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The impact of the shutdown policy on the asymmetric interdependence structure and risk transmission of cryptocurrency and China's financial market

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A B S T R A C T

By taking Bitcoin, Litecoin, and China's gold and RMB/US dollar exchange rate market as research objects, this paper apply the MF-ADCCA and time-delayed DCCA methods to study the impact of China's mainland shutdown of cryptocurrencies trading on the non-linear interdependent structure and risk transmission of cryptocurrencies and its financial market. Empirical results show that the cross-correlation between cryptocurrencies and China's financial market has a long memory and asymmetric multifractal characteristics. After the shutdown, the long memory between cryptocurrencies and Chinese gold has weakened, and the long memory between cryptocurrencies and the RMB/US dollar exchange rate market was strengthened. China's shutdown policy has a certain risk prevention effect. Specifically, after the implementation of the policy, the risk transmission of cryptocurrencies to China's financial market has weakened, but the influence of China's financial market has gradually strengthened.

1. Introduction

With the deepening of international economic integration and financial globalization, the linkage effects of global financial markets have become more frequent, and the contagion of risks in different financial markets and between different countries has become more obvious (Bellenzier, Vitting Andersen, & Rotundo, 2016; Gkillas, Tsagkanos, & Vortelinos, 2019). The financial crisis in 2008 caused great turbulence in the global financial system. As a representative of emerging financial market, China is more vulnerable to systemic financial risk than developed capital market. With the increase of cross-market contagion of financial risk, the interdependent structure of financial assets, risk spillovers, and prevention of systemic financial risk have become the focus of scholars.

As an emerging virtual financial asset, cryptocurrency has recently attracted widespread attention from scholars, investors, and financial sector regulators. Since the birth of Bitcoin (BTC) in 2008, various forms of cryptocurrencies have emerged, and their scale is continuously expanding. As of January 6, 2021, the total number of cryptocurrencies surpassing 8100 with a total market

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capitalization of 950.21 billion US dollars that are being traded in more than 34,000 platforms worldwide[1]. Among them, 1997 kinds of cryptocurrencies can be directly traded in US dollars, thereby transforming the cryptocurrency market into an important financial market (Yuan & Geng, 2020). Each country has developed different attitudes toward cryptocurrency, 131 or 50.97% of all countries in the world have legalized cryptocurrency trading, whereas only 3% have considered such activity illegal[2]. On September 4, 2017, the China Securities Regulatory Commission, together with 7 ministries and commissions including the People's Bank of China and the Ministry of Industry and Information Technology, jointly issued the "Announcement on preventing the financing risk of token issuance" (hereinafter referred to as "policy"), which explicitly prohibits the trading of cryptocurrencies in Mainland China. This leads to the question: will the implementation of this policy significantly affect China's financial markets? Although this policy forbids mainland China from trading such assets, cryptocurrencies can still be traded over the internet. For example, many investors in mainland China continue to engage in cryptocurrency investment activities through P2P (Borri & Shakhnov, 2020). Therefore, under this background, studying the cross-correlation and risk transmission between cryptocurrencies and China's financial market is important for China to protect itself from systemic financial risk stemming from cryptocurrencies and to formulate the corresponding regulatory policies and has certain theoretical and practical significance for investors engaged in cross-market investment portfolios.

At present, a strand of the literature on the dependence structure and risk spillover of the financial market. Previous studies mainly focused on traditional financial markets such as stock, bond, exchange rate, commodities, and so on. With the development of cryptocurrencies, a lot of attention has been paid by scholars. Over the past decade, the research on cryptocurrencies has also made considerable achievements, but the research is relatively insufficient. Existing studies have mainly focused on the market efficiency of cryptocurrencies (Al-Yahyaee, Mensi, Ko, Yoon, & Kang, 2020; Ferreira, Kristoufek, & Pereira, 2020; Naeem, Bouri, Peng, Shahzad, & Vo, 2021), price fluctuation (Dyhrberg, 2016; Katsiampa, 2017), risk spillover (Handika, Soepriyanto, & Havidz, 2019; Matkovskyy, Jalan, & Dowling, 2020), dependent structure (Bouri, Gupta, Lahiani, & Shahbaz, 2018; González, Jareño, & Skinner, 2021; Manavi, Jafari, & Rouhani, 2020) and portfolio (Mensi, Rehman, Al-Yahyaee, Al-Jarrah, & Kang, 2019; Platanakis, Sutcliffe, & Urquhart, 2018). In sum, while many studies have examined the cross-correlation between cryptocurrencies and the stock, foreign exchange, and gold markets in developed European and American countries, relatively few researchers have focused on the cryptocurrencies and financial markets of developing countries. China is currently the largest emerging economy in the world that differs from developed countries in terms of its financial environment, regulatory systems, and investor rationality. Compared with developed capital markets, China's financial market are more vulnerable to systemic risks (Gong & Xiong, 2020). Therefore, the impact of cryptocurrencies on China's financial market or their cross-correlation warrants further research. Some scholars believe that cryptocurrencies have a hedging function similar to gold (Symitsi & Chalvatzis, 2019), whereas others contend that cryptocurrencies do not have a stable hedging function (Klein, Pham Thu, & Walther, 2018). For investors, the interdependence of assets is crucial to the returns of their investment portfolios. In China's capital market, retail investment often dominates, investors are often irrational and blindly follow suit, and many of these investors continue to perceive gold as a stable hedging tool. Therefore, will the current high-return cryptocurrencies affect China's gold market? After joining the Special Drawing Rights, the degree of internationalization of the RMB has continuously increased, the closeness of international trade has established a close risk relationship between the foreign exchange market and cryptocurrencies, and an increasing number of cryptocurrencies are being directly traded in US dollars. Therefore, some Chinese investors may become increasingly dependent on the US dollar.

Given these, this article selects China's gold and the RMB/US dollar exchange rate as its research objects for China's financial market and performs an in-depth study of the interdependence and risk transmission of cryptocurrencies and China's financial market. At the same time, given that the interdependence and risk transmission of cryptocurrencies and China's financial market has been rarely examined in the literature, how the implementation of the policy affected such interdependence and risk transmission remains unknown. To fill this gap, this article examines such policy effects in-depth to supplement cross-studies on cryptocurrencies and China's financial market. We contribute to the literature in three ways. First, We focus on the interdependence and risk transmission between emerging assets (cryptocurrencies) and China's traditional financial assets, which is different from the existing literature (Zhang, Bouri, Gupta, & Ma, 2021). Second, we employ the non-linear MF-ADCCA and time-delay DCCA methods to study the asymmetric multifractal and dynamic time-varying characteristics of the cross-correlation under different fluctuation trends and amplitudes as well as the cross-market risk transmission between cryptocurrencies and China's financial market. Third, we fully consider the policy effect of banning cryptocurrency trading in mainland China, and the results confirm that the shutdown policy has a certain effect on risk prevention.

The structure of the paper is as follows: Section 2 provides a brief overview of financial market's interdependence structure and risk transmission. Section 3 introduces the models used in this paper. Section 4 presents the data and empirical results. Section 5 performs robustness tests, and Section 6 concludes the paper.

2. Literature review

The interdependence of financial markets has a long research history. Some scholars often used the Granger causality test, VAR model, and GARCH derivative model to study such structure. For instance, Kawaller, Koch, and Koch (1987) performed a Granger causality test to study S&P 500 stock index futures and spot prices. Stoll and Whaley (1990) used the VAR model to study the leading-lag relationship between S&P500 and major market index futures and the spot market and found that the futures market leads the spot

[1] Data source: Statistics from the official website of CoinkMarketCap, retrieved on January 6, 2021.
[2] Data were taken from the official website of Coin Dance

market by approximately 5 min. Hong, Liu, and Wang (2009) performed a cointegration analysis and a Granger causality test to study the extreme downside risk spillover between Euro Area countries and Japanese financial markets. Hyde, Bredin, and Nguyen (2007) used the AG-DCC-GARCH model to study the relationship between the stock markets of Asia-Pacific countries, Europe, and the US and found a significant time-varying conditional correlation between the stock markets of China and other countries. However, these traditional research methods often assume that financial time series follows a normal distribution, and they often only analyze the linear dependence between time series, which cannot accurately describe the complex dependence between financial markets under non-linear and non-normal distributions. Some scholars later used the Copula function to study the interdependence between financial markets (Sukcharoen, Zohrabyan, Leatham, & Wu, 2014), but this function requires the time series to be independent and identically distributed, which cannot be easily achieved in real financial markets. Several studies have revealed that the financial market has leptokurtosis, fat-tails, skewness, long memory multifractal characteristics, and power-law cross-correlations (Grech, 2016; Zunino et al., 2008), which are often manifested as a non-stationary complex system. To accurately characterize the cross-correlation between two non-stationary time series, Podobnik and Stanley (2008) proposed detrended cross-correlation analysis (DCCA), which was later expanded by Zhou (2008) to multifractal detrended cross-correlation analysis (MFDCCA) for studying the non-linear interdependence structure of financial markets. Since then, Lin, Shang, and Zhao (2012) proposed a time-delay DCCA method to study the lead-lag relationship (risk transmission direction) between financial markets. Meanwhile, the asymmetric multifractal detrended cross-correlations (MF-ADCCA) method proposed by Cao, Cao, and Xu (2013) can characterize asymmetric multifractal characteristics under different time scales and trends (upward or downward) and has been widely used in examining global stock markets, foreign exchange markets, bonds, energy, and other fields (Gajardo & Kristjanpoller, 2017; Mensi, Sensoy, Vo, & Kang, 2020).

Some scholars have also examined the interdependence of cryptocurrencies. These studies can be divided into two streams. The first stream focuses on the autocorrelation of a single asset or the cross-dependence of multiple assets in the cryptocurrency market. A large number of studies have shown that cryptocurrencies have typical asymmetric multifractal features with peaks, fat-tails, skewness, and long memory (Mensi, Al-Yahyaee, & Kang, 2019; Wątorek et al., 2020). Stosic, Stosic, Ludermir, and Stosic (2019) studied the multifractal characteristics of the returns and transaction volume change rates of fifty cryptocurrencies and found that their price fluctuation behavior is more complex than their transaction volume change rate behavior, that the multifractal characteristics of returns are more significant under large fluctuations, and that the multifractal characteristics of transaction volume change rate under small fluctuations are more significant than those under large fluctuations. Liu, Wan, Zhang, and Zhao (2020) studied the correlation between BTC futures and returns and revealed a significant negative correlation. However, they also observed a significant positive correlation between BTC futures and seven other types of cryptocurrencies. Meanwhile, the second stream focuses on the cross-correlation between cryptocurrencies and other financial markets. Zhang, Wang, Li, and Shen (2018) examined nine cryptocurrencies and found that the cryptocurrency market is generally inefficient and that the synthetic Cryptocurrency Composite Index (CCI) has a long-term cross-correlation with the Dow Jones Industrial Average. Other scholars empirically examined Bitcoin or several top cryptocurrencies by market capitalization and found that these cryptocurrencies and the world's mainstream currencies, equity funds, gold, crude oil, the dollar index, and other assets have persistent and asymmetrical multifractal characteristics (Gajardo, Kristjanpoller, & Minutolo, 2018; Zhang, Yang, & Zhu, 2019; Kristjanpoller & Bouri, 2019; Kristjanpoller et al., 2020).

At the same time, several papers have tested the risk spillover of cryptocurrencies, mainly for the transmission of risks between the internal assets of the cryptocurrencies and between the cryptocurrencies and other financial markets. Borri (2019) studied the conditional tail risks of cryptocurrencies and showed that cryptocurrencies are highly exposed to tail-risk within crypto markets and that portfolios of cryptocurrencies offer better risk-adjusted and conditional returns than individual cryptocurrencies. Tiwari, Adewuyi, Albulescu, and Wohar (2020) investigate the interdependence structure and risk transmission between Bitcoin, Litecoin, and Ripple based on Copula methods, and showed that there is a strong and prevalent upper and lower-tail dependence of each pair of cryptocurrencies. Nguyen, Chevapatrakul, and Yao (2020) reveal a striking finding that the right tail dependence among the cryptocurrencies is significantly stronger than the left tail counterpart, and the combination of cryptocurrencies can effectively diversify risks. Gkillas, Bouri, Gupta, and Roubaud (2020) reports the high-order moment risk spillover effects between Bitcoin, crude oil and gold, and showed that there is a high-order moment dependency and risk transmission between Bitcoin and the other two assets. Urom, Abid, Guesmi, and Chevallier (2020) studied the quantile dependency structure and risk spillovers between Bitcoin and twelve stocks, gold, and crude oil, indicating that there is a positive (or negative) dependency between Bitcoin and other assets, and Bitcoin can be as an effective tool for risk diversification. Zhang et al. (2021) argue that there is a significant time-varying downside risk spillover between Bitcoin and stocks, bonds, currencies, and commodities.

3. Methodology

3.1. MF-ADCCA method

The original MF-ADCCA method proposed by Cao et al. (2013) can be described as follows.

Suppose two time series $\{x^{(1)}(t)\}$ and $\{x^{(2)}(t)\}$, where $t = 1, 2, \cdots, N$, and N is the length of the time series.

Step 1: We determine the "profile" $y^{(i)}(j)$ for each time series $\{x^{(i)}(t)\}$, where $i = 1, 2$:

$$y^{(i)}(j) = \sum_{t=1}^{t} \left(x^{(i)}(t) - \overline{x^{(i)}}\right), j = 1, 2, \cdots, N, i = 1, 2 \tag{1}$$

where $\overline{x^{(i)}} = \frac{1}{N}\sum_{t=1}^{N} x^{(i)}(t)$ represents the mean value of time series $\{x^{(i)}(t)\}$.

Step 2: We divide the time series $\{x^{(i)}(t)\}$ and its corresponding profile $y^{(i)}(j)$ into $N_n = int(N/n)$ non-overlapping segments of equal length n. Given that the length N of the series does need to be a multiple of the considered time scale n, a short part at the end of the series will remain. In order not to discard this part, we repeat the same procedure starting from the other end of each series. Therefore, we obtain $2N_n$ segments. Let $S_j^{(i)} = \{s_{j,k}^{(i)}, k = 1,2,\cdots,n\}$ denote the j-th sub-time series of length n, and let $Y_j^{(i)} = \{y_{j,k}^{(i)}, k = 1,2,\cdots,n\}$ denote the corresponding profile series in the j-th sub-time series. Therefore, we can generalize that

$$s_{j,k}^{(i)} = x^{(i)}((j-1)n+k), \quad y_{j,k}^{(i)} = y^{(i)}((j-1)n+k), \quad j = 1,2,\cdots,N_n \tag{2}$$

$$s_{j,k}^{(i)} = x^{(i)}(N-(j-N_n)n+k), \quad y_{j,k}^{(i)} = y^{(i)}(N-(j-N_n)n+k), \quad j = N_n+1, N_n+2,\cdots,2N_n \tag{3}$$

Following Peng et al. (1994), the value of n is usually set to $5 \le n \le N/4$.

Step 3: For each sub-time series $S_j^{(i)}$ and $Y_j^{(i)}$, we calculate the local trends via a least-square linear fit, $L_{S_j^{(i)}}(k) = a_{S_j}^{(i)} + b_{S_j}^{(i)}k$ and $L_{Y_j^{(i)}}(k) = a_{Y_j}^{(i)} + b_{Y_j}^{(i)}k$, where k is the horizontal coordinate, $i = 1,2$. We use the slope $b_{S_j}^{(i)}$ to distinguish the trend of $S_j^{(i)}$ (up or down) and $L_{Y_j^{(i)}}$ to eliminate the trend of $Y_j^{(i)}$. We then determine the following variance functions:

$$F_j(n) = \frac{1}{n}\sum_{k=1}^{n}\left|y_{j,k}^{(1)} - L_{Y_j^{(1)}}(k)\right|\left|y_{j,k}^{(2)} - L_{Y_j^{(2)}}(k)\right|, \quad j = 1,2,\cdots,2N_n \tag{4}$$

Step 4: We calculate the average fluctuation function when the time series $x^{(i)}$ has different linear trends, and $b_{S_j}^{(i)} > 0$ (or $b_{S_j}^{(i)} < 0$) indicates that the sequence $x^{(i)}$ has an upward (or downward) trend on the sequence $S_j^{(i)}$. We then calculate the following directional q-order fluctuation functions:

$$F_q^+(n) = \left(\frac{1}{M^+}\sum_{j=1}^{2N_n}\frac{sign\left(b_{S_j}^{(1)}\right)+1}{2}\left[F_j(n)\right]^{q/2}\right)^{1/q} \tag{5}$$

$$F_q^-(n) = \left(\frac{1}{M^-}\sum_{j=1}^{2N_n}\frac{-\left[sign\left(b_{S_j}^{(1)}\right)-1\right]}{2}\left[F_j(n)\right]^{q/2}\right)^{1/q} \tag{6}$$

where $M^+ = \sum_{j=1}^{2N_n}\frac{sign(b_{S_j}^{(1)})+1}{2}$ and $M^- = \sum_{j=1}^{2N_n}\frac{-[sign(b_{S_j}^{(1)})-1]}{2}$ denote the numbers of sub-time series having positive or negative trends, respectively. If $b_{S_j}^{(1)} \neq 0$ for all $j = 1,2,\cdots,2N_n$, then $M^+ + M^- = 2N_n$.

Likewise, the conventional MF-DCCA method proposed by Zhou (2008) can be obtained by calculating the following fluctuation function:

$$F_q(n) = \left(\frac{1}{2N_n}\sum_{j=1}^{2N_n}\left[F_j(n)\right]^{q/2}\right)^{1/q} \tag{7}$$

Step 5: If the power-law cross-correlation exists, then the scale relationship satisfies the following conditions:

$F_q(n) \sim n^{H_{12}(q)}$; $F_q^+(n) \sim n^{H_{12}^+(q)}$; $F_q^-(n) \sim n^{H_{12}^-(q)}$. where $H_{12}(q)$, $H_{12}^+(q)$, and $H_{12}^-(q)$ denote the overall, upward, and downward trends of time series $\{x^{(1)}(t)\}$ generalized Hurst exponents, respectively.

These generalized Hurst exponents can be obtained by analyzing the following double logarithmic plots:

$$lnF_q(n) = H_{12}(q)ln(n) + lnA_1 \tag{8}$$

$$lnF_q^+(n) = H_{12}^+(q)ln(n) + lnA_2 \tag{9}$$

$$lnF_q^-(n) = H_{12}^-(q)ln(n) + lnA_3 \tag{10}$$

In addition, if $H_{12}^+(q) \neq H_{12}^-(q)$, then an asymmetric property is observed in the cross-correlation between two time series. The scaling exponent obtained when one of two series has a positive trend differs from that obtained when either of these series has a negative trend. If $H_{12}^+(q) = H_{12}^-(q)$, then we consider the cross-correlation symmetric.

When $q > 0$, $H_{12}(q)$, $H_{12}^+(q)$, and $H_{12}^-(q)$ represent the scaling behavior caused by the overall, upward, and downward large fluctuations in the time series $\{x^{(1)}(t)\}$, respectively. Otherwise, when $q < 0$, these parameters represent the scaling behavior caused by small fluctuations. If $H_{12}(q)$ changes along with q, then the cross-correlation between two time series has multifractal characteristics; otherwise, these time series do not have multifractal characteristics. Similarly, if $H_{12}^+(q)$(or $H_{12}^-(q)$ changes with q, then when time series $\{x^{(1)}(t)\}$ has an upward (or downward) trend, the cross-correlation between $\{x^{(1)}(t)\}$ and $\{x^{(2)}(t)\}$ has multifractal characteristics;

otherwise, these time series do not have multifractal characteristics.

We define the degree of asymmetry of the cross-correlation as follows:

$$\Delta H_{12}(q) = H_{12}^{+}(q) - H_{12}^{-}(q) \tag{11}$$

For a constant q, a larger absolute value of $\Delta H_{12}(q)$ corresponds to a stronger asymmetry. If $\Delta H_{12}(q) > 0(\Delta H_{12}(q) < 0)$, then the persistence of cross-correlation under the rising (falling) trend of sequence $\{x^{(1)}(t)\}$ is stronger than that under the falling (rising) trend. If $\Delta H_{12}(q)$ does not significantly deviate from 0, then the cross-correlation of the sequence under different trends is symmetrical.

3.2. Time-delayed DCCA method

Lin et al. (2012) proposed a time-delay-based DCCA method for studying the cross-correlation relationship between different time dimensions of stock markets. This non-linear method, which adds a time delay variable Δt, is mainly used to determine the non-linear lead-lag relationship of time series under different time lags and to analyze the direction of risk transmission in the financial market. This method is divided into four steps as follows:

Step 1: Suppose that we have two time series $\{x(t)\}$ and $\{y(t)\}$ whose length is N. When the sequence $\{y(t)\}$ has a Δt lag period, then this sequence becomes time series $\{y(t+\Delta t)\}$, and let

$$X(m) = \sum_{t=1}^{m}(x(t) - \overline{x}) \tag{12}$$

$$Y(m) = \sum_{t=1}^{m}(y(t+\Delta t) - \overline{y}) \tag{13}$$

where $m = 1, 2, \cdots, N - \Delta t$, $\overline{x} = \frac{1}{N-\Delta t}\sum_{t=1}^{N-\Delta t} x(t)$, $\overline{y} = \frac{1}{N-\Delta t}\sum_{t=1}^{N-\Delta t} y(t+\Delta t)$, and $\Delta t < N$.

Step 2: We divide the time series $X(m)$ and $Y(m)$ into $N_s = int((N-\Delta t)/s)$ non-overlapping subintervals, where the length of each subinterval is s. Generally, $N - \Delta t$ is not divisible by s. In order not to discard the remaining data at the end, we apply the same segmentation process for the time series from back to front, and we obtain $2N_s$ sub-intervals.

Step 3: We use least squares to fit the local trend on each subinterval $v(v = 1, 2, \cdots, 2N_s)$ obtained in Step 2 to obtain the fitting equations $\widetilde{X_v}(k)$ and $\widetilde{Y_v}(k)$, and then detrend the sequence in the following subinterval:

$$F_v^2(s) = \frac{1}{s}\sum_{k=1}^{s}\left|X_v(k) - \widetilde{X}_v(k)\right|\left|Y_v(k) - \widetilde{Y}_v(k)\right| \tag{14}$$

Step 4: We calculate the detrending cross-covariance volatility function as

$$F_{x\Delta y}(s) = \left[\frac{1}{2N_s}\sum_{v=1}^{2N_s} F_v^2(s)\right]^{1/2} \tag{15}$$

If a cross-correlation is observed between time series $\{x(t)\}$ and $\{y(t)\}$, then we have the following power-law relationship:

$$F_{x\Delta y}(s) \sim s^{H_{x\sim\Delta y}^{\Delta t}} \tag{16}$$

According to the double logarithm diagram of $F_{x\Delta y}(s)$ and s, the slope of the double logarithmic curve is the Hurst exponent $H_{x\sim\Delta y}^{\Delta t}$. At this time, when $0 < H_{x\sim\Delta y}^{\Delta t} < 0.5$, an anti-persistence is observed between the original sequence $\{x(t)\}$ and delayed sequence $\{y(t)\}$. When $H_{x\sim\Delta y}^{\Delta t} = 0.5$, no cross-correlation is observed, and when $0.5 < H_{x\sim\Delta y}^{\Delta t} < 1$, a long-range cross-correlation is observed.

To identify the risk transmission direction between time series $\{x(t)\}$ and $\{y(t)\}$ with the Δt lag period, we define

$$\Delta H^{\Delta t} = H_{x\sim\Delta y}^{\Delta t} - H_{\Delta x\sim y}^{\Delta t} \tag{17}$$

If $\Delta H^{\Delta t} > 0$, then the risk is mainly transmitted from $\{x(t)\}$ to $\{y(t)\}$ during the delay period Δt. If $\Delta H^{\Delta t} = 0$, then the risks are mutually transmitted. If $\Delta H^{\Delta t} < 0$, then the risk is mainly transmitted from $\{y(t)\}$ to $\{x(t)\}$ during the delay period Δt.

4. Data and empirical analysis

4.1. Data and descriptive statistics

Bitcoin (BTC) and Litecoin (LTC) are two of the first developed cryptocurrencies in the world that rank first and fifth in terms of market value, respectively. This paper then selects BTC and LTC as representative cryptocurrencies from the perspectives of time span and market value. Due to the high returns of cryptocurrencies, it can often be used as a tool for risk diversification, and traditional gold is often used as a hedging tool. This article attempts to study the interdependence between cryptocurrencies and Chinese gold, and the AU99.95 gold spot price in the Shanghai Gold Exchange (hereinafter referred to as AU) is relatively active, so this article selects the AU99.95 gold spot price in the Shanghai Gold Exchange as the proxy variable for the Chinese gold market. Given that China's foreign exchange reserves are mainly US dollar assets, and the US dollar always has a strong influence as an international settlement currency, and at the same time, it is most convenient for cryptocurrencies to directly use US dollars for payment. Therefore, this article selects the RMB/US dollar middle rate (hereinafter referred to as ER) as a proxy variable for China's exchange rate market.

Since the cryptocurrency data website CoinMarketCap began to collect statistics on April 28, 2013, to increase the sample length as much as possible and keep the time consistent with China's financial assets, the sample time range is from May 2, 2013, to December 18, 2020. After deleting the data for Saturday, Sunday, legal holidays, and inconsistent periods, the sample was aligned, and a total of 1862 trading days were obtained. The cryptocurrency data were obtained from the CoinMarketCap website (https://coinmarketcap.com/), the gold prices were obtained from the World Gold Council website (https://www.gold.org), and the exchange rate data were collected from the website of China Foreign Exchange Trading Center (http://www.chinamoney.com.cn/chinese/bkccpr/).

First, the returns sequence was calculated according to the daily closing price of each asset as follows: $r_{i,t} = log(P_{i,t}) - log(P_{i,t-1})$, where $r_{i,t}$ represents the asset returns, and $P_{i,t}$ represents the asset closing price at period t. The change trend of the returns of each financial asset time series is shown in Fig. 1, and a basic statistical description of the returns is presented in Table 1.

As can be seen from Fig. 1, the returns of cryptocurrencies and China's gold and US dollar exchange rate markets all demonstrated volatility clustering characteristics. Moreover, the volatility of cryptocurrencies was significantly higher than that of China's gold and US dollar exchange rate markets. The volatilities of these assets were also closely related to some financial events. For example, BTC was heavily hyped in 2014, but from 2017 to 2018, some dramatic fluctuations were observed in its value. These fluctuations were particularly salient during the COVID-19 pandemic. Meanwhile, China's gold and exchange rate markets significantly fluctuated during the same period. For instance, after the 8.11 exchange rate reform in 2015, the volatility of China's exchange rate market significantly increased.

Table 1 shows that the average BTC return is 0.2898%, which is much higher than those of China's gold and US dollar exchange rate markets. However, the fluctuation in cryptocurrencies was also far greater than those of these markets. Among these four assets, BTC and China's gold market had a skewness of less than 0 (skewed to the left), whereas LTC and the US dollar exchange rate market had a skewness of greater than 0 (skewed to the right). The kurtosis of these assets was all greater than 3 and showed characteristics of sharp peaks and fat-tails. The Jarque-Bera statistics of each return series rejected the null hypothesis of normal distribution at a significance level of 1%, thereby indicating that each sequence of asset returns shows non-normal characteristics. The t values of the ADF unit root test of return series are significant at 1% significance level, which indicates that the return series of assets are stationary.

4.2. Asymmetric dependency and risk transmission of cryptocurrencies and China's financial market

4.2.1. Asymmetric dependent structure test

Although this paper mainly studies the impact of China's shutdown policy on the asymmetric interdependence structure and risk transmission of cryptocurrencies and China's financial markets, to make our conclusions reliable and convincing, we test the asymmetric dependence structure and risk transmission between cryptocurrencies and China's financial market using our full sample. This section mainly considers the cross-correlation between the trends (upwards and downwards) of cryptocurrencies and those of China's gold and US dollar exchange rate markets. Given the limited space, this article will only present the results of the empirical analysis.

BTC, LTC, and China's gold and US dollar exchange rate markets were cross-correlated with generalized Hurst indexes $H_{12}(q)$ (overall), $H_{12}^{+}(q)$ (upwards), and $H_{12}^{-}(q)$ (downwards), all of which change along with q. The decreasing function of q shows that the cross-correlation among these assets has asymmetrical multifractal characteristics. Regardless of increasing or decreasing returns, the generalized Hurst index of such cross-correlation was significantly greater than 0.5, but when q is positive and large, the generalized Hurst index of the cross-correlation between cryptocurrencies and China's gold market was less than 0.5. The cross-correlations of BTC and LTC with China's gold market was highly and strongly persistent in the case of small and strongly anti-persistent with large fluctuations, respectively. Meanwhile, the cross-correlation between BTC and the US dollar exchange rate market was highly persistent in a downward trend, whereas that between LTC and the US dollar exchange rate market was highly persistent in an upward trend.

When $q = 2$, the Hurst index, which is cross-correlated with China's gold and US dollar exchange rate markets, was calculated when the cryptocurrencies show different trends. Results suggest that the cross-markets $H_{12}(2)$ of cryptocurrencies and China's gold and US dollar exchange rate markets were all greater than 0.5, thereby indicating a long-term correlation among these cross-markets.

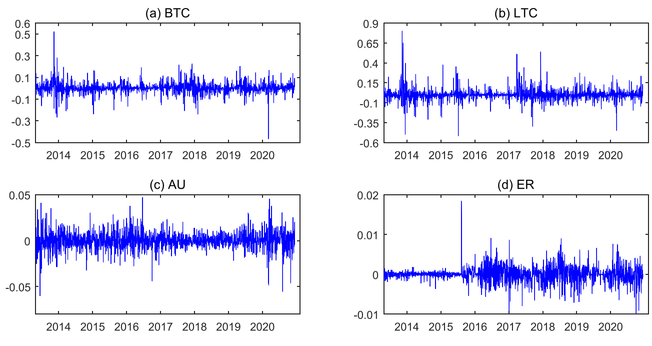

Fig. 1. Daily returns of BTC, LTC, AU, ER.

Table 1
Summary statistics.

	Number of samples	Mean	Std. Dev	Skewness	Kurtosis	JB	ADF
BTC	1862	0.2898%	5.0917%	−0.0119	16.06	13231.60***	−45.06***
LTC	1862	0.1870%	7.6518%	1.5092	21.45	27100.86***	−41.75***
AU	1862	0.0165%	0.9300%	−0.2286	7.58	1642.61***	−44.81***
ER	1862	2.73E-5	0.1957%	0.6815	12.48	7120.55***	−37.90***

Note: JB statistic is Jarque-Bera statistic, which is used to test the normal distribution of time series. ADF is the *t* value of the Augmented Dickey-Fuller test (in this paper, we only use the test with intercept term). *** representative rejected the original hypothesis at 1% significance level.

For $H_{12}^{+}(2)$ and $H_{12}^{-}(2)$, except in the case with rising BTC returns, the other cross correlations are exceeded 0.5, thereby suggesting that regardless of whether the returns have an upward or downward trend, the cross-market is almost always persistent. When $H_{12}^{+}(2) \neq H_{12}^{-}(2)$, the cross-correlation between cryptocurrencies and China's gold and US dollar exchange rate markets was asymmetric. From the value of $\Delta H_{12}(2)$, we can see that LTC and the US dollar exchange rate cross-markets have a stronger long-term correlation when their returns increase, whereas the other three cross-markets have a stronger long-term correlation when their returns decrease. The $|\Delta H_{12}(2)|$ of BTC and China's gold market is greater than that of BTC and the US dollar exchange rate market, whereas the $|\Delta H_{12}(2)|$ of LTC and China's gold market is greater than that of LTC and the US dollar exchange rate market. This finding suggests that the multifractal asymmetry degree of the correlation between cryptocurrencies and China's gold cross-market is stronger than that of the cross-market correlation between cryptocurrencies and the US dollar exchange rate market.

4.2.2. *Risk transmission direction test*

The risk transmission direction between cryptocurrencies and China's gold and US dollar exchange rate markets was then examined based on the time-delay DCCA model. Given that the gold and exchange rate markets do not operate during holidays and weekends, the number of normal trading days per month in these markets is generally 22. Therefore, the value range of the time delay parameter Δt was set to the interval $[1, 22]$, and each additional unit represents a 1-day increase in time delay. Given the lack of space, only the empirical analysis will be presented in this paper.

The cross-correlation Hurst index between BTC and China's gold and US dollar exchange rate markets was greater than 0.5 under different lag days, thereby suggesting that whether or not the returns of BTC or China's gold and exchange rate markets are lagging behind, the cross-market shows a long-term correlation. At the same time, when BTC lags, $H_{\Delta BTC \sim AU}(2)$ decreased along with an increase Δt, thereby indicating that when BTC's time lag is delayed, the cross-market long-term correlation is weakened. However, when China's gold market lags, $H_{BTC \sim \Delta AU}(2)$ increased along with Δt, thereby indicating that as the gold market lags, the cross-correlation between BTC and China's gold market shows an increasing trend. With the time lag, $H_{\Delta LTC \sim AU}(2)$ is always greater than $H_{LTC \sim \Delta AU}(2)$, thereby suggesting that the risk of China's gold market as a whole is mainly transmitted to LTC during this period. When LTC lags and as the time lag increases, the cross-correlation between LTC and the US dollar exchange rate increased. When the US dollar exchange rate lags, with the time lag increased, the correlation of cross-market increases first and then decreases. The above analysis shows varying degrees of bi-direction risk transmission between cryptocurrencies and China's financial market.

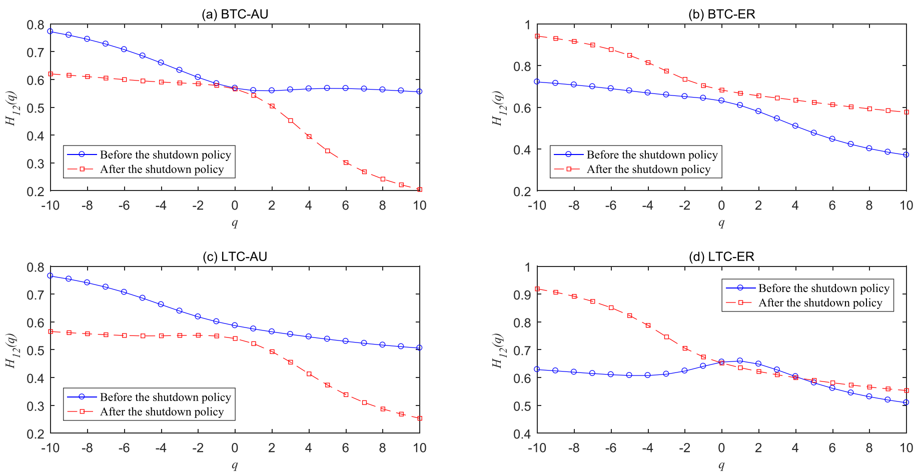

Fig. 2. Cross-correlation between cryptocurrencies and China's gold and US dollar exchange rate markets before and after the cryptocurrencies trading ban.

4.3. Overall impact of the shutdown on asymmetric dependent structure

By taking the cryptocurrency trading ban in Mainland China on September 4, 2017, as the time point, we divided the entire dataset into two sub-periods to study the differences in the interdependence structures of cryptocurrencies and China's gold and US dollar exchange rate markets before and after the ban. The empirical results are shown in Fig. 2.

As shown in Fig. 2, before the ban, the generalized Hurst indexes of the cross-correlation between BTC and China's gold market and that between LTC and China's gold market under different q were all greater than 0.5, thereby indicating a long-term correlation. However, after the ban, these Hurst indices and the persistence of small fluctuations were all greatly reduced, whereas the anti-persistence of large fluctuations became more obvious. At this time, the generalized Hurst index of BTC and the US dollar exchange rate market exceeded 0.5, which was greater than that reported before the implementation of the policy, thereby indicating that the long-term correlation between BTC and the US dollar exchange rate was stronger after the ban. Meanwhile, the cross-correlation between LTC and the US dollar exchange rate market increased, and the long-term correlation of small fluctuations became more obvious.

The Hurst index of the cross-correlation between China's gold and US dollar exchange rate markets was calculated before and after the introduction of the policy, during which BTC and LTC showed different trends at $q = 2$. Results are shown in Table 2.

Table 2 shows that except for the cross-market of BTC and US dollar exchange rate market, the Hurst index of cross-correlation has decreased in the overall situation and when the cryptocurrency has an upward trend in the other three cross-markets. In addition, when the cryptocurrency returns declined, the cross-correlation between cryptocurrencies and the US dollar exchange rate market increased. In other words, before and after the implementation of the policy, the cross-correlation between cryptocurrencies and China's gold and US dollar exchange rate markets underwent significant changes, thereby highlighting the effectiveness of the policy. The correlation between China's gold market and cryptocurrencies was reduced, but the cross-correlation between the US dollar exchange rate market and cryptocurrencies increased. These findings echo the conclusions of Borri and Shakhnov (2020). While the regulatory changes in China significantly reduced the cryptocurrency trading volume, relevant investors in the mainland are still able to trade cryptocurrencies through P2P, thereby explaining the close relationship between cryptocurrencies and the US dollar exchange rate market.

4.4. Local dynamic asymmetric dependence before and after the shutdown policy

We then studied the impact of China's shutdown policy on the local dynamic asymmetric interdependence structure between cryptocurrencies and China's financial market by using the same two sub-samples described in the previous section. Following Wang and Xie (2013), we set our sliding window width to 250 trading days (or approximately 1 trading year) and step size to 1 day. The Hurst index of the cross-correlation between cryptocurrencies and China's financial market is shown in Fig. 3.

Fig. 3 shows that the cross-correlation between cryptocurrencies and China's financial market has time-varying, unstable, and asymmetric characteristics. Regardless of the overall trend or returns, the Hurst index of the local correlation between BTC and China's gold market in most sliding windows exceeded 0.5 before the shutdown and significantly decreased to less than 0.5 after the shutdown, thereby suggesting that the anti-persistence of BTC and China's gold market increased during this period. Before the shutdown and under different trends, BTC and the US dollar exchange rate market showed a strong cross-correlation in certain periods, but such cross-correlation fluctuated greatly. After the shutdown, such cross-correlation was slightly stabilized and almost exceeded 0.5. Meanwhile, the cross-correlation between LTC and China's gold market decreased after the shutdown regardless of the trend. However, after the shutdown, such cross-correlation generally increased over time. In sum, the implementation of China's shutdown policy greatly affected the correlation between cryptocurrencies and China's financial market, but the cross-correlation between cryptocurrencies and the US dollar exchange rate market continued to increase.

To further ensure the robustness and effectiveness of our results, we selected 200 and 300 trading days as our sliding windows and recalculated the local dynamic cross-correlation between cryptocurrencies and China's gold and US dollar exchange rate markets. The results obtained are consistent with those in Fig. 3 (not included here due to space limitations), thereby validating the effectiveness of our results.

4.5. Impact of the shutdown policy on risk transmission

To test the direction of risk transmission between cryptocurrencies and China's gold and US dollar exchange rate markets before

Table 2
Cross-correlation index of cryptocurrencies and China's gold and US dollar exchange rate markets before and after the shutdown policy.

Cross-market	Before the shutdown policy			After the shutdown policy		
	$H_{12}(2)$	$H_{12}^{+}(2)$	$H_{12}^{-}(2)$	$H_{12}(2)$	$H_{12}^{+}(2)$	$H_{12}^{-}(2)$
BTC-AU	0.5593	0.4681	0.6339	0.5045	0.5073	0.5159
BTC-ER	0.5792	0.6340	0.5186	0.6551	0.5914	0.7125
LTC-AU	0.5644	0.5688	0.5401	0.4932	0.4930	0.5003
LTC-ER	0.6484	0.7183	0.5601	0.6216	0.5612	0.6851

Note: BTC-AU stands for the cross market of Bitcoin and Chinese gold, and others are similar.

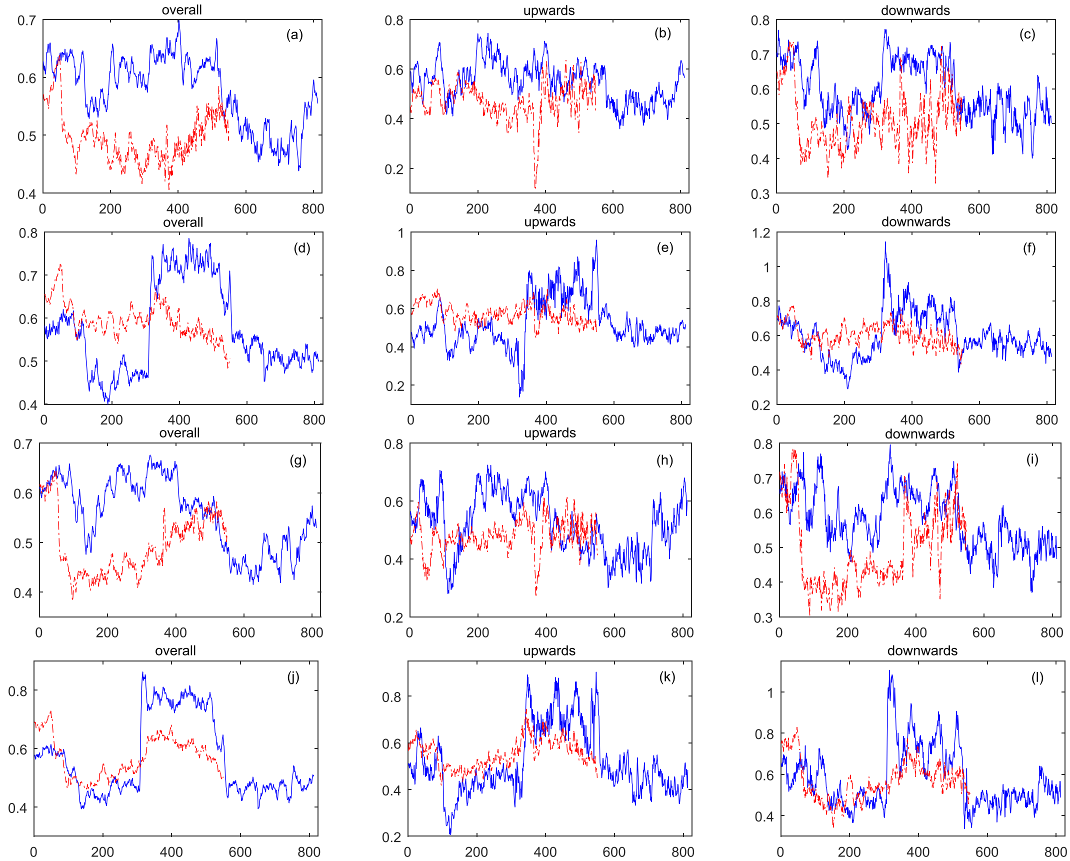

Fig. 3. Local dynamic asymmetric Hurst index of cryptocurrencies and China's financial market. The blue solid and red dotted lines indicate before and after the implementation of the shutdown policy, respectively. (a) ~ (c), (d) ~ (f), (g) ~ (i), and (j) ~ (l) denote the BTC ~ AU, BTC ~ ER, LTC ~ AU, and LTC ~ ER cross-markets, respectively. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

and after the implementation of the shutdown policy, we chose the day when the mainland China's shutdown policy is released as the time point, divided our sample into two, and set Δt to $[1,22]$. Figs. 4 and 5 show the trends in the Hurst indices of cryptocurrencies and China's financial market under different time lags before the implementation of the policy, whereas Figs. 6 and 7 show the trends after the implementation.

Fig. 4 shows that when the lag is 1 to 22 days, the Hurst index between BTC and China's gold market ranges between 0.55 and 0.575, whereas that between BTC and the US dollar exchange rate market ranges between 0.56 and 0.62. Fig. 5 also shows that the

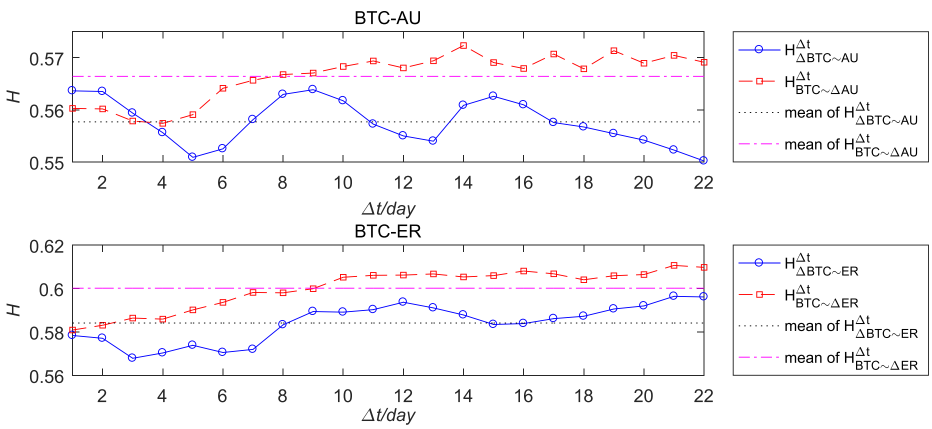

Fig. 4. Cross-relationship between BTC and China's financial market before the shutdown policy with a 1- to 22-day delay.

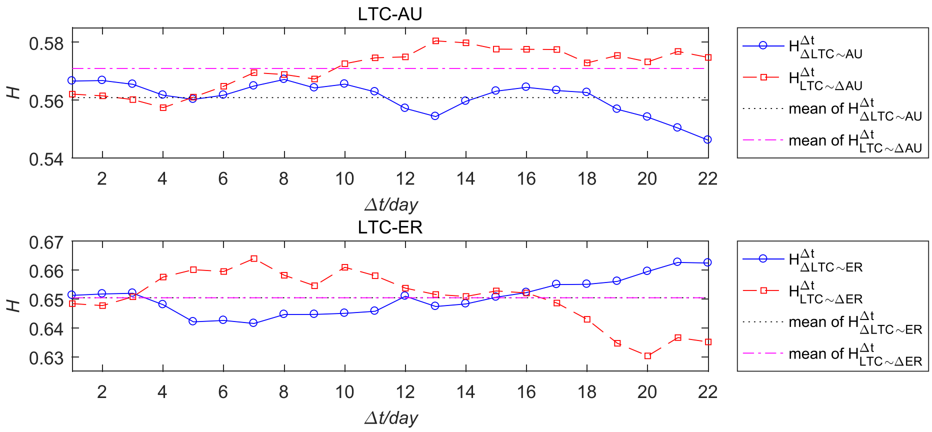

Fig. 5. Cross-relationship between LTC and China's financial market before the shutdown policy with a 1- to 22-day delay.

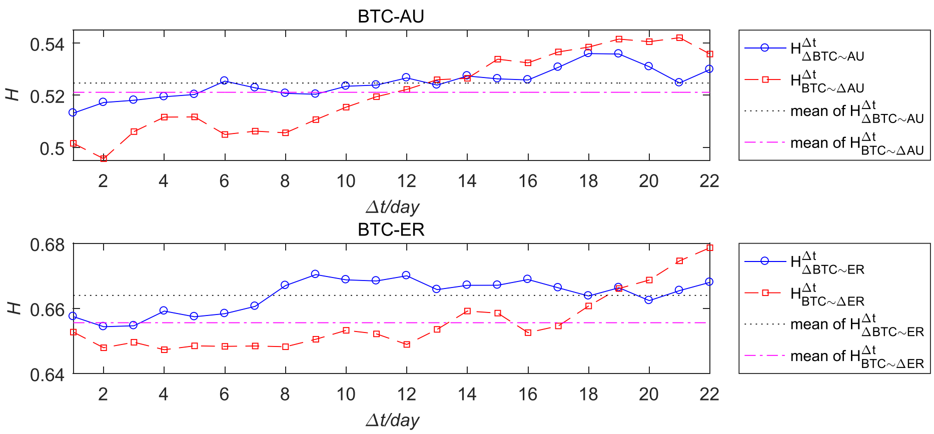

Fig. 6. Cross-relationship between BTC and China's financial market after the shutdown policy with a 1- to 22-day delay.

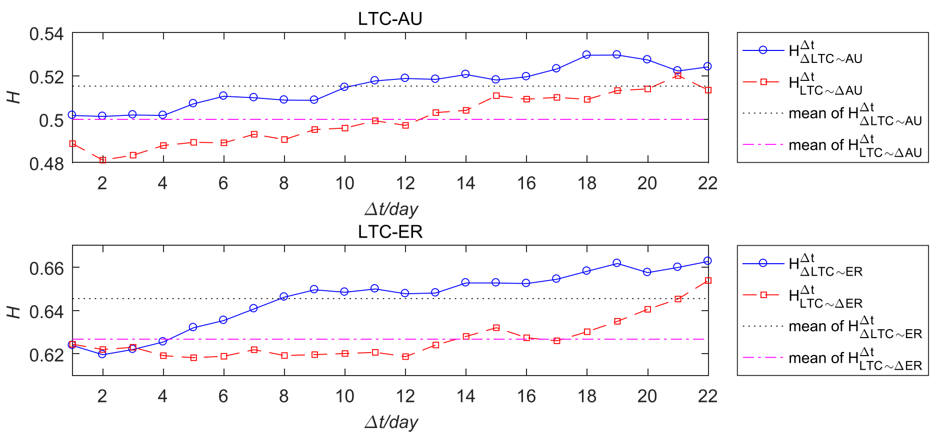

Fig. 7. Cross-relationship between LTC and China's financial market after the shutdown policy with a 1- to 22-day delay.

Hurst index between LTC and China's gold market ranges between 0.54 and 0.58, whereas that between LTC and the US dollar exchange rate market ranges between 0.625 and 0.67. In sum, before the implementation of the shutdown policy, regardless of lag, a long-term correlation can be observed between cryptocurrencies and China's gold and US dollar exchange rate markets.

Figs. 6 and 7 show that the Hurst index between BTC and China's gold market ranges between 0.5 and 0.54, whereas that between BTC and the US dollar exchange rate market ranges between 0.64 and 0.68. Meanwhile, the Hurst index between LTC and China's gold market ranges between 0.48 and 0.54, whereas that between LTC and the US dollar exchange rate market ranges between 0.61 and 0.67. After the implementation of the shutdown policy, regardless of lag, a long-term correlation can be observed between BTC and China's gold and US dollar exchange rate markets. However, after the implementation of the policy, when LTC lags, a long-term correlation can be observed between LTC and China's gold market. Meanwhile, if China's gold market lags for less than 13 days, then LTC and China's gold market demonstrate anti-persistence. When the lag exceeds 13 days, LTC and China's gold market show a long-term correlation. By contrast, the long-term correlation between LTC and the US dollar exchange rate market is maintained regardless of lags.

The above analysis reveals a risk transmission between cryptocurrencies and China's financial market before and after the implementation of the shutdown policy. In addition, the long-term correlation of BTC and LTC with China's gold market under different lag levels was weakened after the implementation of the policy. While this policy strengthened the cross-correlation between BTC and the US dollar exchange rates market, the opposite was observed for the cross-correlation between LTC and the US dollar exchange rate market.

We used formula (17) to further examine the impact of this policy on the direction of risk transmission. We calculated the risk transmission direction analysis indicators ΔH^1 and ΔH^2 as well as their averages of ΔH^1toΔH^{22}, and the empirical results are shown in Table 3.

Table 3 shows that at a 1- or 2-day lag, theΔH^1andΔH^2values of BTC, LTC, and China's gold market are greater than 0 before and after the implementation of the shutdown policy, which suggests that in the short term, the shutdown will not change the direction of risk transmission and that the short-term risk is mainly transmitted from China's gold market to cryptocurrencies. The-ΔH^1andΔH^2values of BTC and the US dollar exchange rate market were less and greater than 0 before and after the policy implementation, respectively, but the opposite was observed for the ΔH^1 and ΔH^2 values of LTC and the US dollar exchange rate market. Therefore, in the short term, the risk before the policy implementation is mainly transmitted from BTC to the Chinese exchange rate market and from the US dollar exchange rate market to LTC. The direction of risk transmission has changed after the implementation of the shutdown policy.

With a 1- to 22-day lag (equivalent to 1 month), the average values of ΔH^1 to ΔH^{22} between cryptocurrencies and China's financial market were less and greater than 0 before and after the implementation of the shutdown policy, respectively, which suggests that within a 1-month lag (long term), the risk is mainly transmitted from cryptocurrencies to China's financial market before the shutdown and from China's financial market to cryptocurrencies after the shutdown. Therefore, a bi-directional risk transmission is observed between cryptocurrencies and China's financial market. While the shutdown policy weakened the impact of cryptocurrencies on China's financial market, the associated risks cannot be completely eliminated.

5. Robustness test

5.1. Robustness under different local polynomial fitting orders

In the previous analysis, when using asymmetric multifractals to study the dependence of cryptocurrencies and China's gold and US dollar exchange rate markets, the order of least squares fitting was fixed to 1 in the local detrending. However, in reality, the local trend of time series is highly complex. Therefore, we recalculated the Hurst indices of the cross-correlations of cryptocurrencies and China's gold and US dollar exchange rate markets when the local least squares fitting orders are 2 and 3. Table 4 presents the empirical results.

Table 4 shows that when cryptocurrencies show different trends as a whole, the four cross-market correlation Hurst indices become close to one another, whereas the overall index exceeds 0.5. For example, when the local fitting orders were 2 and 3, the Hurst indices of the cross-correlation of BTC with the US dollar exchange rate market were 0.6210 and 0.6289, respectively. Similarly, when cryptocurrencies show different trends, except for a few values, under different fitting order, the Hurst index of cross-market can reach the same conclusion, thereby highlighting the robustness of our cross-correlation results under different local polynomial fitting orders.

5.2. Robustness of different multifractal methods

In the first part, we only use MFDCCA to study the relationship between cryptocurrency and China's financial market. To test the stability of its results, we applied MFXDMA (Jiang & Zhou, 2011) to re-examine the cross-correlation of cryptocurrencies with China's gold and US dollar exchange rate markets. Fig. 8 shows that the calculations of MFDCCA and MFXDMA are close under different

Table 3
Risk transmission direction indicators of cryptocurrencies and China's financial market.

statistic	Before the shutdown policy				After the shutdown"policy			
	BTC ~ AU	BTC ~ ER	LTC ~ AU	LTC ~ ER	BTC ~ AU	BTC ~ ER	LTC ~ AU	LTC ~ ER
ΔH^1	0.0034	−0.0025	0.0045	0.0029	0.0116	0.0048	0.0130	−0.0006
ΔH^2	0.0033	−0.0060	0.0053	0.0040	0.0216	0.0065	0.0202	−0.0024
mean value	−0.0087	−0.0160	−0.0101	0.0000	0.0036	0.0084	0.0153	0.0188

Note: BTC-AU stands for the cross market of Bitcoin and Chinese gold, and others are similar.

Table 4
Cross-correlation indices under different local polynomial fitting orders.

statistical indicators	$H_{12}(2)$	$H^{+}_{12}(2)$	$H^{-}_{12}(2)$
The order of local polynomial fitting is 2			
BTC-AU	0.5228	0.4679	0.5725
BTC-ER	0.6210	0.6201	0.6085
LTC-AU	0.5328	0.4827	0.5723
LTC-ER	0.6415	0.6561	0.6221
The order of local polynomial fitting is 3			
BTC-AU	0.5428	0.5742	0.5037
BTC-ER	0.6289	0.6251	0.6010
LTC-AU	0.5490	0.5750	0.5139
LTC-ER	0.6267	0.6172	0.6113

Note: BTC-AU stands for the cross market of Bitcoin and Chinese gold, and others are similar.

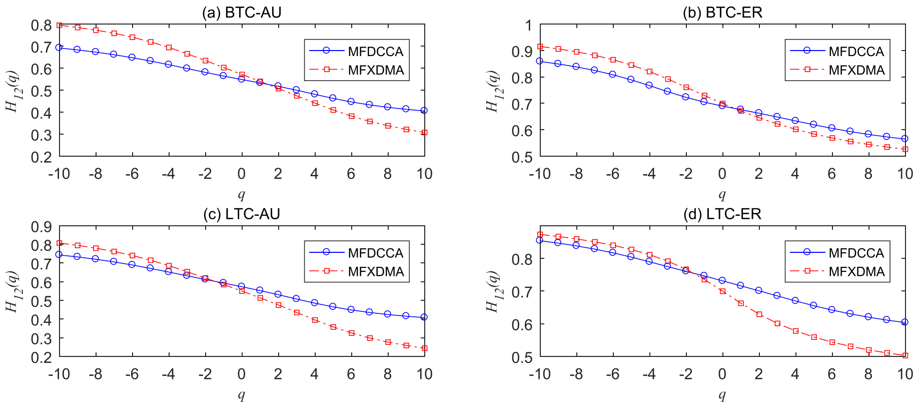

Fig. 8. Cross-correlation indices of cryptocurrencies and China's financial market as obtained by different methods.

volatility ranges. In particular, when $q = 2$ the results obtained by the two different multifractal methods show that the overall situation of cryptocurrency and China's financial market maintains long-memory cross-correlation. Therefore, the results of our empirical analysis have certain robustness.

5.3. Non-linear Granger causality test of risk transmission direction

Given that BTC, LTC, and China's gold and US dollar exchange rate markets have non-linear multifractal characteristics, we performed a non-linear Granger causality test to check the robustness of their relationship. The detailed steps of the test are not repeated here; readers can instead refer to Hiemstra and Jones (1994) or Diks and Panchenko (2006). Following the parameter settings in Hiemstra and Jones (1994), we set the lag order to $Lx = Ly = 1 \sim 5$ and the bandwidth to 0.62. Table 5 presents the empirical test results.

Table 5 shows that when the lag order is less than 3, at a significance level of 10%, the null hypothesis "BTC is not the Granger cause of AU" is rejected. When the lag order is less than 5, at a significance level of 10%, the original hypothesis "AU is not the Granger cause of BTC" is rejected, thereby suggesting that BTC and China's gold market have an interaction relationship. Similarly, when the lag order is less than 5, at a significance level of 1%, the original hypothesis "BTC is not the Granger cause of ER" is rejected, thereby indicating that BTC affects the US dollar exchange rate market. LTC also has a weak influence on China's gold market, but this market has a non-linear Granger causality relationship with LTC. Meanwhile, LTC and the US dollar exchange rate market have a bi-direction non-linear Granger causality relationship. These results confirm the findings of the time-delayed DCCA method, but the non-linear Granger causality test can only determine whether different lag orders are mutually Granger causes, whereas the time-delay DCCA method determines the long-range correlation between two time series. Based on the Hurst index, the cross-correlation of different time lags is displayed accurately, hence clearly highlighting the risk transmission relationship between cryptocurrencies and China's gold and US dollar exchange rate markets.

6. Conclusion and discussions

This article mainly uses MF-ADCCA to study the non-linear interdependence structure between cryptocurrencies and China's gold and US dollar exchange rate markets under different trends and fluctuation ranges and applies the time-delay DCCA method to study the risk transmission direction. This article also examines how China's ban on cryptocurrency transactions affects the interdependence

Table 5
Non-linear Granger test of risk transmission of cryptocurrencies and China's financial market.

$L_x = L_y$	1	2	3	4	5
BTC is not the Granger cause of AU	1.911**(0.02799)	1.662**(0.04823)	1.432*(0.07601)	1.255(0.10466)	1132(0.12884)
AU is not the Granger cause of BTC	1.455*(0.07288)	1.480*(0.06943)	1.385*(0.08370)	1.367*(0.08575)	1.257*(0.10430)
BTC is not the Granger cause of ER	3.394***(0.00034)	3.508***(0.00023)	3.293***(0.00050)	3.232***(0.00061)	3.066***(0.00108)
ER is not the Granger cause of BTC	1.248(0.10603)	1.085(0.13903)	1.036(0.14999)	1.018(0.15436)	1.076(0.14099)
LTC is not the Granger cause of AU	0.973(0.16534)	0.932(0.17555)	0.794(0.21361)	0.6710.25125	0.583(0.27997)
AU is not the Granger cause of LTC	2.520***(0.00586)	3.002***(0.00134)	2.732***(0.00315)	2.546***(0.00545)	2.400***(0.00820)
LTC is not the Granger cause of ER	2.272**(0.01153)	2.342***(0.00960)	2.041**(0.02060)	2.128**(0.01667)	2.137**(0.01629)
ER is not the Granger cause of LTC	3.396***(0.00034)	3.580***(0.00017)	3.540***(0.00020)	3.488***(0.00024)	3.439***(0.00029)

Note: The number of rows in each cell represents the *Tn* statistic of the non-linear Granger causality test, and the value in parentheses represents the corresponding *P* value. *, **, and *** indicate that the null hypothesis is rejected at the 10%, 5%, and 1% significance levels, respectively.

structure and risk transmission of cryptocurrencies and China's financial market.

Cryptocurrencies and China's financial market have peaks, fat-tails, and skewed non-normal multifractal characteristics. Their long-range cross-correlation also shows asymmetric multifractal and dynamic time-varying characteristics. Cryptocurrencies and China's gold cross-market have a stronger long-term correlation with small fluctuations when the returns are upwards, when the returns are downwards, the long-term correlation with large fluctuations is stronger. The downwards trend of BTC is more correlated with the US dollar exchange rate, and the upwards trend of LTC with the US dollar exchange rate cross long memory is stronger. After the shutdown, the cross-correlation between cryptocurrencies and China's gold market was significantly reduced, the anti-persistence increased, and the long-term correlation between cryptocurrencies and the US dollar exchange rate market was strengthened. A mutual influence was observed between cryptocurrencies and China's gold and US dollar exchange rate markets. In sum, the risk of BTC is mainly transmitted to China's financial market, and the influence of China's gold and US dollar exchange rate markets on LTC is stronger than that on BTC. Therefore, the cryptocurrency trade ban in 2017 achieved significant results since its implementation. Specifically, this policy significantly reduced the long-memory correlation between cryptocurrencies and China's gold market and strengthened the long-memory cross-correlation between cryptocurrencies and the US dollar exchange rate market. After the shutdown, China's financial market risk were also mainly transmitted to cryptocurrencies.

Cryptocurrencies, represented in this paper by BTC and LTC, have a significant non-linear dependence on China's gold and exchange rates and have a relatively strong risk transmission. While the ban on cryptocurrency trading in China mainland achieved certain results, this policy also strengthened the correlation between exchange rates and cryptocurrencies. In view of these results and combined with China's national conditions, the following policy recommendations are put forward. First, the internationalization of RMB should be steadily promoted, the stability of RMB/USD exchange rates should be ensured while simultaneously maintaining their flexibility, the supervision of cross-border asset flows should be improved, and the impact of the external market on the RMB exchange rate market should be reduced. Second, given the widespread trading of cryptocurrencies and the rapid innovations in financial technology, it is not enough to reduce risk through shutdown policy. Therefore, China should incorporate cryptocurrency into its regulatory system, learn from past international cryptocurrency supervision experiences, and promote international cooperation in cryptocurrency supervision. Third, China is currently accelerating its advancement of a legal digital currency. While encouraging financial innovation, the country should also pay attention to risk prevention, promote the international competitiveness of RMB as a sovereign digital currency, and hedge and prevent the impact and influence of cryptocurrencies.

This article takes the closure of cryptocurrencies in mainland China as an entry point to prevent systemic risks in the financial market and studies the impact of policy effects on the interdependent structure and risk transmission of cryptocurrencies and China's financial market. Previous studies only surface that cryptocurrencies have risk transmission to the traditional financial market (Gkillas et al., 2020; Zhang et al., 2021), but it does not fully consider the change of dependent structure and the impact of policy effects on risk. Therefore, this article continues to study the interdependent structure and risk transmission of cryptocurrencies and China's financial market, which is a supplement to the existing literature. However, this paper only selects China's gold and US dollar exchange rate markets as representatives, there are other financial markets in China, such as stock markets, bond markets, and commodity markets, etc., so how cryptocurrency affects other financial markets has not been studied. At present, there are many types of cryptocurrencies, therefore, in the future, more cryptocurrencies and Chinese financial assets should be selected for research in order to obtain more general conclusions. At the same time, our research on the interdependent structure of cryptocurrencies and China's financial market is helpful to cross-market investment portfolios, so it is a very good direction to study cross-market investment portfolios in the future. Finally, we can make useful explorations on the influencing factors or mechanisms of risk spillover, which is also worth studying.

CRediT authorship contribution statement

Guangxi Cao: Conceptualization, Visualization, Writing - review & editing. **Wenhao Xie:** Visualization, Supervision, Validation, Data curation, Software, Writing - review & editing.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.najef.2021.101514.

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