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Is there any correlation between digital currency price fluctuation? Based on the DCC-GARCH and wavelet coherence analysis

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ABSTRACT

The existing studies rarely reveal the reasons for the digital currency price fluctuation from the perspective of internal interaction and contagion. Therefore, to fill this research gap, this paper comprehensively adopts the dynamic conditional correlation (DCC-) GARCH model and wavelet coherence analysis (WTC) to reveal the internal correlation and formation reasons of digital currency price fluctuations. Our research has the following findings: (1) the price fluctuations of digital currency are highly related. Through the observation of the dynamic conditional correlation coefficient graph, it is found that the price fluctuations have a strong time-varying trend, manifested as a 'contagious' characteristic. (2) During the outbreak of COVID-19, most digital currencies have shown positive resonance in the short, medium, and long term, suggesting that the COVID-19 pandemic has increased the correlation and contagion of digital currency price fluctuations. (3) In the short term, Bitcoin is the main 'contagious source' of digital currency price fluctuation. But in the medium and long term, Ethereum and Ripple, which are closely related to the real economy, have a greater impact and become the new 'contagious source'. Generally speaking, Bitcoin, Ethereum, and Ripple are the internal causes of instability in the digital currency market. Finally, based on the empirical conclusion, this paper proposes that the digital currency portfolio should be optimized to meet the investment demand; strengthen digital currency regulatory cooperation, and improve regulatory efficiency. Let the digital currency return to the 'currency' attribute and serve the real economy.

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1. Introduction

Financial technology (FinTech) is at the forefront of financial innovation and development in the world. The statistical data showed that global investment in FinTech (mainly loans) has increased from \$4.05 billion in 2013 to \$12.21 billion in 2014. By

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the first half of 2018, the investment had reached $57.9 billion (KPMG, 2019). FinTech development attracted much attention, especially the blockchain technology and its application (Zhao, 2019), which has been extended to digital finance, the Internet of Things, intelligent manufacturing, supply chain management, digital asset transactions, etc. From the maturity of technology applications, digital currency is the practical application of blockchain technology, as well as the most mature application field. Since the emergence of Bitcoin in 2009, about 1500 other digital currencies were introduced, of which more than 600 transactions were active (ElBahrawy et al., 2017), such as Litecoin, Ripple, and Dogecoin. According to the latest trading data of Coin Market Cap, as of September 29, 2021, there were 6,483 cryptocurrencies, with a total market value of 183.9 billion dollars. It can be seen that the development of digital currency is not only diverse but also fast. Nowadays, the digital currency market has become an important part of the global financial system.

Digital currency is the pronoun for 'decentralization'. On the one hand, the payment, transaction, and inheritance rules of digital currency were gradually recognized and accepted, which made digital currency gradually become a medium of exchange for daily payments (Rogojanu & Badea, 2014). On the other hand, as the digital currency market has become the mainstream financial market, the digital currency has gradually evolved into an 'encrypted digital asset', which was regarded as an online investment product (ElBahrawy et al., 2017). To some extent, the transformation of digital currency from commodity trading medium to investment product has reduced costs and promoted efficiency, enhancing the ability to serve the real economy (Ante, 2020). Besides, central banks participated in the practice of digital currency to build a digital currency system, attempting to promote the legalization of digital currency (Dow, 2019; Edwin & Kwangjo, 2020; Qian, 2019).

However, the 'dual' attributes of digital currencies will make them face increasing uncertainty, which will also have some imaginable and unpredictable effects in the future. In terms of exchange medium, the digital currency may cause destructive consequences to central banks, monetary policies, the value of legal tender, and the whole world economy (Dyhrberg, 2016). At the same time, as a highly fluctuant alternative asset similar to gold, the violent price fluctuation of digital currency is an important factor affecting the global financial market. Besides, from the perspective of the trading system, the digital currency market is open 24 hours a day without a price limit (Hayes, 2017), so the price is easy to be manipulated by investors. For instance, on January 29, 2021, Elon Musk, the CEO of Tesla, unexpectedly changed his Twitter account to Bitcoin. This behavior made the price of Bitcoin rose from 32,000 dollars to more than 38,000 dollars in a few hours (Hamurcu, 2022). Moreover, the price skyrocketing and fall is not only reflected in a single currency but manifested as the significant correlation and contagion between digital currencies. According to Market Watch, Elon Musk announced that Tesla Inc. would cooperate with Dogecoin to improve the transaction efficiency on May 31, 2021. This news caused a drop in Bitcoin and a sharp rise in Dogecoin.

The high attention, profit rate, and volatility accompanied by digital currency not only brought enormous risks to investors but also harmed global financial development. As the significant correlation between digital currencies, then why do digital currency price fluctuations maintain such a similar coordinated synergy rate? Will it constitute a 'contagion'? What are the underlying reasons? These are the scientific problems to be solved in this paper. The necessity of this research lies in the following aspect. For one thing, digital currencies are neither stocks nor bonds, so the returns on investment in digital currencies depend entirely on their price changes. For another thing, this paper aims to explain the correlation and contagion of digital currency based on their price fluctuation law, which will contribute to revealing the mechanism of price fluctuation and laying a solid foundation for the development of digital currency. Therefore, this paper is equipped with quite prominent theoretical significance and practical value.

The main contributions of this study are as follows. First, this paper selected Bitcoin (BTC), Ethereum (ETH), Ripple (XRP), Litecoin (LTC), Binance Coin (BNB), and Stellar (XLM) as the research objects. Through the comparison between different digital currencies, this paper can figure out the common characteristics and heterogeneity of price fluctuations, which greatly enriched the research conclusions. Second, based on the price fluctuation law of digital currency, this paper explained the 'internal reason' of the price change in the digital currency market. The current research is still dominated by the 'external effects' of digital currency price fluctuation, paying more attention to the impact of digital currency price fluctuation on safe-haven assets such as gold, U.S. dollar, Euro, and RMB. To this end, it is unique to put the research perspective between digital currencies. Third, this paper reexamined the price fluctuation mechanism of digital currency from correlation and contagion. In particular, the utilization of the contagion model in price fluctuation analysis can expand its application scope and improve interpretation capability. Forth, this paper made innovative use of the DCC-GARCH model and wavelet coherence analysis (WTC), which is a great contribution and breakthrough. To be specific, the price fluctuation correlation, time-varying characteristics, and 'contagion' of digital currency are demonstrated by the DCC-GARCH model, while the 'lead-lag' relationship and 'contagious source' of digital currency price fluctuation are revealed by wavelet coherence analysis (WTC). These methods can elaborate the characteristics of digital currency price fluctuation and clarify its mechanism comprehensively.

Highlights from our findings are provided. First, this paper focused on six typical digital currencies in the digital currency market to reveal the correlation and contagion of digital currency price fluctuation. Second, this study took the COVID-19 pandemic into consideration, and extended research data to observe the heterogeneity characteristics manifested by the correlation and contagion of digital currency price fluctuation. Third, this paper effectively combined the DCC-GARCH model with the wavelet coherence analysis (WTC) method, which is conducive to judging the correlation and contagion of digital currency price fluctuation, revealing their time-varying characteristics, and further confirming the internal 'contagious source'. Fourth, research conclusions reflected that the digital currency price fluctuation has a strong correlation and increasing time-varying characteristics, with an obvious 'contagious' feature. In short-term price fluctuation, Bitcoin was in a leading position, being the major 'contagious source' of digital currencies. Whereas, in the medium-term and long-term, Ethereum and Ripple had greater impacts, being the 'contagious source' of digital currencies.

The following chapters are organized as follows. Section 2 presents the literature review; Section 3 details the theoretical analysis framework of the correlation of digital currency price fluctuation; Section 4 explains the empirical model and describes variables; Section 5 is the empirical results and analysis. Finally, Section 6 summarizes our research conclusions and puts forward recommendations.

2. Literature review

The digital currency market has always been the focus of the global financial market (Antonakakis et al., 2019). However, scholars still prefer to take Bitcoin as the main research object and reveal the price skyrocketing and falling phenomenon from the supply and demand of digital currency. At the demand level, investors' hedging demand and investment demand for digital currency are the main drivers (Obryan, 2019; Rodrigo, 2020). In terms of supply, Bouoiyour et al. (2016) regarded digital currency as a 'special commodity'. Besides, some scholars utilized the theories of behavioral finance to reveal this price fluctuation. Trabelsi (2018) insisted that uninformed investors invested in digital currencies mostly to find suitable investment tools, and investors did not care whether the digital currency can become a 'new trading system', which will lead to the 'herding effect' and amplify investors' expectations of the rise in digital currency prices. In general, these studies still mainly use the analytical framework of economics to explore the causes of digital currency price volatility. The fact is that this string of code, of which the digital currency exists, is worth intrinsically nothing. So, the conclusions of this analysis have also been widely questioned.

Accordingly, scholars have also begun to focus their research on the interplay between the prices of different assets such as U.S. dollars, gold, and stocks., trying to explore the mechanism of digital currency price fluctuations. Dyhrberg (2016) explored the financial capacity of bitcoin. He found that Bitcoin has some similarities with gold and the U.S. dollar, which has a place in the financial market and portfolio management. What's more, Antoniadis et al. (2018) adopted the GJR-GARCH model to test the impact of Bitcoin on the U.S. dollar index. The results showed that Bitcoin has a significant negative impact on the return of the U.S. dollar index, and the relationship between Bitcoin and the U.S. dollar index was asymmetric. However, some scholars, such as Baur et al. (2018), hold different opinions on it. They declared that Bitcoin had its unique risk-return characteristics and followed different return processes, so Bitcoin was not related to gold, currency, or stocks. At this stage, the excess returns and price fluctuation of Bitcoin indicated that it was more like a highly invested asset.

Moreover, in the latest research, the price fluctuation between digital currencies has become the highlighted area for scholars. Antonakakis et al. (2019) found that the price correlation between digital currencies increased significantly, which is more significant during high price fluctuations. Besides, they pointed that Bitcoin remains the most disruptive digital currency in the market while Ripple is a key currency. Elsayed et al. (2022) found that there was a significant return spillover effect between Bitcoin and Ethereum in the third quarter of 2017, but this return spillover effect declined in the fourth quarter of 2017. And the further autoregressive estimation showed that the current level of Bitcoin depended on the previous level of RMB, while the current level of Ripple largely lied in the previous level of Bitcoin, followed by the level of Ethereum, which profoundly indicated that there was a significant causal relationship between digital currencies. Nevertheless, Corbet et al. (2018) and Omane-Adjepong and Alagidede (2019) disagreed with this view. They believed that the feedback relationship and communication mode between digital currencies were extremely complicated, and no digital currency market can be identified as the main sender or receiver of volatility shocks. That is to say, even the largest digital currency markets such as Bitcoin and Ripple are vulnerable to relatively small volatility shocks. These studies have provided effective support for this paper. However, the existing research has the following problems.

First, in terms of research objects, scholars paid more attention to Bitcoin but few focused on the correlation of digital currency price fluctuation. Therefore, the relative studies were still in their infancy, and the number of the research results was not only small in total but also less focused on digital currencies. Compared with the existing research, this paper expanded the research object to six typical digital currencies, namely Bitcoin (BTC), Ethereum (ETH), Ripple (XRP), Litecoin (LTC), Binance Coin (BNB), and Stellar (XLM). It can be seen that the coverage of research objects was wider, and the reasons for the price fluctuation of digital currency prices would be more thorough.

Second, most sample data used in the existing research on the price fluctuation of digital currencies was before the COVID-19 pandemic (before 2019), so there was no consideration about the data after the outbreak of the COVID-19 pandemic. Actually, from the characteristics of digital currency price fluctuation, it can be seen that the phenomenon of skyrocketing and fall of digital currency price is more obvious after the COVID-19 pandemic, and the contagion characteristics are more significant. That is to say, if the external shock of the COVID-19 pandemic cannot be considered, then the conclusion of the correlation and contagion of digital currency price fluctuation will be largely unreliable. To this end, this study included the data after the outbreak of the COVID-19 pandemic in the analysis, which not only expanded the sample size but also greatly improved the scientific and credibility of the research.

Third, the existing research usually utilized the GARCH model to reveal the price fluctuation correlation of digital currency, which can well depict the overall characteristics but cannot reflect the internal 'contagious source' of price fluctuation. In this regard, the DCC-GARCH model can well portray the time-varying characteristics of digital currency price fluctuations, and wavelet coherence analysis (WTC) has significant advantages in reflecting the correlation details and 'lead-lag' relationship of digital currency price fluctuations. Therefore, this article combined the DCC-GARCH model and wavelet coherence analysis (WTC) to comprehensively reflect the correlation, contagion, and 'contagious source' of digital currency price fluctuations, which will enrich the research contents and improve the explanatory ability of research conclusions.

3. The theoretical framework

Compared with the traditional financial market, the digital currency market is significantly different. Although globally oriented, the digital currency market is indeed a not fully supervised financial market that springs up exuberantly. Therefore, the uncertainty

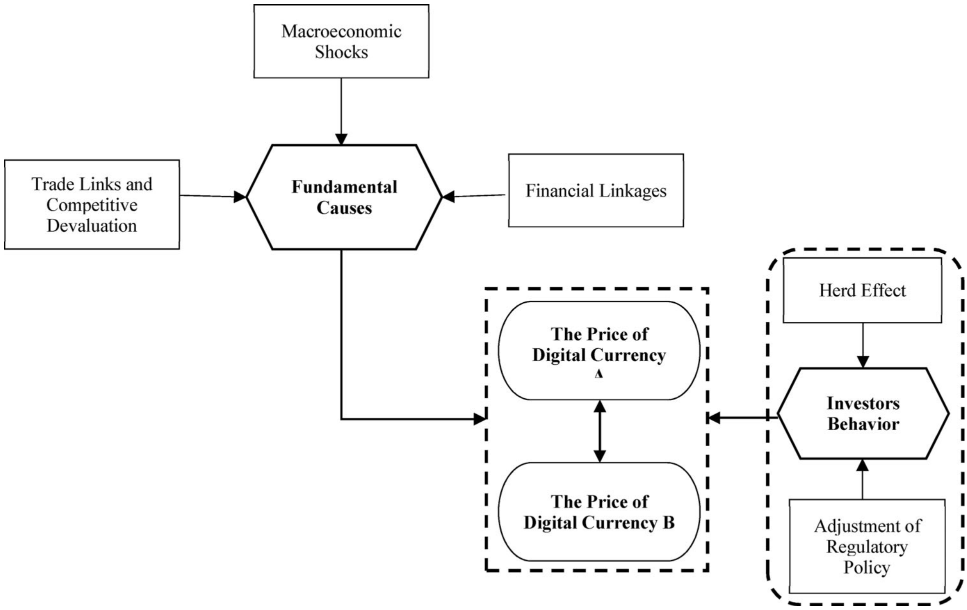

Figure 1. The price fluctuation mechanism of digital currencies.
Source: Self drawn by the author according to theoretical relationship.

and information asymmetry in the digital currency market is significantly prominent. The phenomena of price skyrocketing and falling are common, and digital currencies are highly correlated. So, does the correlation of different digital currencies cause the price to skyrocket and fall? Does this high rate of price fluctuation constitute a 'contagion'? In other words, does the interdependent digital currency market have something to do with the similar synergy between different digital currencies? This section will adopt the 'contagion model' to explain and analyze these problems from the theoretical level.

In general, contagion measures the 'common movement' formed by the significantly enhanced cross-financial markets and cross-regional connections after external shocks, with the ways of comparing asset prices or capital flows in times of stability and volatility (Dornbusch et al., 2000). Under this approach, contagion is defined as a significant increase in market correlation during volatility periods (Forbes & Rigobon, 2002). Why? The current theoretical framework generally summarizes the mechanism as two aspects, namely fundamental causes and investors' behavior. Thereinto, the fundamental causes include macroeconomic shocks, trade links, and competitive devaluation, as well as financial linkages. While the investors' behavior maintains herd effect, regulatory policy adjustment, and other factors (Dornbusch et al., 2000; Kaminsky et al., 2003). Based on the two aspects, the transmission mechanism of the price fluctuation correlation and contagion between digital currencies is plotted in Figure 1.

3.1. Fundamental causes

3.1.1. Macroeconomic shocks

Since the global economic crisis in 2008, the macroeconomic and financial system has cast a shadow of 'distrust', and the 'contagion' characteristics of global financial assets and investments have become more pronounced (Antoniadis et al., 2018; Bouri et al., 2017). However, digital currencies are hailed as the 'latest pursued currency' for their resilience, hedging, and risk aversion in global economic adversity. Take Bitcoin as an example, it is regarded as 'digital gold', which has been placed in a predominant position like the U.S. dollar, gold, and bulk products in terms of value recognition (Selmi et al., 2018). Meanwhile, it's worth noting that the correlation and contagion of digital currency price fluctuation reflect its ability of hedging in response to global economic policy uncertainties (Demir et al., 2018). Therefore, the price movement of digital currencies will maintain a high rate of synergy when faced with macroeconomic shocks, so the correlation and contagion of digital currency price fluctuation are self-evident.

There's no doubt that digital currency will not only maintain a high synergy rate with the prices of safe-haven assets such as the U.S. dollar, gold, and bulk products on the overall level, but its synergy characteristic within the digital currency system is quite distinct. This is highly related to the mechanism of currency design. Since Bitcoin has achieved broad consensus and obtained enormous investment for research and development, other digital currencies have taken Bitcoin as the benchmark to some degree. For instance, when Ethereum (ETH) is initially raised for public sale, clients need to purchase Bitcoin first, then exchange ETH with a specified rate of Bitcoin: ETH = 1:1337. But the subsequential issued digital currencies are implemented through smart contracts and ICO mechanisms. As a consequence, Bitcoin has become the 'anchor' of other digital currencies. When confronted with external shocks, the price fluctuations of other digital currencies will maintain a high rate of synergy with Bitcoin, forming a pattern of coordinated fluctuations.

3.1.2. Trade links and competitive devaluation

According to the basic paradigm of contagion theory, trade links and competitive devaluations will form local shocks and lead to a sharp devaluation of currencies. This will not only cause the decline of domestic asset prices and capital outflow but also make the countries in trade competition face enormous pressure of currency devaluation. Moreover, as for the degree of impact, the currency depreciation caused by the 'competitive devaluation' game is more severe than that caused by fundamental changes (Corsetti et al., 2000). In other words, if market participants develop an expectation of 'competitive devaluation', they will sell the financial assets of other countries. There is also an obvious phenomenon of 'competitive devaluation' in the digital currency market. When analyzing the history of Bitcoin's price skyrocketing and falling, it is easy to find that, with the European sovereign debt crisis and the outbreak of the Cyprus banking crisis, 'competitive devaluation' between digital currencies and other financial assets is noticeable. Meanwhile, from the perspective of the internal market of digital currency, this phenomenon is also prominent. Generally speaking, the appreciation of Bitcoin has not brought about the appreciation of other digital currencies but sharply depreciation, which is manifested as an obvious 'siphonic effect'. Therefore, the correlation and contagion of digital currency price fluctuation are axiomatic.

3.1.3. Financial linkages

Some studies pointed out that the contagion of asset price fluctuation is directly related to financial linkages (Kaminsky et al., 2003). It's generally accepted that the common movement of asset prices has something to do with the level of openness and integration of financial markets. In theory, in an open financial market, leveraged investors facing margin calls need to sell assets at a low price in the event of a price drop. However, in reality, the problem of the 'lemon market' usually occurs because of information asymmetry. That is to say, investors tend not to sell falling assets under such circumstances but sell other assets in their portfolios, which will further cause the price decline of other assets and spread the initial disturbance in the market (Kaminsky et al., 2003). In the meantime, the ICO and token markets are also plagued by 'lemon market' problems (Jiang, Qiu, et al., 2022; Jiang, Zhou, et al., 2022). For this reason, when an external shock or benefit occurs, investors may sell other digital currencies in their portfolios, making 'common movement' and risk exposure of all digital currencies, then the contagion is formed.

3.2. Investors' behavior

3.2.1. Herd effect

The 'herd effect' of investors' behavior makes the price fluctuations of digital currencies correlated and contagious. Investors' behavior, whether rational or irrational, will spread shocks from one country to another (Pritsker, 2013). This is also adaptable to the digital currency market. As a kind of financial asset, the price fluctuation spillover effect of digital currency is mainly caused by the behavior of market traders. Although the digital currency market has a large scale, it is still an emerging financial market in the growth stage, where exists the problems such as information uncertainty and one-sided cognition. Therefore, the behavior that investors investing in digital currencies can be interpreted as a typical 'herd effect'. At present, the herd effect on digital currency investment has been supported and proven by many kinds of literature and research (Da Gama Silva et al., 2019). In general, investment decisions are often influenced by other market participants, which will ultimately lead to the failure of the price adjustment mechanism and ignorance of the hidden risk factors of digital currency. Precisely, these influences are manifested as following the leading authority of the market, investing in the currency chosen by most traders, and excessively focusing on media reports, etc. Different digital currencies may have the same investors. Although each investor makes different decisions, they will influence and imitate each other, forming a linkage effect. This is the most obvious micro embodiment of the price fluctuation of digital currencies.

3.2.2. Adjustment of regulatory policy

The change of regulatory policies assesses investment transactions simultaneously change as well, leading to the spread of digital currency price fluctuation. Trace back the price skyrocketing and falling of digital currencies such as Bitcoin and Ethereum, we can find that the phenomenon that digital currencies influence each other is closely related to the adjustment of regulatory policy. For example, due to the confidence crisis arising from the Cyprus banking crisis from 2013 to 2015, a more friendly regulatory policy towards digital currencies was adopted by all countries. This is beneficial to the price of digital currency, so the price of digital currency coordinately rises. However, the digital currency has entered a cycle of collapse since December 2013, which is partly related to the adjustment of regulatory policies in major countries. Take China as an example. Restrictive regulatory policies such as the *Notice on Preventing Bitcoin Risks* and *Announcement on Preventing Token Issuance Financing Risks* were successively issued, inducing the decline of digital currency prices to a certain extent. In particular, it's worth noting that although the digital currency market is an emerging financial market, countries are aligned in the formulation of regulatory policies. Therefore, the coordination of regulatory policy adjustments will promote the correlation and contagion of price fluctuations in the digital currency market.

4. Empirical model and variable description

4.1. Establishment and description of the DCC-GARCH model

In general, the generalized autoregressive conditional heteroscedasticity model (GARCH) is mostly used to depict the volatility law of time series, stemming from the autoregressive conditionally heteroscedastic model (ARCH) proposed by Engle (1982). ARCH model is usually used to analyze the heteroscedasticity of the time series. Specifically, larger fluctuations (variances) and smaller fluctuations (variances) clustered together respectively to reveal the aggregation of time series. In the operation of econometrics, due to the large number of parameters that the ARCH model needs to estimate, it is easy to lose sample size. Therefore, Bollerslev (1986) proposed the GARCH model with wider applicability and generality. The model adds an autoregressive equation of σ_t^2 based on the ARCH model, which can be set to:

$$\text{Mean value equation}: \quad y_t = \gamma x_t + u_t \tag{1}$$

$$\text{Conditional variance equation}: \quad \sigma_t^2 = \omega + \sum_{i=1}^{q} \alpha_i u_{t-i}^2 + \sum_{j=1}^{p} \beta_j \sigma_{t-j}^2 \tag{2}$$

Subsequently, many scholars extended and constructed the ARCH-M, TGRCH, EGARCH, and Component GARCH models (Dimitriou et al., 2013). The GARCH model system is constantly improving. However, these models all take a single variable as the research object, so their applicability is relatively limited, and they cannot reflect the interaction and impact between variables. To solve the multivariate volatility correlation problem, Bollerslev (1990) proposed the constant conditional correlation (CCC-) GARCH model which assumed the conditional correlation coefficient was constant, but it is difficult to meet the real-time economic characteristics of time-varying dynamics. Hence, Engle (2002) calculated the dynamic conditional correlation coefficient through the weighted average of the standardized disturbance terms based on the CCC-GARCH model, and then proposed a dynamic conditional correlation model (DCC-GARCH). This model is suitable for estimating the dynamic correlation between two or more time-series variables, which can not only demonstrate the correlation of digital currency but also observe its time-varying characteristics. By analyzing the evolutionary trend of the overall correlation strength of the digital currency, it can preliminarily judge whether there is a 'contagion' characteristic between digital currencies based on the correlation.

In the existing studies, the DCC-GARCH model has a strong ability to interpret reality, and the practical application is relatively rich. For example, Chittedi (2015) used the DCC-GARCH to analyze the contagion effect between the stock market of the United States and that of India. Corbet et al. (2020) employed the model to analyze the correlation between cryptocurrencies and the Chinese stock market. Furthermore, Dimitriou et al. (2013) improved this model. They used the FARARCH-DCC model to investigate the financial contagion of BRICS. DCC-GARCH model is mainly divided into two steps. The first step is to build a series of single variable GARCH models and obtain standard residuals. The second step is to calculate the dynamic conditional correlation coefficient matrix based on the unconditional variance matrix of the standard residual that is estimated in the first step. The DCC-GARCH model utilized in this paper is constructed as follows:

$$r_t|\emptyset_{t-1} \sim N(0, H_t) \tag{3}$$

$$H_t = D_t R_t D_t \tag{4}$$

Among them, r_t is the digital currency rate of return or volatility, and $\emptyset_{t-1}$ is all the information collected before the t period. $r_t|\emptyset_{t-1}$ follows the normal distribution with mean 0 and conditional covariance matrix H_t, and H_t is a positive definite matrix. D_t represents the diagonal matrix of order $k \times k$ formed by the conditional standard variance. R_t is the matrix of dynamic conditional correlation coefficients, and each element R_t is calculated as the following equation.

$$\rho_{ij,t} = \frac{\sum_{s=1}^{t-1} \alpha^s \varepsilon_{i,t-s} \varepsilon_{j,t-s}}{\sqrt{\left(\sum_{s=1}^{t-1} \alpha^s \varepsilon_{i,t-s}^2\right)\left(\sum_{s=1}^{t-1} \alpha^s \varepsilon_{j,t-s}^2\right) = [R_t]_{ij}}} \tag{5}$$

In equation (5), $\varepsilon_{i,t-s}$ is the standard disturbance term, and α^s is the time-varying geometric weight, that is, the closer to t period, the value of α^s increases geometrically. Write it in matrix form as:

$$R_t = diag\{Q_t\}^{-1/2} Q_t diag\{Q_t\}^{-1/2} \tag{6}$$

$$Q_t = \overline{Q}(1 - a - b) + a\varepsilon_{t-1}\varepsilon_{t-1}^{'} + bQ_{t-1} \tag{7}$$

$$\overline{Q} = \frac{1}{T}\sum_{1}^{T} \varepsilon_t \varepsilon_{t-1} \tag{8}$$

Among them, $\overline{Q}$ is the unconditional variance matrix of the standard residuals, and ε_t is the standardized disturbance term. a and b, which are non-negative, are the parameters estimated by the DCC-GARCH model, and they satisfy the constraint of $0 \leq a + b < 1$.

Meanwhile, to display the dynamic conditional correlation between the two sequences intuitively, the time series of the correlation coefficients are drawn into the dynamic conditional correlation coefficient graph. The graph of the dynamic conditional correlation coefficient can reveal the trend characteristics of correlation, and judge whether there is 'contagion' according to the significant enhancement of correlation trend. The significant increase in dynamic correlation coefficients provided substantial evidence in favor of contagion effects due to herding behavior in the financial markets (Syllignakis & Kouretas, 2011).

4.2. Establishment and description of wavelet coherence analysis (WTC)

In this paper, the DCC-GARCH model can reveal the correlation of digital currency price fluctuation, and we can judge whether the price fluctuations of digital currency are contagious by observing the dynamic conditional correlation coefficient graph which can be decomposed from this model. However, the DCC-GARCH model has limitations in itself. It cannot reveal the 'source' of correlation and contagion of digital currency price fluctuation, which suggests that this paper requires other methods to solve this problem. Therefore, we introduce wavelet coherence analysis to reflect the 'contagious source' of digital currency price fluctuation. Wavelet coherence analysis (WTC) is a new signal analysis technique, which can figure out the correlation details and 'lead-lag' relationship between two time series in the local time domain and frequency domain. Its application can not only reveal the multi-scale correlation characteristics of the correlation of digital currency price fluctuation but find out which digital currency has been in the leading position and play the role of 'contagious source'. The specific steps of WTC constructed in this paper are as follows:

Continuous wavelet transform is performed for a given time series $x_n(n = 1, 2, \ldots, N)$. It should be noted that, as the mother wavelet, the Morlet wavelet is defined as Equation (9), where η denotes the dimensionless time, ω_0 represents the dimensionless frequency. When $\omega_0 = 6$, the wavelet scale parameter is almost equal to the Fourier period (Grinsted et al., 2004; Torrence & Compo, 1998). The continuous wavelet transform of the time series is based on the convolution of the scaled and standardized wavelet mother function and the time series $x_n(n = 1, 2, \ldots, N)$, and the $W_n^X(s)$, as the transformation result is shown in Equation (10). In which, s is telescopic scale, δt means the uniform time step, n' indicates the integer value from 1 to N, and $*$ is on behalf of the complex conjugate. Besides, the $|W_n^X(s)|^2$ represents is the wavelet power spectrum, which is equal to the sum squares of the real and imaginary parts of $W_n^X(s)$.

$$\psi_0(\eta) = \pi^{-1/4} e^{i\omega_0\eta} e^{-\eta^2/2} \tag{9}$$

$$W_n^X(s) = \sqrt{\frac{\delta t}{s}} \sum_{n'=1}^{N} x_{n'} \psi^* \left[(n' - n) \frac{\delta t}{s} \right] \tag{10}$$

Suppose $W_n^X(s)$ and $W_n^Y(s)$ to be different continuous wavelet transform of time series respectively, then their cross-wavelet spectrum is $W_n^{XY}(s) = W_n^X(s) W_n^Y *(s)$. Thereinto, $*$ indicates the complex conjugate, its corresponding cross wavelet power spectrum is $|W_n^{XY}(s)|$. Wavelet coherence analysis is performed on the two-time series based on the results of continuous wavelet spectrum and cross wavelet spectrum. The wavelet coherence spectrum is shown in Equation (11), where S is the smoothing operator and $S(W) = S_{scale}(S_{time}(W_n(s)))$. Besides, S_{scale} denotes the smoothing along the wavelet scale axis, while S_{time} represents smoothing in time. The larger the value of $R_n^2(s)$ is, the stronger the correlation between the two-time series is, and vice versa.

$$R_n^2(s) = \frac{|S(s^{-1} W^{XY}(S))|^2}{S\left(s^{-1}|W^X(S)|^2\right) \times S\left(s^{-1}|W^Y(S)|^2\right)} \tag{11}$$

As the value of $R_n^2(s)$ is limited in the positive number from 0 to 1, it can only reflect the intensity of correlation, but it is difficult to reveal the positive and negative directions of correlation as well as the ‘lead-lag’ relationship. Therefore, to obtain the ‘lead-lag’ relationship, this paper introduces the phase difference that manifested as Equation (12). Where I represents the imaginary part, and R denotes the real part. Besides, the phase difference in wavelet coherent spectrum can be reflected by the arrow direction (→, ←, ↘, ↙, ↘, ↘). Section 5.3 shows the details.

$$\Phi_{XY} = \tan^{-1}\left(\frac{I(S(W_{XY}))}{R(S(W_{XY}))}\right), \Phi_{XY} \in [-\pi, \ \pi] \tag{12}$$

It’s worth noting that, this part aims to reveal the correlation and ‘contagious source’ of digital currency price fluctuation through wavelet coherence analysis. Therefore, Section 5 only shows the final results of wavelet coherence analysis, but the ones of continuous wavelet transform and cross wavelet transform are not listed.

4.3. Index quantification and data source

This article regarded the 24H price fluctuation of digital currency as the quantified index. As the issuance time of each digital currency is inconsistent, this paper ultimately selected 1267 observations from November 9, 2017 to April 28, 2021 for pairwise combination and comparative analysis. At the same time, it is impossible to include all digital currencies in the analysis framework because of their large scale. So, this article selected six typical digital currencies as research objects, including Bitcoin (BTC), Ethereum (ETH), Ripple (XRP), Litecoin (LTC), Binance Coin (BNB), and Stellar (XLM).

It is mainly based on the following three considerations: First, these six digital currencies are at the forefront of the digital currency market in terms of market value and transaction size, and they are also the main investment channels. Taking them as the research objects is relatively representative to some extent. Second, the underlying

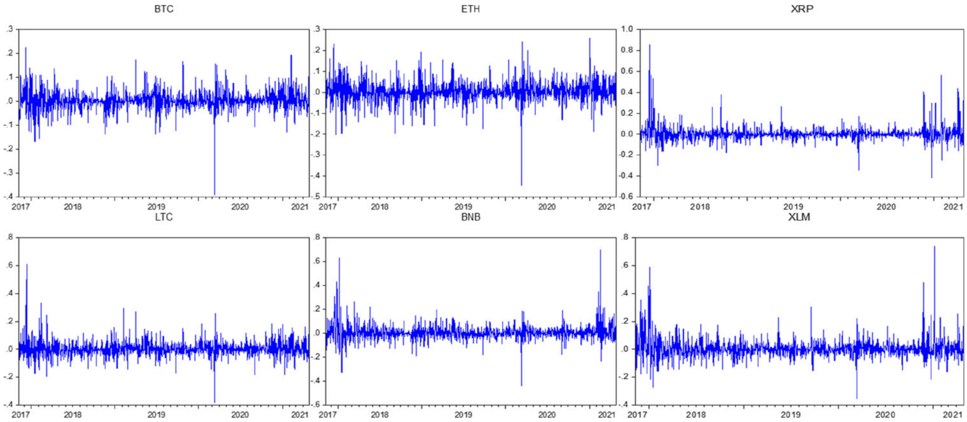

Figure 2. The price change rate trends of six digital currencies.
Source: Drawn by Eviews 10.0.

technology is relevant. For example, Litecoin and Bitcoin have the same technical realization principle, and Stellar is developed based on Ripple. The price volatility caused by the correlation of the underlying technology can provide new ideas and directions for building a digital currency supervision system. The third is that, in addition to having similar characteristics, the selected digital currency also has a certain degree of heterogeneity.

The sample data come from *Investing.com*. The price change rate trends of six digital currencies are shown in Figure 2. It can be seen that there is obvious clustering of the change rates of six digital currency prices, and the phenomenon of 'same high and same low' is significantly marvelous. Judging from the overall trend, the change rates of these six digital currency prices have a phased convergence. But it's worth noting that there are obvious structural contradictions in the change rates of digital currency prices. From November 2017 to March 2018, the price change rates of the six selected digital currencies had similar trends but presented large differences. In addition, the difference between the price change rates of the six selected digital currencies gradually weakened and became consistent from March 2018 to October 2019. This shows that the change rates of digital currency prices not only have a certain correlation but also have time-varying characteristics. Furthermore, the change rates of the six digital currency prices remained highly consistent during the COVID-19 pandemic since 31 December 2019. Does it indicate the existence of contagion in the digital currency market? If so, what are the causes? Obviously, these questions need to be further verified by empirical models.

5. Empirical results and analysis

In the above analysis, this paper has revealed the price fluctuation characteristics of six digital currencies respectively. So, is there a correlation between the price fluctuations of the six digital currencies? Is this correlation a contagion? Therefore, in this part, this paper first uses the DCC-GARCH model to demonstrate the correlation of price fluctuations of

Table 1. Stationarity test result.

Digital currency	MZa	MZt	MSB	MPT
BTC	−27.0732***	−3.66311***	0.13530***	3.46301***
ETH	−94.7907***	−6.88413***	0.07262***	0.96249***
XRP	−540.759***	−16.4413***	0.03040***	0.17179***
LTC	−83.1270***	−6.43661***	0.07743***	0.31626***
BNB	−520.238***	−16.1270***	0.03100***	0.17735***
XLM	−169.216***	−9.19668***	0.05435***	0.54329***

Note: *** represents the significance level of 1%.
Source: Calculated by Eviews 10.0.

six digital currencies and determine whether the price fluctuations of six digital currencies are contagious through the dynamic conditional correlation coefficient graph.

5.1. Stationarity and ARCH effect test

GARCH model requires the stability of the data. There are many methods for data stability testing, but traditional methods such as ADF and PP testing often have problems of low validity and sample deviation, and the distortion of the research conclusions is also severe, but the Ng-Perron method has certain advantages (Ng & Perron, 2001). The test statistics of this method are more robust, which can better avoid horizontal distortion and maintain a higher test efficiency (Perron & Qu, 2007).The results are shown in Table 1. In the Ng-Perron test results of these six digital currencies, MZa, MZt, MSB, and MPT simultaneously rejected the null hypothesis of unit root at the significant level of 1%, suggesting that the price series of these six digital currencies are stable.

The GARCH model is a general expression of the ARCH model. Hence, to conduct the GARCH model, it is necessary to test whether the residual sequence of digital currency has an ARCH effect. Based on the stationary test of the digital currency series, the ARCH effect test is further carried out by the ARCH-LM method, with the null hypothesis of 'no ARCH effect in the residual sequence'. Therefore, if the null hypothesis is rejected, it indicates that there is an ARCH effect on the residual sequence of digital currency prices. The test results are shown in Table 2. It can be seen that at the corresponding significance level, the test results of the six sets of digital currency residual sequences reject the null hypothesis, indicating that the residual sequence of digital currency prices has an obvious ARCH effect, so the DCC-GARCH model can be further established to reveal the correlation of six sets of digital currency price fluctuations.

5.2. DCC-GARCH model estimation

Generally speaking, the estimation of the DCC-GARCH model should be divided into two steps. First, the univariate GARCH model is estimated for the six digital currency price series, and the corresponding standard residuals are obtained. After many attempts and repeated verifications, this paper selects the GARCH (1, 1) model as the optimal model for estimating standard residuals, with all the estimated results in Table 3. It can be seen that the GARCH (1,1) model performs well, which lays a good foundation for further DCC-GARCH model estimation.

Table 2. ARCH effect of the test results.

Digital currency	F-statistic	Obs*R-squared
BTC	3.670**	7.320**
ETH	4.922***	9.799***
XRP	3.615**	7.212**
LTC	19.308***	37.588***
BNB	6.377***	12.666***
XLM	5.339***	10.630***

Note: *** and ** represent the significance levels of 1% and 5%, respectively.
Source: Calculated by Stata 16.

Table 3. Estimation results of the GARCH (1,1) model.

Digital currency	category	variable	coefficient	Std. Error	z-Statistic	Prob
BTC	mean equation	γ	0.003	0.001	2.153	0.031
	variance equation	ω	7.96E-05	1.07E-05	7.467	0.000
		u_{t-1}^2	0.068	0.008	8.970	0.000
		σ_{t-1}^2	0.887	0.013	68.624	0.000
ETH	mean equation	γ	0.003	0.001	1.739	0.082
	variance equation	ω	0.0001	2.52E-05	5.618	0.000
		u_{t-1}^2	0.068	0.008	8.940	0.000
		σ_{t-1}^2	0.882	0.014	62.334	0.000
XRP	mean equation	γ	−0.001	0.001	−0.639	0.523
	variance equation	ω	0.0003	2.46E-05	13.720	0.000
		u_{t-1}^2	0.467	0.020	23.804	0.000
		σ_{t-1}^2	0.610	0.012	49.151	0.000
LTC	mean equation	γ	0.002	0.002	1.310	0.190
	variance equation	ω	0.0003	3.95E-05	7.005	0.000
		u_{t-1}^2	0.089	0.010	8.572	0.000
		σ_{t-1}^2	0.830	0.019	42.685	0.000
BNB	mean equation	γ	0.003	0.001	2.414	0.016
	variance equation	ω	0.0001	1.41E-05	7.304	0.000
		u_{t-1}^2	0.143	0.010	13.294	0.000
		σ_{t-1}^2	0.843	0.010	82.445	0.000
XLM	mean equation	γ	0.625	0.013	49.014	0.000
	variance equation	ω	0.0003	3.03E-05	10.407	0.000
		u_{t-1}^2	0.404	0.026	15.793	0.000
		σ_{t-1}^2	0.575	0.021	27.456	0.000

Source: Calculated by Stata 16.

In the next section, the DCC-GARCH is established based on the results of the GARCH (1, 1) model. The estimation results are shown in Table 4. From the estimation results in Table 4, it can be seen that all the DCC-GARCH models operate well and stably. In other words, the dynamic relationship revealed by the model is effective, which can reveal the correlation between digital currency price fluctuations.

Specifically, the correlation coefficient is positive and passes the test at a significance level of 1%, which fully proves that there is a significant correlation between the digital currency price fluctuations. From the perspective of the impact coefficient, the calculated correlation coefficients are in the interval [0.719, 0.933]. According to the correlation strength classification criteria of 0.1–0.3 for weak correlation, 0.3–0.5 for medium correlation, and 0.5–1 for strong correlation, it can be judged that there is a strong correlation in the digital currency price fluctuations. Among them, the dynamic conditional correlation coefficients of Bitcoin-Ethereum (BTC-ETH), Ethereum-Ripple (ETH-XRP), Ethereum-Binance Coin (ETH-BNB), Ripple-Litecoin (XRP-LTC), Ripple-Binance Coin (XRP-BNB), and Litecoin-Binance Coin (LTC-BNB) are above 0.85, suggesting that the strength of the correlation is evident.

Table 4. Estimation results of the DCC-GARCH model.

Digital currency	a	b	Correlation	$a+b$
BTC-ETH	0.111***	0.796***	0.868***	0.907
	(7.44)	(33.83)	(63.37)	
BTC-XRP	0.039***	0.945***	0.781***	0.984
	(7.78)	(157.71)	(22.89)	
BTC-LTC	0.087***	0.788***	0.834***	0.875
	(8.00)	(46.67)	(60.26)	
BTC-BNB	0.037***	0.954***	0.795***	0.991
	(5.84)	(129.08)	(15.74)	
BTC-XLM	0.109***	0.811***	0.719***	0.920
	(4.76)	(15.52)	(25.58)	
ETH-XRP	0.039***	0.949***	0.858***	0.988
	(8.30)	(182.60)	(31.64)	
ETH-LTC	0.045***	0.943***	0.925***	0.988
	(8.02)	(151.70)	(39.86)	
ETH-BNB	0.086***	0.879***	0.779***	0.965
	(4.77)	(32.75)	(24.09)	
ETH-XLM	0.068***	0.890***	0.812***	0.958
	(6.45)	(80.35)	(34.48)	
XRP-LTC	0.047***	0.947***	0.901***	0.994
	(9.61)	(193.46)	(17.47)	
XRP-BNB	0.024***	0.975***	0.917***	0.999
	(6.93)	(253.35)	(5.07)	
XRP-XLM	0.084***	0.805***	0.847***	0.889
	(7.77)	(43.30)	(61.38)	
LTC-BNB	0.059***	0.936***	0.933***	0.995
	(11.31)	(6.64)	(95.95)	
LTC-XLM	0.086***	0.888***	0.790***	0.974
	(6.82)	(56.79)	(20.68)	
BNB-XLM	0.040***	0.951***	0.724***	0.991
	(4.58)	(93.53)	(11.04)	

Note: *** represents the significance levels of 1%.
Source: Calculated by Stata 16.

The dynamic condition correlation coefficients of the remaining digital currency 'pairs' also exceed 0.6, which is greater than the lower limit critical value '0.5' of strong correlation criteria.

Besides, the reason for the high correlation between the price fluctuations of Ethereum-Litecoin (ETH-LTC) and Ripple-Stellar (XRP-XLM) is the consistency of underlying technology. Ethereum and Litecoin have similar technical implementation principles, and the development of Stellar is based on Ripple. Furthermore, the correlation of Bitcoin-Ethereum (BTC-ETH), Bitcoin-Litecoin (BTC-LTC), and Bitcoin-Binance Coin (BTC-BNB) are closely concerned with endogenous anchoring. In other words, the developments of these digital currencies anchor to Bitcoin, so they have a natural 'strong connection' with Bitcoin. The remaining digital currency 'pairs', such as Bitcoin-Ripple (BTC-XRP), showed a high correlation between price fluctuations, which was quite different from the above situations. Their underlying technology has a low correlation, and they are less endogenously anchored. So, the high correlation of price fluctuation of this digital currency 'pair' mainly stems from investment followership. The immature development of the digital currency market and incomplete information lead investors to blindly follow the authority, resulting in an obvious 'herding effect' that plays a role in the correlation of all digital currency price fluctuations to some extent. Generally speaking, the correlation of digital currency price fluctuations is relatively robust, with strong continuity and heterogeneity.

a and *b* described the influence of past information and hysteresis on the correlation of digital currency price fluctuations. In all models, the values of *a* are significantly positive at the 1% significance level, meaning that past information has a positive effect on the correlation of digital currency price fluctuations. This is consistent with the correlation mechanism of digital currency price fluctuations portrayed in theoretical analysis. In comparison, Bitcoin-Ethereum (BTC-ETH) has the largest *a* value, with a coefficient of 0.111. Whereas, Ripple-Binance Coin (XRP-BNB) has the smallest *a* value, with a coefficient of 0.024. This shows that the correlation of price fluctuations between Bitcoin-Ethereum (BTC-ETH) is the most sensitive to information, but the one of Ripple-Binance Coin (XRP-BNB) is less sensitive. In addition, the *b* values are positive at the significance level of 1%. This indicates that the correlation of digital currency price fluctuations has obvious path dependence characteristics, that is, it will be affected by the previous dynamic condition correlation coefficients. More precisely, Bitcoin-Binance Coin (BTC-BNB), Ripple-Binance Coin (XRP-BNB), Binance Coin-Stellar (BNB-XLM) all have higher *b* values with coefficients of 0.954, 0.975, and 0.951, respectively, showing a strong persistence effect of price fluctuation correlation. Besides, the values of the remaining digital currency 'pairs' also exceed 0.7, with a smaller difference. It can be seen that the path dependence of the digital currency price fluctuations is a general feature.

The above part has described the correlation of digital currency price fluctuation in a general way. Hence, what are the dynamic and time-varying characteristics of this correlation? Is there a 'contagion' in the digital currency market amid the impact of the COVID-19 pandemic? This section will describe the overall time-varying trend of digital currency price fluctuations, and find out whether there is 'contagion' among digital currency price fluctuations by observing and comparing the time-varying characteristics of the dynamic conditional correlation coefficient before and after the outbreak of the COVID-19 pandemic. In addition, it should be noted that December 31, 2019 is identified as the date of the outbreak of the COVID-19 pandemic, so this paper uses the day as a boundary to divide the study timelines into before the COVID-19 and during the COVID-19 pandemic. COVID-19 is a new virus and is so insidious that it is difficult to date its true outbreak. Therefore, for this study, the first exposure time of COVID-19 is assumed as the start time. According to the herd effect, only when COVID-19 is reported by media and known by investors can it have an impact on the investment behavior of digital currency market. Hence, after data retrieval, this paper determines December 31, 2019 as the outbreak date. At that time, Wuhan, China reported its first COVID-19 outbreak. Figure 3 shows the time-varying trend of the dynamic conditional correlation coefficients.

In terms of the overall trend, the dynamic correlation coefficients of the selected digital currencies show an upward trend, indicating the correlation of digital currency price fluctuations will continue to be increased and strengthened as time goes. By comparing the trend of dynamic correlation coefficients, it can be seen that the phenomenon of increasing correlation of digital currency price volatility is particularly evident in the first three months since the COVID-19 outbreak. During this period, the dynamic conditional correlation coefficients of the 15 digital currency 'pairs' generally show an increasing trend, which is in line with the definition of 'contagion'. In

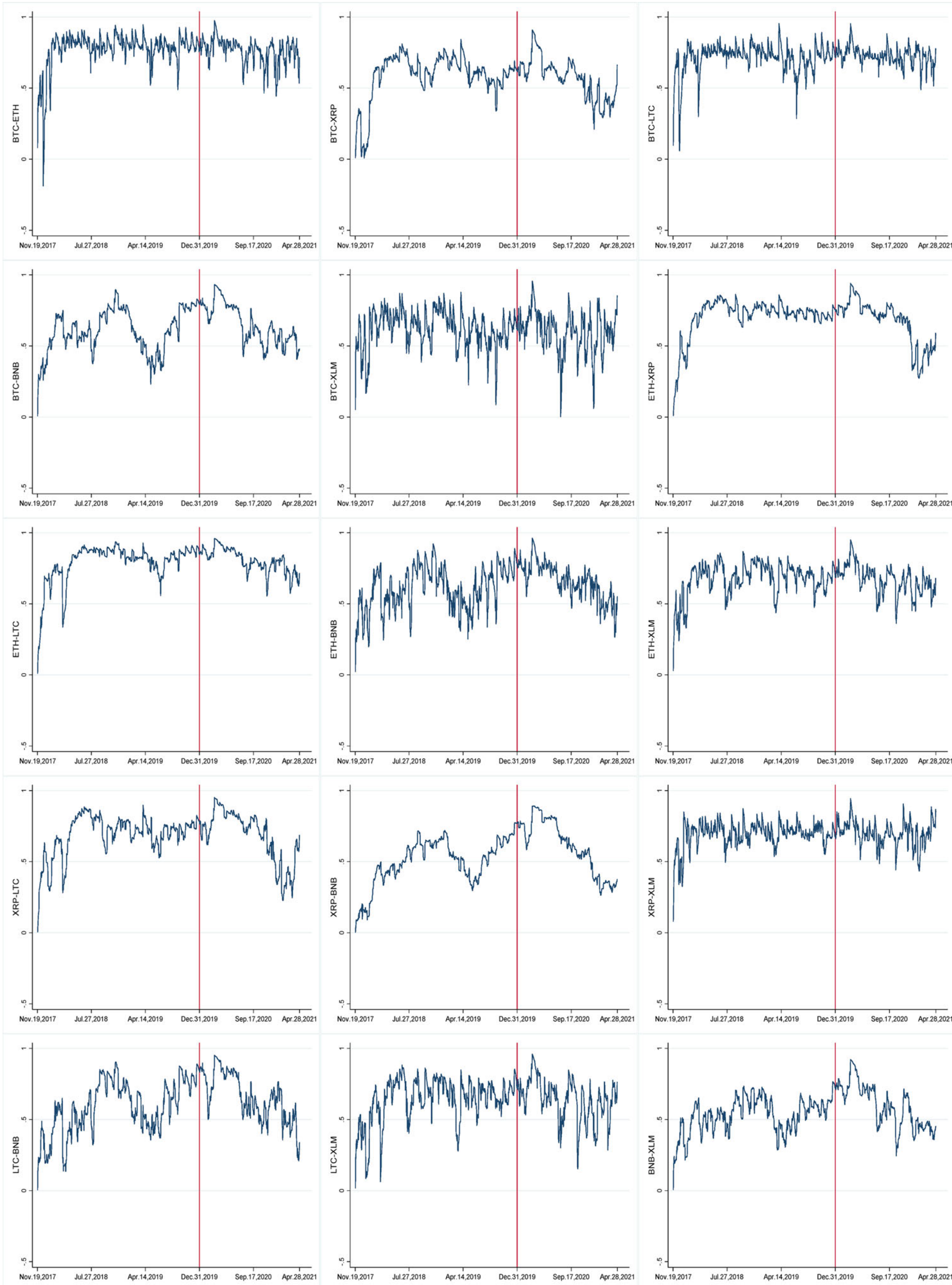

Figure 3. Dynamic conditional correlation coefficient graph of digital currency.
Source: Drawn by Eviews 10.0.

addition, when associating Figure 3 with Figure 2, it can be seen that 'contagion' in the digital currency market is correlated with price fluctuations during the COVID-19 pandemic, which is consistent with the findings of Antonakakis et al. (2019). That is to say, the global COVID-19 pandemic will significantly increase market uncertainty, which coheres with the theoretical framework of this paper. Furthermore, the dynamic conditional correlation coefficients increase less in the first month of the COVID-19 pandemic and more in the second and third months, which may be related to extent of the COVID-19 pandemic outbreak and the information lag between the digital currency market and macroeconomic market.

5.3. Further discussion

The analysis mentioned above pointed out that there is a significant correlation between digital currency price fluctuations, manifested as the resonance phenomenon. So, which was the first to initiate the resonance phenomenon of price fluctuations among many digital currencies? In other words, where is the source of the correlation of digital currency price fluctuations? These questions cannot be answered by the DCC-GARCH model. Therefore, in this part, wavelet coherence analysis (WTC) was employed to detect the correlation strength, duration, influence direction, and the 'lead-lag' relationship, and further to find the 'contagious source' of price fluctuations. The wavelet coherence spectrum of 15 digital currencies 'pairs' was given in Figure 4. Thereinto, the color scale bar on the right side means the strength of the correlation (0–1) between the time series. The larger the value is, the stronger the correlation will be, otherwise, the correlation is weaker. In the meantime, the direction of the arrow reflects the phase relationship between each digital currency 'pair'. Arrow direction from left to right (→) indicates in-phase (positive correlation) between two time series, and that from right to left (←) means anti-phase (negative correlation). Besides, arrow directions of upper-right (↗) and lower-left (↙) suggest that the first variable is ahead of the second. But the arrows with upper-left (↖) and lower-right (↘) directions reflect that the first variable is lagging behind the second (same below).

In terms of correlation strength and duration, there was a significant price fluctuation correlation between digital currencies, existing in the short, medium, and long term. In addition, the further comparative analysis revealed that the price fluctuation correlation between Bitcoin and the other five digital currencies is stronger in the short term. This is particularly evident in the price fluctuations of Binance Coin-Ethereum (BTC-ETH) and Bitcoin-Litecoin (BTC-LTC), which are closely related to Bitcoin's position in the digital currency market. Specifically, Bitcoin has the largest market share and the highest market capitalization in the digital currencies market. Therefore, its 'every movement' will cause price fluctuations of other digital currencies. In particular, when subject to external shocks, Bitcoin will become the 'contagious source' of price fluctuations and create a synergistic fluctuation in the digital currency market. Moreover, the correlations of Ethereum-Ripple (ETH-XRP), Ethereum-Litecoin (ETH-LTC), and Ripple-Stellar (XRP-XLM) are also significant in the short, medium, and long term. Among them, the high correlation of Ethereum-Ripple (ETH-XRP) may be ascribed to the fact that they are closely linked to the real economy. Nevertheless, the high correlations of Ethereum-Litecoin (ETH-LTC) and Ripple-Stellar (XRP-XLM) are caused by similar technical implementation principles.

As for the influence direction and the 'lead-lag' relationship, the arrow directions between Bitcoin, Ethereum with the other five digital currencies were dominated by the upper-right(↗) in the short term. This forecasted that the price fluctuations of

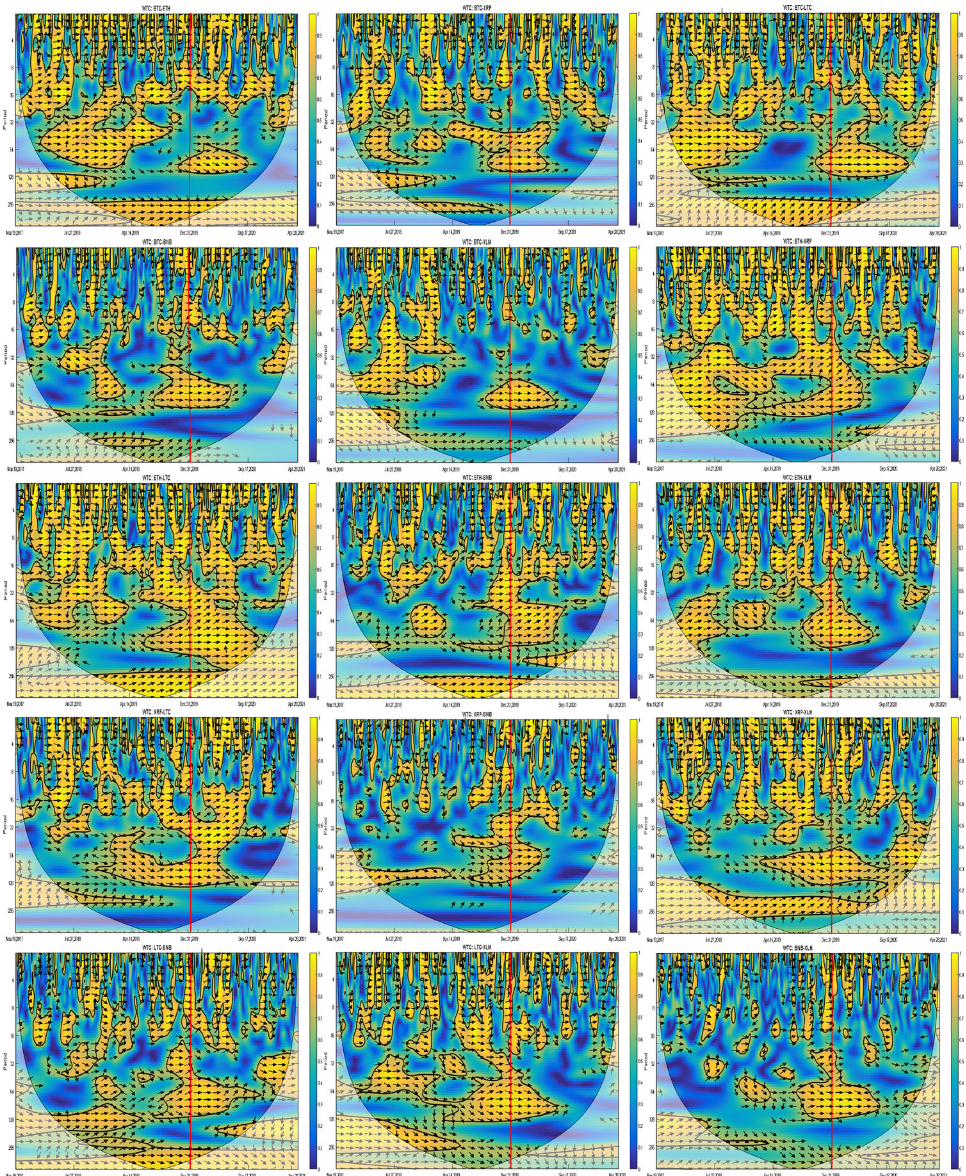

Figure 4. Wavelet coherence spectrum.
Source: Drawn by Matlab 2021a.

Bitcoin and Ethereum were ahead of those of other digital currencies in the short term. Whereas, in the medium term, the arrow direction of Bitcoin and Ethereum (BTC-ETH) shifted to the lower-right(↘), indicating that Bitcoin lags behind the price fluctuations of ETH. In addition, the arrow directions between Bitcoin, Ethereum, and Ripple with the rest of the digital currencies were both upper-right (↗) and lower-right (↘), but predominantly upper-right (↗), indicating that Bitcoin, Ethereum, and Ripple were ahead of those of other digital currencies. In the end, the arrow directions of Bitcoin-Ethereum (BTC-ETH) and Bitcoin-Ripple

(BTC-XRP) were lower-right(↘) in the long term, suggesting that Bitcoin lags behind Ethereum and Ripple.

Take the COVID-19 pandemic outbreak as an example. In Figure 4, the left area of the red line is in the period of pre-COVID-19 pandemic and the right area is during the COVID-19 pandemic. Focus on the right area of the red line, it can be seen that the right region has a higher percentage of yellow coverage (highly relevant regions) than the left region. Besides, the yellow coverage covers the short, medium, and long term, and the color scale is deeper in the medium and long term in the right region. This indicates that when the digital currency market is shocked by the COVID-19 pandemic, most digital currencies have shown positive resonance in the short, medium, and long term. That is, the COVID-19 pandemic has increased the correlation and contagion of digital currency price fluctuations. Moreover, in the right region, the price fluctuations of Bitcoin, Ethereum, and Ripple were ahead of other digital currencies, which is nearly consistent with the analysis of the overall 'lead-lag' relationship.

Based on the above analysis, it can be found that Bitcoin often takes the lead in price fluctuation in the short term. When Bitcoin is subject to market disruptions, it will react quickly and contagiously to other digital currencies, becoming a highly correlated 'contagious source' of digital currency prices in turbulent times. What's more, the price fluctuations of Ethereum and Ripple were ahead of other digital currencies in the medium and long term, becoming the contagious source for medium- and long-term price fluctuations. However, this may have something to do with the broad and diversified application scenarios of Ethereum. At present, applications of Ethereum have covered finance, Internet of Things, farmland, dining table, smart grid, etc. These scenarios are closely related to the economic environment and are key areas of government industrial policy focus, so they are more sensitive to the information of the real economy. Meanwhile, as a 'bridge currency', Ripple is an 'intermediary' used to exchange traditional fiat currencies, aiming to release capital that financial institutions would use as reserves, thus improving the efficiency of international remittances. In a sense, Ripple is a decentralized and full-currency financial transaction system. In the end, it can be seen that in the future, the price fluctuation of digital currency will not only affect the digital currency market itself but also have an impact on the real economy. Therefore, promoting digital currency to serve the real economy will be the focus of policy attention in the new era.

6. Conclusion and recommendations

This article used the 'contagion' model to reveal the theoretical mechanism of digital currency price fluctuation. Besides, based on theoretical analysis, this paper made comprehensive use of the DCC-GARCH model and wavelet coherence analysis (WTC) to prove the correlation, contagion, and 'contagious source' of digital currency price fluctuations. The results of the DCC-GARCH model indicated that there was a 'strong correlation' attribute in the price fluctuation of digital currency, and the spillover effect of different digital currency price fluctuation was extremely obvious. Meanwhile, from the perspective of evolutionary trends, the correlation had significant time-varying characteristics and generally showed an increasing trend, reflecting the characteristics of ‘contagion’. In addition, it’s particularly noteworthy that, to some extent, the outbreak of the COVID-19 pandemic magnified the correlation and contagion of digital currency price fluctuation. Furthermore, through the wavelet coherence analysis (WTC), this paper confirmed the ‘contagious source’. It is found that Bitcoin was in a leading position in short-term price fluctuation, being the major ‘contagious source’ of digital currencies. Whereas, in the medium and long run, Ethereum and Ripple, which were closely related to the real economy, had greater impacts on the price fluctuation of digital currencies, being the ‘contagious source’ of digital currencies. Based on the above findings, the policy recommendations implied in the study are as follows.

6.1. First, optimize the digital currency investment portfolio to meet the investment needs

The spillover effect of digital currency price fluctuation has different directions in different cycles. Therefore, accurately grasping relevant information is conducive to guiding institutional or individual investors to optimize their investment portfolios of digital currencies, enhance the rationality of investment structure, satisfy various investment needs. For risk-averse investors, when investing in short- and medium-term digital currencies, they should focus on holding digital currencies that are weakly correlated to Bitcoin, or portfolios with weak correlation. In this way, the correlation of assets in the portfolio can be largely reduced, then the overall return expectation of this portfolio can be further improved. But in the long-term investment, risk-averse investors should hold digital currencies such as Bitcoin, Ethereum, and Binance Coin that have opposite price fluctuations simultaneously to achieve the hedging of the investment portfolio. By contrast, risk-loving investors should focus on short-term and medium-term investment in digital currencies, and restock digital currencies associated with Bitcoin in their investment portfolio. Thus, the correlation between digital currencies is much higher, with a bigger risk. That is, high risk means high return, which is what risk-loving investors prefer.

6.2. Second, strengthen the cooperation of digital currency supervision and improve the efficiency of supervision

Empirical evidence revealed that there was a significantly strong correlation and contagion between digital currency price fluctuations. Therefore, at the regulatory level, digital currency regulation cannot have multiple standards, and it is bound to form a unified regulatory standard. If all countries supervise the digital currency according to their wishes, it will surely cause the duplication of regulation, regulatory gaps, and inefficiency of the digital currency. When confronted with such an open market, some countries can’t regulate while others do not, which would lead to an unhealthy operation. Therefore, countries need to reach a consensus through active and effective international cooperation on the legal definition of digital currency, issuance access mechanism, ICO fundraising, exchange, taxation, and regulatory conflicts. Besides, countries should adhere to the principle of ‘moderate regulation’ and the policy of ‘regulation in development, development in regulation’ to maintain the flexibility of regulatory policies and jointly build a balanced, safe, stable, and efficient global digital currency regulatory system to protect the global development of the digital currency. Meanwhile, in terms of the selection of regulatory objects, Bitcoin, Ethereum, and Ripple are the main contagious sources of digital currency price fluctuations, hence, countries should take these three digital currencies as the key regulatory objects when making regulatory rules.

6.3. Third, let digital currency return to the ‘currency’ attribute and serve the real economy

The empirical analysis revealed that in the long run, Ethereum and Ripple, which were closely related to the real economy, had greater impacts on the price fluctuation of digital currencies, being the ‘contagious source’ of digital currencies. Therefore, the supervision of digital currency should accurately distinguish the operating mechanism of various digital currencies, focus on standardizing the digital currency used for speculation, implement an approval system for the mining business, and effectively prevent the risk of digital currency price bubbles. At the same time, policy support should be provided for digital currencies that are diversified, wildly applied, and closely linked to the traditional economic system, to avoid the phenomenon of ‘bad currency expelling good currency’. Then, it is also much important to build bridges between this kind of digital currencies and the real economy, fully utilize the advantages of digital currencies as a means of payment, and better serve the real economy with the features of decentralization, low transaction costs, and high security.

Several issues need further focus in this paper. First, the range of digital currencies in this paper needs to be further expanded. In this article, only six typical digital currencies are selected as the research objects, but there are various digital currencies whose associated mechanisms are intricated, so necessary to expand the sample scope to make the research conclusion reflect the general law of digital currency price fluctuation on a larger scale and determine the ‘contagious source’ among digital currencies. Second, due to the limitations of data types, this paper does not establish an external mediation effect model to analyze the correlation of the digital currency price fluctuation. Third, this paper only reveals the general law and reason of the price fluctuation correlation and contagion. Nevertheless, the paper does not make an empirical analysis of how this price fluctuation contagion will affect a country’s financial system, monetary policy, and exchange rate system. All the limitations mentioned above will be improved in the future, meanwhile, these are also important research directions for our further research.

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Author contributions

S.J. and J.Z. conceived and designed the research questions. S.J. constructed the models and analyzed the optimal solutions. S.J., J.Z., S.Q. wrote the paper. J.Z., S.Q. reviewed and edited the manuscript. All authors have read and agreed to the published version of the manuscript.

Disclosure statement

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