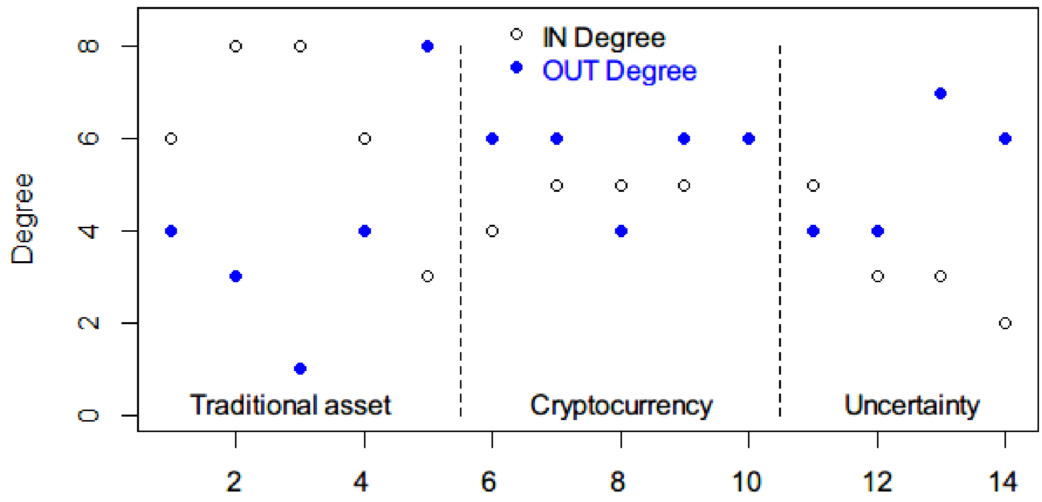

Fig. 5. Out degree and in degree

3.3.1. Dynamic result

We have already done the static analysis of the information spillover network, but the characteristic of the network may be time-variant. To examine the time variability of the network, we use the rolling window analysis. We adopt each window to correspond to one year, with 250 observations for each window span.

Fig. 6 shows the results of the total spillover index of the system. There are two periods of increase. The index increases generally from August 2016 to September 2017, and maintains a high value in the next 4 months. Then it drops quickly from January 2018 to March 2018, and shows an upward trend in the next 13 months except for a sharp fall recorded during November 2018. Finally, it shows a downward trend from October 2019 to January 2020, and at the end of sample period it reaches a low value which is similar with the value at the beginning.

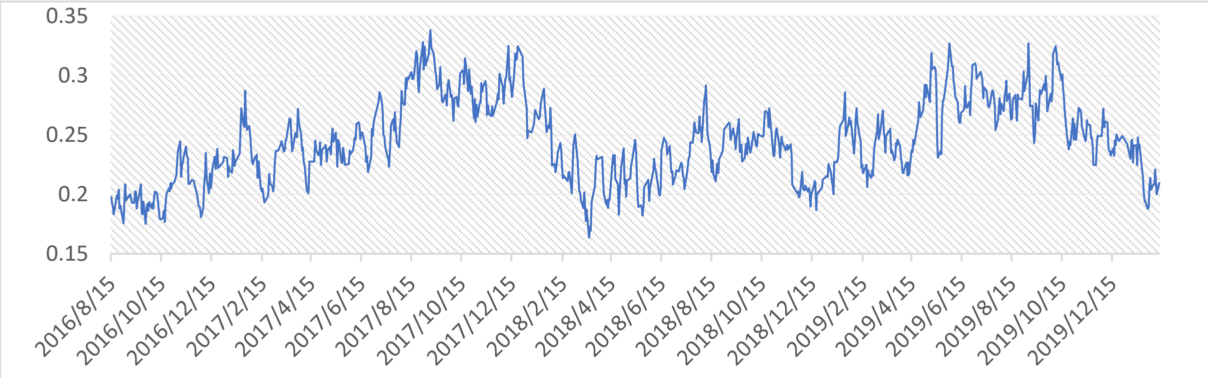

Fig. 6. The total spillover index of the system.

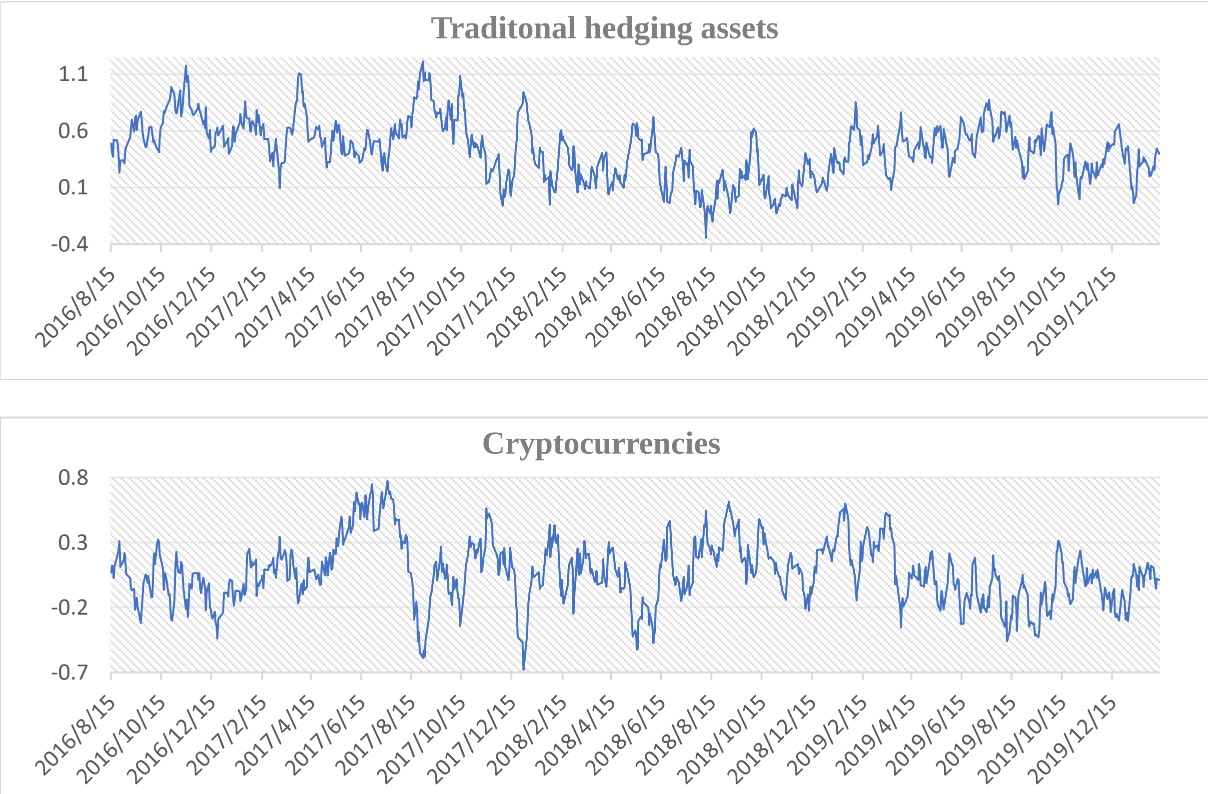

Fig. 7. The total net spillover of the groups.

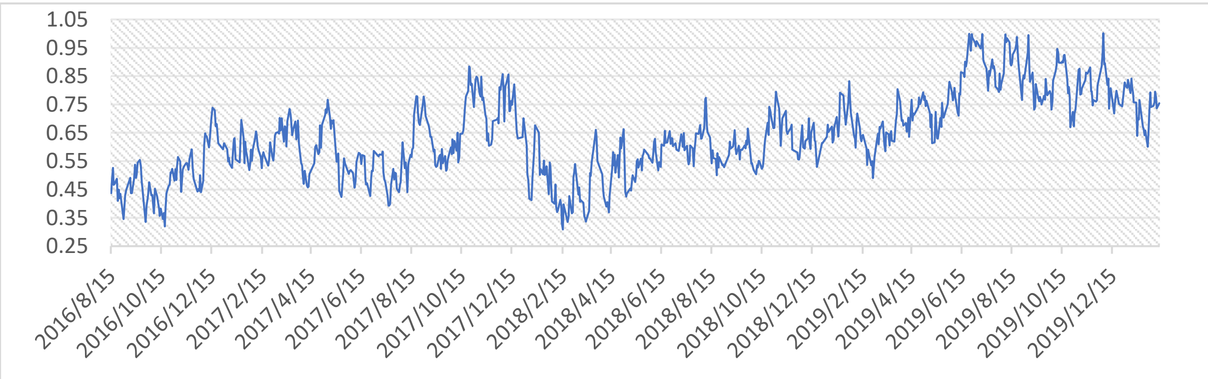

Fig. 8. The total out spillover of uncertainty.

We also present the total net spillovers of the groups of the traditional asset and the cryptocurrency in Fig. 7. For the traditional assets, the value is positive most of the time. It peaks in November 2016, April 2017 and August 2017, but reaches the bottom in August 2018. For the cryptocurrency, the value of it fluctuates, and the role of it changes frequently between a transmitter and a receiver. The value increases from April 2017 to July 2017, and then dives sharply in the next month. Another sharp fall is recorded in December 2017. Interestingly, after those two times reaching bottom, the value increases quickly in the next months. This is likely connected to the dramatic soar of the price of Bitcoin in 2017. Additionally, we exhibit the total out spillover of the uncertainty in the Fig. 8. There is a drop in the junction of 2017 and 2018. After the value increases in June 2019, it maintains a high level in the remaining sample period.

Focus on the vertexes, for the hedging assets, we present summary statistics of net spillover of them in Table 5. The mean value is quite different with the net ETE in the whole sample period from Table 2. All of the mean values of them, except the USDT, are positive. USD is the most significant transmitter with the highest value. USDT is not only the most significant receiver but also the asset whose net spillover has the biggest standard deviation. The result also shows that each asset sometimes is transmitter and sometimes is receiver. For the uncertainty measures, we present summary statistics of total out spillover of them in Table 6. The mean value of VIX is the highest, and VIX is the most significant transmitter of uncertainty group for the system.

Table 5
Summary statistics of net spillover.

	Mean	Stdev	Min	Max	Skewness	Kurtosis
Oil	0.0749	0.1459	-0.3307	0.3616	-0.4612	-0.5593
USD	0.1206	0.1441	-0.4240	0.5194	-0.0070	0.3023
Silver	0.0285	0.1659	-0.5096	0.3753	-0.7406	0.3168
Gold	0.0948	0.1179	-0.5417	0.3804	-0.5396	1.1036
CRB	0.1131	0.1496	-0.5055	0.4570	-0.9164	1.9548
Bitcoin	0.1078	0.1441	-0.3517	0.5028	-0.2481	0.1961
Ethereum	0.0778	0.1471	-0.2794	0.4582	0.3690	-0.2916
Ripple	0.0502	0.1574	-0.6119	0.4481	-0.5280	0.5762
USDT	-0.2264	0.2440	-1.1349	0.1359	-1.8618	3.5106
Litecoin	0.0637	0.1242	-0.4310	0.4326	-0.4614	0.6752

Table 6
Summary statistics of total out spillover.

	Mean	Stdev	Min	Max	Skewness	Kurtosis
GPR	0.0365	0.2785	0.1399	0.0485	0.3842	-0.3684
EPU	0.0072	0.3059	0.1137	0.0548	0.5423	0.2176
VIX	0.0534	0.4924	0.2608	0.0785	0.1144	-0.2832
EMU	0.0133	0.3189	0.1218	0.0435	0.3201	0.5887

Besides, we also examine the three topology structure indices and show in the Fig. 9. The trends of GD and CC are very similar, and they reach the bottom in November 2017, March 2018 and March 2019. It is worth mentioning that on 21 June, 16 and 29 August 2019, the GD is 1, and the CC is 1, which means every vertex is connected with each other. For the APL, it fluctuates between 1.5 and 1.8 in the most time. These results show that the information transfers quickly in the system during the most sample period. However, in September 2017, it maintains a high level, and the information transfers the most slowly comparatively.

Table 7
Centrality indices of vertexes.

	Degree	Closeness	Betweenness
Oil	4	0.034	48
USD	2	0.026	22
Silver	3	0.032	39
Gold	4	0.037	53
CRB	1	0.026	0
Bitcoin	2	0.026	12
Ethereum	1	0.024	0
Ripple	2	0.020	12
USDT	1	0.016	0
Litecoin	2	0.026	12
GPRD	1	0.023	0
EPU	1	0.020	0
VIX	1	0.026	0
EMU	1	0.020	0

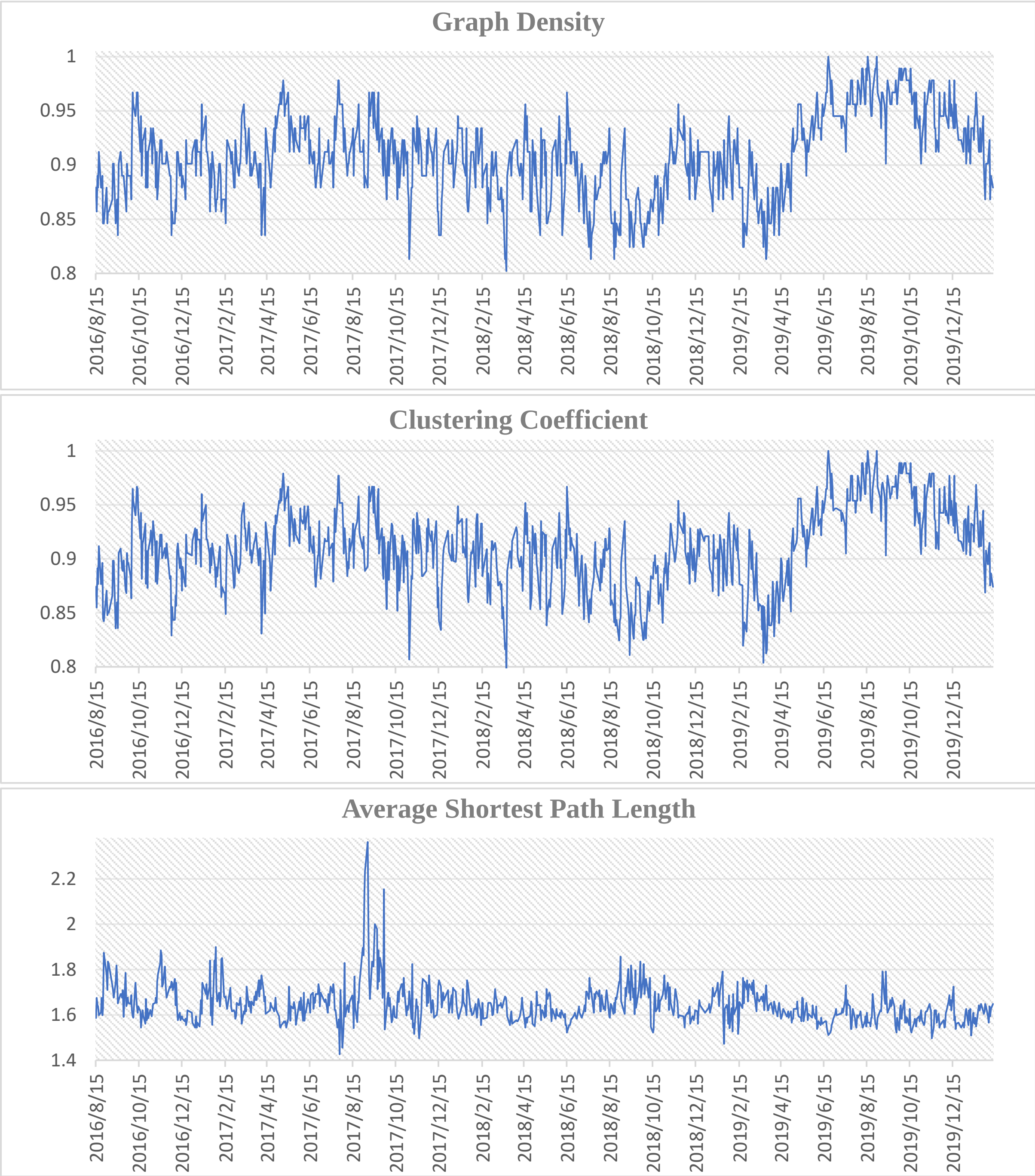

Fig. 9. The topology structure indices.

3.4 Information integration network analysis

We use the distance based on the sum of the ETE between two certain variables as the weight of the edge to construct an undirected network to measure the intensity of information spillovers between hedging assets and between hedging assets and uncertainty measures. In this part, we focus on the centrality of the vertexes and the integration of the structure for the information flow. We use MST to examine the core connection and do the analysis in the both static perspective and dynamic perspective.

3.4.1. Static result

To analyze the core connection between hedging assets and between hedging assets and uncertainty measures, Fig. 10 shows the information integration network. We calculate three centrality indices of each vertex, showing in Table 7. The most central vertexes are oil and gold, and they have high values in three indices. The vertexes with high value are almost in the group of the traditional asset. Therefore, this group is the core group of the MST and those vertexes have a powerful effect on the system. For the group of the cryptocurrency, Bitcoin, Ripple and Litecoin are more central in the MST than other vertexes in this group. The vertexes in the group of the uncertainty are not important in the MST.

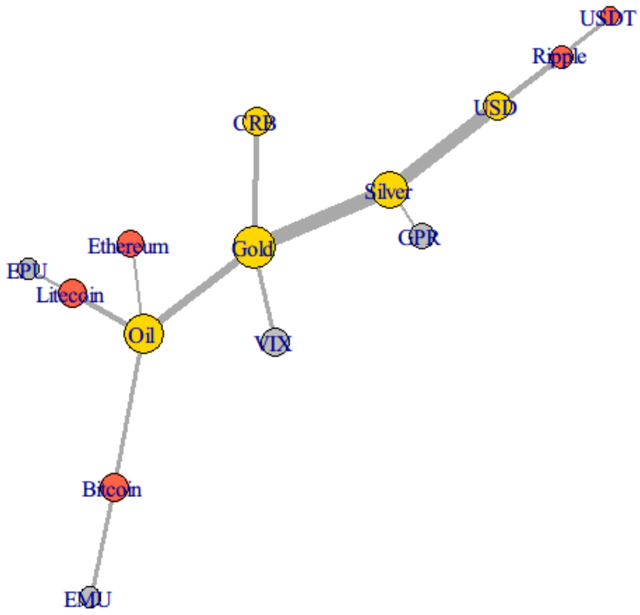

Fig. 10. The MST of information integration network.

Table 8

The integration degree between groups.

	Traditional asset	Cryptocurrency	Uncertainty
Traditional asset	1.80	2.88	2.85
Cryptocurrency		4.00	3.85
Uncertainty			4.17

To measure the integration among three groups, we calculate the integration degree between groups, which is the mean of the sum of all the pairwise shortest paths between a vertex in the one group to another vertex in the other group (or the one group itself). The result is showed in the Table 8. The vertexes in the traditional asset are the closest. Additionally, the vertexes in the cryptocurrency are not close to each other. Last but not least, the uncertainty is closer to the traditional asset than the cryptocurrency.

3.4.2. Dynamic result

In the dynamic analysis, we also use rolling window analysis, and the analysis is based on the time-varying MST.

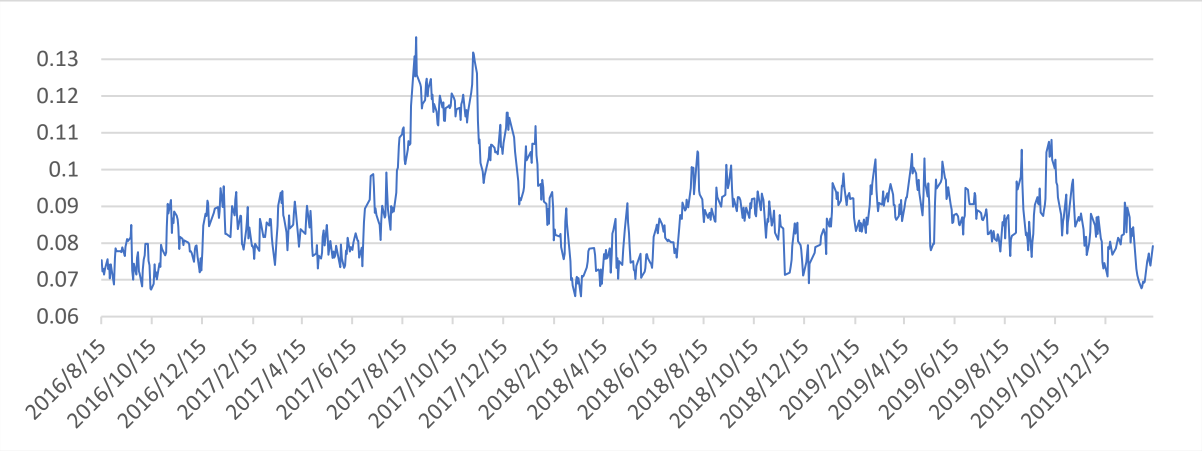

Fig. 11. The system integration index.

Fig. 11 shows the system integration index, which is the sum of the pairwise ETE of the edges that exist in the MST. A big change is recorded in the second half of 2017. It increases sharply in the July and August, and maintains a high value in the next two months. However, in the remaining two months of 2017 and the first three months of 2018, it mainly shows a downward trend, and reaches the bottom. The total spillover index has two time periods when it increases significantly, but the system integration index only increases significantly in the first periods. This suggests that the increase in information spillovers in the second period is not contained in the MST. In other words, the core connection does not increase in the second period.

Focusing on the importance of each group, we calculate the integration degree of each group, which is the mean of the sum of all the pairwise shortest paths between one vertex in the one group and another vertex in other groups. We show the result in the Fig. 12. They fluctuate most of the time, and their trends are generally similar. During the second half of 2017 and most of the time in 2019, the integration degree of the cryptocurrency is less than the traditional hedging asset, so the cryptocurrency is more integrative in the system in those periods. In other periods, the traditional hedging asset is more integrative in the system. In 2017, the prices of cryptocurrencies soar dramatically in 2017, and cryptocurrencies receive media attention. However, these prices dive in the beginning of the 2018, and maintain a low level in the whole year. In 2019, the prices of some cryptocurrencies, such as Bitcoin and Litecoin, raise again. The fluctuation of cryptocurrencies coincides with the alternation of the relative integration degree of the two groups.

To examine the centrality of each vertex, we present the summary statistics of three centrality indices in the Table 9. For the traditional asset, USD and CRB are the core vertexes of the system. The vertexes with high degree or betweenness are mainly in this group. For the cryptocurrency, USDT is the core vertex. Surprisingly, its three indices are the highest. Vertexes of this group, except Litecoin, have a high value of closeness centrality. For the uncertainty, the EMU is the core vertex.

Table 9

Summary statistics of three centrality indices.

	Degree		Closeness		Betweenness	
	Mean	Stdev	Mean	Stdev	Mean	Stdev
Oil	1.675	0.908	0.024	0.005	12.734	17.072
USD	1.892	1.011	0.026	0.006	16.436	18.563
Silver	1.903	1.286	0.025	0.006	14.824	19.832
Gold	1.735	0.956	0.025	0.005	14.097	18.162
CRB	1.947	1.195	0.026	0.006	16.201	18.936
Bitcoin	1.753	0.958	0.026	0.006	13.804	17.610
Ethereum	1.823	0.933	0.026	0.006	15.068	17.430
Ripple	1.757	0.983	0.025	0.006	14.278	18.220
USDT	2.696	1.823	0.028	0.009	24.311	24.145
Litecoin	1.693	0.881	0.025	0.005	12.974	16.274
GPR	1.499	0.762	0.022	0.005	8.164	13.432
EPU	1.763	0.980	0.023	0.006	12.798	16.939
VIX	1.880	0.899	0.025	0.005	14.625	15.810
EMU	1.982	1.383	0.024	0.007	15.611	20.697

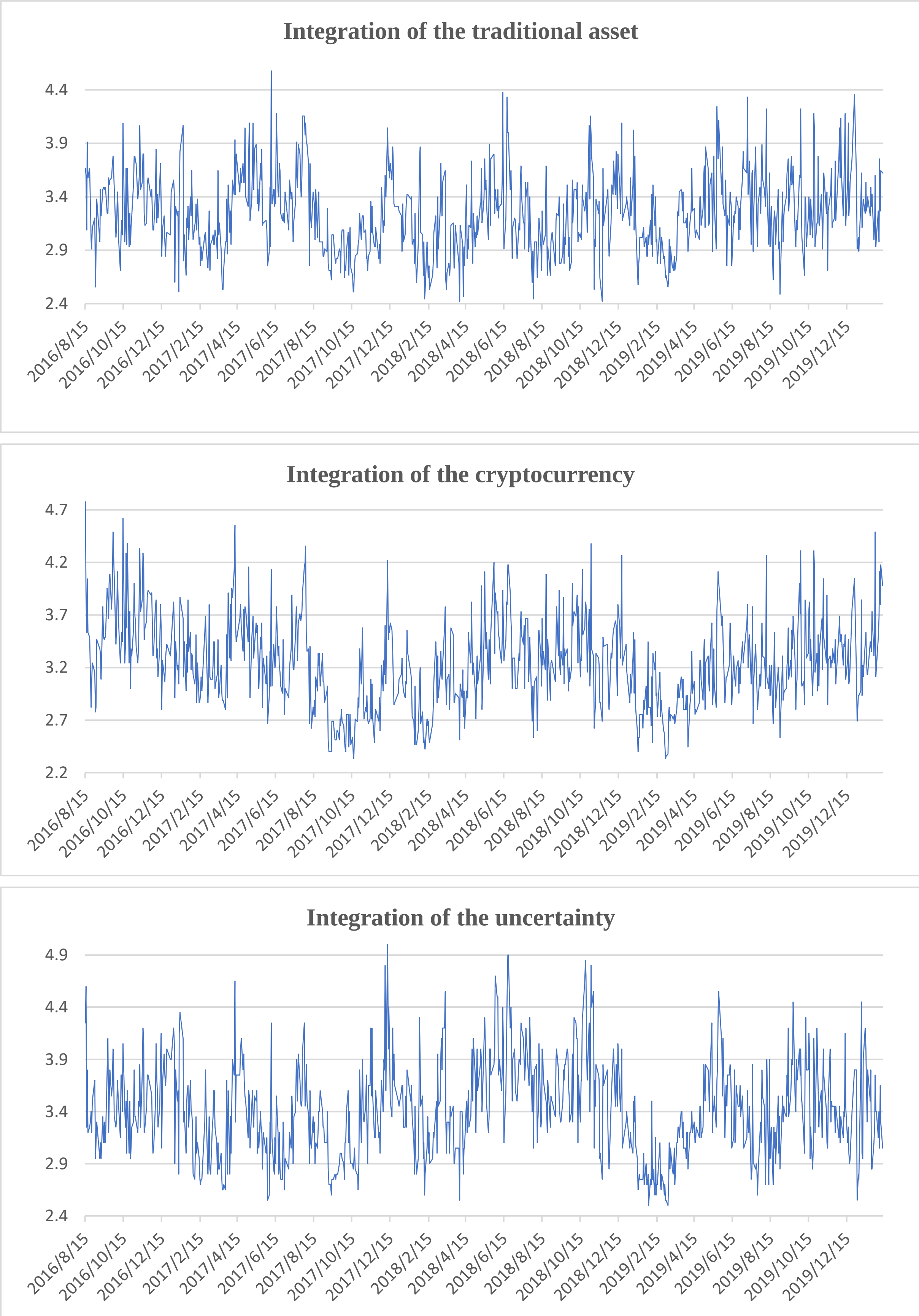

Fig. 12. The integration degree of each group

There are some differences between this dynamic result and the static result. Oil and gold are not important in the dynamic result, and USDT and EMU become the core vertexes. There are several possible reasons. As we can see, the standard deviation of indices of USDT and EMU are quite large. As the length of the windows is 250, some extreme events can influence many windows and cause many extreme values. These extreme values influence the average strongly. Besides, the influences from one asset to another are different in different periods, and they may offset when we research the date of the whole sample period. Alternatively, some influence is not obvious in short periods, but it may accumulate and become powerful when we research the date of the whole sample period. Additionally, because of the production of the MST, some short edges may be absent in the MST of some periods, replaced by other shorter edges in these periods, but they exist in the MST of the whole sample period.

4. Conclusion

This study innovatively regards traditional hedging assets, cryptocurrencies and uncertainty measures as a system to study the information spillovers across them, and we construct a complex network from the static and dynamic perspectives for analysis. Moreover, different from most researches on the similar topics, this study not only includes bitcoin, but also four other leading cryptocurrencies, and uncertainty measures are diverse. Furthermore, in order to quantify the information spillovers, the effective entropy transfer method is used in this study. Because of the asymmetry of this method, it can show the dominant direction of information spillover. In addition, it can capture both linear and nonlinear relationship, and it is more stable than VAR model in dynamic analysis. On the basis of transfer entropy, this method corrects the bias of transfer entropy.

The empirical results show that all assets and uncertainty measures are generally well integrated in the system, and there are information spillovers among them. We built two networks. One is the information spillover network which focuses on the dominance direction of the information spillovers in the system. The results show that the USD is the biggest net transmitter, while silver is the biggest net receiver. Furthermore, All the cryptocurrencies, except Ethereum, act as net transmitters in the system. Not only Bitcoin but also other leading cryptocurrencies play important roles in the information transfer of the whole system. Therefore, investors should not ignore the information spillovers from digital hedging asset markets when making risk management decisions. For uncertainty measures, GPR mainly affects silver and gold. EPU affects the least hedging assets, only two cryptocurrencies, Ethereum and Litecoin, so investors should choose other cryptocurrencies or traditional assets to hedge against EPU during COVID-19 pandemic, when the sharp increase of EPU brings tremendous negative effects. VIX affects the most hedging assets, especially gold and oil. The information flow from EMU to CRB, Bitcoin and Ethereum is significant. Investors are demanded to be particularly wary of these two uncertainties. Additionally, compared to the traditional hedging asset, the cryptocurrency is less affected by uncertainty. The other network is the information integration MST, which focuses on the centrality of variables and the integration of the system. We discover that the most central assets are oil and gold, which have a powerful effect on the system. Thus, the investors must pay attention to the fluctuation of these two markets and modify their strategies before the risk spreads from there. Moreover, the traditional assets are the closest to each other, while the cryptocurrencies are not close. Last but not least, we use rolling windows to capture the time-varying of information spillovers, and discover that the values of the nature of the network fluctuate with no significant trends. In the light of the time-varying of information spillovers, investors should build dynamic investment strategies and adjust portfolios with new information. These empirical findings contribute to great insights into practices of portfolio diversification and risk management.

For the interesting future avenues, it is meaningful to measure the changes of the connection among hedging assets during COVID-19 pandemic. Besides, how to utilize our results to the portfolio diversification is also significant. Last but not least, the volatility spillovers among hedging assets and their relationship to uncertainty measures can also be researched.

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