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Co-movement between RMB and Bitcoin with Effects of DCEP Using Wavelet Coherence Analysis

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Utilizing wavelet coherence analysis, we investigate the correlation of fluctuations and phase differences between Bitcoin and RMB to identify capital flows between the two currencies. The effects of Digital Currency Electronic Payment (DCEP) on their co-movement are further analyzed. Our findings reveal that the RMB exchange rate leads the price of Bitcoin in all significant co-movement areas. Furthermore, it appears that from February 2017 to September 2018, the Sino-US trade frictions and US dollar interest rate hikes may have resulted in a long-term negative co-movement, which seems to have been driven by RMB and possibly indicated capital flows from RMB to Bitcoin. The short-term positive co-movement between November 2019 and July 2020 could be attributed to the COVID-19 pandemic. Finally, we also demonstrate that the DCEP trial event has the potential to strengthen the positive co-movement between these currencies.

Keywords: Bitcoin; DCEP; RMB exchange rate; wavelet coherence analysis.

1. Introduction

Bitcoin has always been an important research object in the fields of digital economy and blockchain since it was proposed by Nakamoto. There exist a variety of studies on different aspects of Bitcoin such as the hedging ability of Bitcoin [1, 2], the effects

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of critical events [3, 4], the market efficiency and long memory of Bitcoin [5, 6], the relationship and co-movement with other assets [7, 8], and the day-of-the-week effects of Bitcoin markets [9].

It is known that Bitcoin has the characteristics of decentralization, transaction anonymity and irrevocability which make it difficult to trace its transactions, thus providing a convenient way for capital flows without supervision which may relate to transnational financial crimes, especially in China [10]. Additionally, it has been found that Bitcoin has a stronger ability to resist panic shocks during the COVID-19 period compared to the S&P 500 index, FTSE 100 index and Shanghai Composite Index [11]. So we focus on the co-movement between Chinese currency (renminbi, RMB) and Bitcoin and try to find the capital flows between them.

Co-movement is widely studied in the field of finance. Shao *et al.* have several papers that use the symmetric thermal optimal path (TOPS) method to investigate co-movement and lead–lag relationships in financial markets [12, 13], focusing on the different lead–lag relationships in emerging and developed markets as well as the lead–lag structure between the crude oil spot and futures markets [14, 15]. Zhao and Dai studied the multifractal cross-correlation of economic policy uncertainty between China and US [16]. Co-movement represents a significant research area in relation to Bitcoin. Several studies have addressed the co-movement between Bitcoin and other influential variables. For instance, Dirican and Canoz presented evidence supporting a long-term co-movement between Bitcoin and major stock indexes [17]. Kang *et al.* examined the correlation and co-movements between the gold futures and Bitcoin markets [18]. Kumar and Ajaz investigated the time-varying co-movement patterns of cryptocurrency prices [19]. Goodell and Goutte employed wavelet analysis to study the co-movement between COVID-19 death and Bitcoin [7]. Shao *et al.* studied the multifractal behaviors of cryptocurrencies before and during COVID-19 [20]. Rehman and Kang explored the presence of a time-frequency co-movement between Bitcoin prices and Bitcoin mining, including energy commodities [21]. Using ARDL methodology, Ciaian *et al.* found that Bitcoin price changes were independent of other cryptocurrency price changes [22]. Bhuiyan *et al.* utilized wavelet analysis to analyze the lead–lag relationships between Bitcoin and multiple other assets [23]. Some studies have focused on the co-movement between Bitcoin and exchange rates. Chu *et al.* found evidence supporting the co-movement of Bitcoin exchange rates and standard exchange rates [24]. Kristjanpoller and Bouri investigated long-range cross-correlations and asymmetric multifractality between Bitcoin and major world currencies [25]. Baumöhl used the quantile cross-spectral method and found that major foreign exchange rates and cryptocurrencies (including RMB and Bitcoin) are significantly negatively correlated in both the long and short terms [26]. Palazzi *et al.* demonstrated that RMB affects the returns of Bitcoin via nonlinear causality and multivariate filter-BEKK-GARCH [27].

Wavelet analysis has been an effective tool for processing data of time series and stochastic process [28]. Likewise, to study the co-movement between two time series, one of the most important methods is wavelet coherence analysis [29]. There are some relevant studies using wavelet coherence analysis, as in [7, 23]. The wavelet coherence analysis can real-timely identify the degree and direction of co-movement between two time series and reveal the lead–lag relationship in time-frequency space [29]. However, for the co-movement between Bitcoin and exchange rates, the existing related studies have mainly adopted correlation-based approaches [27] that couldn't catch the lead–lag relationship real-timely which is important for the capital flows considered in this paper. Thus we adopt the wavelet coherence analysis to further study the co-movement between RMB and Bitcoin.

Furthermore, we take into account the impact of the forthcoming Digital Currency Electronic Payment (DCEP), which is China's sovereign digital currency and is currently being prepared for issuance by the People's Bank of China. This official digital currency of the central bank has the potential to enhance the internationalization of RMB [30] and facilitate government control of the cash economy in a more convenient manner. We posit that the introduction of DCEP will subtly affect both Bitcoin and RMB, particularly in terms of their co-movement. On the one hand, DCEP embodies the dual characteristics of digital and sovereign currency and may heighten public interest in both RMB and Bitcoin, thereby strengthening the link between the two [31]. On the other hand, DCEP possesses features of centralization and controllable anonymity. The compulsory adoption of DCEP will increase the difficulty of illicit fund transfers [32], potentially causing anxiety among domestic investors engaged in illegal activities, who may then shift their RMB holdings to untraceable assets like Bitcoin. However, the impact of DCEP on both RMB and Bitcoin has not been fully examined in the existing literature [26, 27]. For this purpose, in the ongoing trial phase of DCEP, we provide a preliminary discussion of the effects of DCEP trial events on co-movement. To the best of our knowledge, this paper is the first to consider the impact of DCEP when analyzing the co-movement between Bitcoin and RMB. Our findings provide an important reference for further research in the digital currency field and can assist policymakers in making informed decisions regarding risk prevention.

The paper is organized as follows: Sec. 2 introduces the wavelet coherence analysis used in this paper. The data and DCEP trial events are described in Sec. 3. In Sec. 4, we report and discuss the main results. Our work is concluded in Sec. 5.

2. Wavelet Coherence Analysis

This part introduces the main method used in this paper to estimate the co-movement between RMB exchange rate and Bitcoin price.

The mother wavelet function (ψ) used in this paper is the Morlet function. It has the equation $\psi(t) = \pi^{-\frac{1}{4}} e^{-i\omega_0 t} e^{\frac{-t^2}{2}}$ and is applied on narrow observations. The Morlet wavelet function is a complex variable function. Thus it is still a complex variable function after continuous wavelet transformation.

Given a time series $\{x(t) \in L^2(R)\}$, its continuous wavelet transform (CWT) is

$$W_{x,\psi}(\tau, s) = \langle x(t), \psi^*_{\tau,s}(t)\rangle = \int_{-\infty}^{\infty} x(t)\frac{1}{\sqrt{|s|}}\psi^*\left(\frac{t-\tau}{s}\right)\mathrm{d}t, \tag{1}$$

where s is the scale factor, τ is the translation factor and $*$ denotes the complex conjugate. The position of the wavelet in the time domain is determined by τ, and the position in the frequency domain is determined by s.

The wavelet power spectrum can measure the change of the local variance of time series. The wavelet power spectrum of time series $\{x_n\}$ is defined as

$$(\mathrm{WPS})_x(\tau, s) = |W_x(\tau, s)|^2. \tag{2}$$

The larger the value of $(\mathrm{WPS})_x(\tau, s)$, the greater the volatility of the time series $\{x_n\}$.

CWT is used to analyze the multi-scale analysis of a single variable. Similarly, the cross wavelet is used to study the coherence relationship between two variables in time and frequency. For time series $x = \{x_n\}$, $y = \{y_n\}$, the cross wavelet transform of the two series is defined as

$$W_{xy,\psi(\tau,s)} = W_{x,\psi(\tau,s)} W^*_{y,\psi(\tau,s)}. \tag{3}$$

On the basis of cross-wavelet transform, the cross-wavelet power spectrum of two time series is defined as

$$(\mathrm{XWP})_{xy} = |W_{xy}|. \tag{4}$$

The size of the cross wavelet power spectrum indicates the strength of the coherence of the two time series. The larger the value of $(\mathrm{XWP})_{xy}$, the stronger the coherence of the two time series.

Wavelet coherence measures the coherence relationship between two time series in the time and frequency domain. The wavelet coherence of x and y is defined as follows:

$$R_{xy} = \frac{|S(W_{xy})|}{[S(|W_x|^2)S(|W_y|^2)]^{1/2}}, \tag{5}$$

where S is the smoothing operator, satisfying $S(W) = S_{\mathrm{scale}}(S_{\mathrm{time}}(W_n(s)))$, S_{scale} means smoothing along the scale axis, S_{time} means smoothing along the time axis. R_{xy} ranges from 0 to 1, the larger the value of $R^2(\tau, s)$, the stronger the co-movement of the two time series. However, since the square of wavelet coherence can only take a positive value, this method cannot distinguish between positive and negative co-movements. One way to solve this problem is to use the phase difference to capture the two possible joint motions. Wavelet coherence phase difference is defined as

$$\Phi_{xy}(\tau, s) = \tan^{-1}\left(\frac{\Im\{W_{xy}\}}{\Re\{W_{xy}\}}\right) \in [-\pi, \pi], \tag{6}$$

where $\Im$ and $\Re$ are the imaginary and real parts of the smooth cross wavelet transform, respectively.

The phase is indicated by a black arrow on the wavelet coherence diagram. A phase difference of zero means that the movements of the two time series are consistent. The arrow pointing to the right (left) represents time series of positive (negative) correlated fluctuations. The upward arrow indicates that the first time series leads the second time series by $\pi/2$; the downward arrow indicates that the second time series leads the first time series by $\pi/2$. The lead–lag relationship obtained through wavelet coherence analysis is calculated on the premise of detecting co-movement, revealing certain causality in the sense of the sequence of data fluctuations [33, 34].

Compared to traditional statistical methods, wavelet analysis is capable of analyzing nonlinear and non-periodic time-series data. It does not require strict model assumptions prior to data analysis, making it more flexible to use than traditional statistical methods. Note that the wavelet transform extracts the fluctuation information of series rather than the overall trend. Thus the wavelet coherence provides us with correlations for inherent fluctuations rather than the visible overall trend.

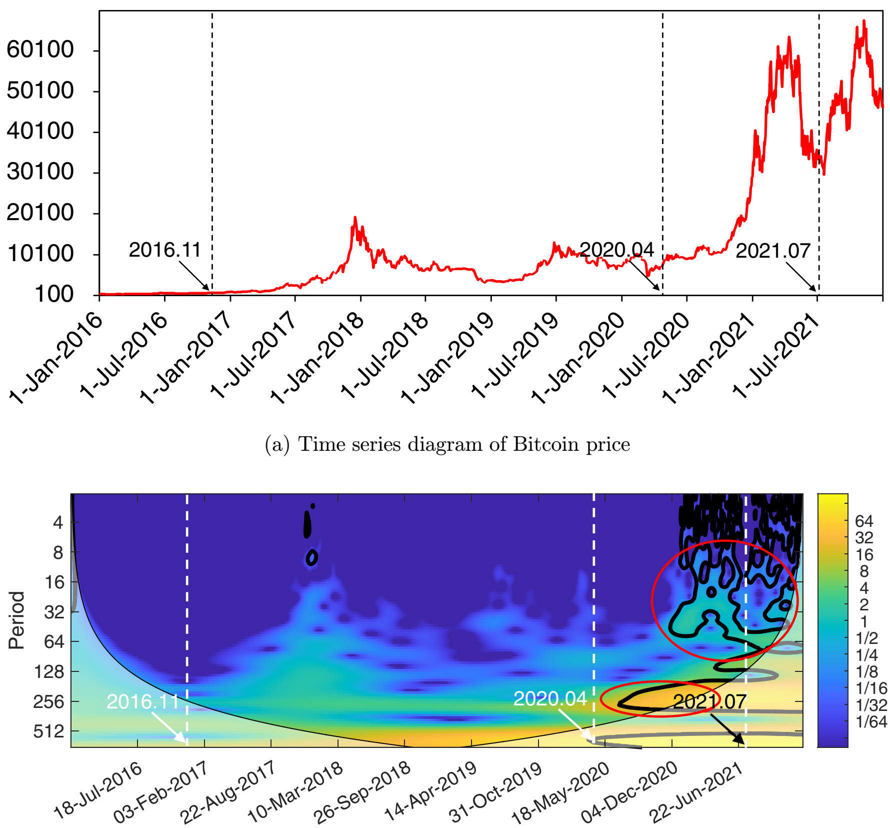
3. Data and DCEP Events

In this section, we introduce the data and related DCEP trial events in this paper. This paper focuses on examining the co-movement between RMB and Bitcoin and exploring the capital flows between them, which are typically reflected through price changes. Thus the prices of Bitcoin and RMB are used in this paper. Besides, the effects of DCEP trial events are further studied. In January 2016, the People's Bank of China held a seminar on digital currency, which clarified the strategic goal of issuing DCEP. Therefore, this date is selected as the starting date for this study.

For the purpose of this analysis, we collect daily prices from 1 January 2016 to 31 December 2021, for analysis. The Bitcoin prices were obtained from the closing price of USD as reported by CoinMarketCap (https://coinmarketcap.com/), while the exchange rate of RMB against USD was obtained from China foreign exchange trade system (refer to http://www.chinamoney.com.cn/). To account for missing values of exchange rates on weekends, we used linear interpolation. The final sample size was 2192. The missing values in our dataset are all from weekends and holidays when there are no exchange rate transactions, and therefore do not contain any volatility or information. The missing value imputation is only for methodological purposes, and any imputation method will add unnecessary volatility information. To avoid this, we use linear interpolation for imputation, which does not affect the calculation of wavelet coefficients due to the vanishing moments property of wavelet transforms (which implies that polynomial interpolation does not affect wavelet coefficient calculations).

The dynamics of the two prices series are shown in Figs. 1(a) and 2(a), respectively. To analyze the effects of DCEP trial events, the following three representative key events of DCEP trial operation are selected.

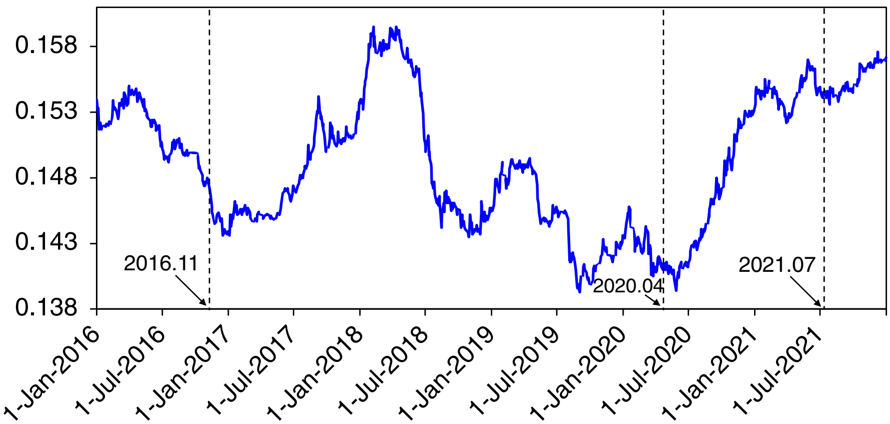
- Event 1: In November 2016, the central bank of China decided to use the digital trading platform as a trial application scenario of DCEP. It marked a development from the exploration of digital currency concept to experimental proof.
- Event 2: In April 2020, DCEP began to carry out trials in multiple cities. marking the entry of DCEP development into the practical stage.
- Event 3: In July 2021, the central bank officially released a white paper on the development of China's Digital RMB, which clarified the legal tender status of DCEP and noted the potential risks of Bitcoin to financial security and social stability, marking a new stage in the development of DCEP.



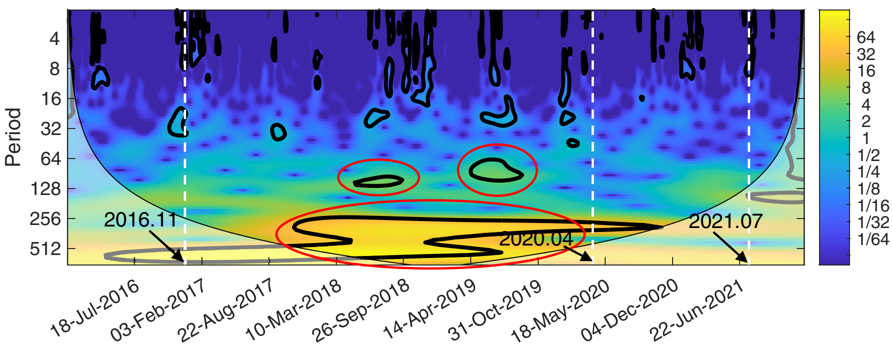
(a) Time series diagram of Bitcoin price

(b) Continuous wavelet power spectrum of Bitcoin Price

Fig. 1. CWT power spectrum of Bitcoin price.



(a) Time series diagram of RMB exchange rate



(b) Continuous wavelet power spectrum of RMB exchange rate

Fig. 2. CWT power spectrum of RMB exchange rate.

4. Results and Discussions

In this section, we present a detailed analysis of the wavelet coherence between Bitcoin price and RMB exchange rate. The trend charts of Bitcoin price and RMB exchange rate against USD are depicted in Figs. 1(a) and 2(a), respectively. To further explore the dynamic behavior of these two time series, we also provide their wavelet power spectra in Figs. 1(b) and 2(b), respectively. The color scale on the right of each spectrum figure represents the energy of the power spectrum. The higher the energy, the larger the variance of the time series and the stronger the fluctuation. The black outlines represent the significance level of 5% for fluctuation. However, it is important to note that the areas outside the cone curve may be affected by the boundary effect and thus have little significance for analysis.

The wavelet power spectrum of Bitcoin price, as shown in Fig. 1(b), displays two distinct warm-colored areas (marked with red circles) indicating strong fluctuations in the series. The first area is located in the top-right corner of the figure, spanning from December 2020 to December 2021, with fluctuation periods of 8–64 days. The second area, in the bottom-right corner of the figure, begins in May 2020 and lasts until December 2021, with a fluctuation period of 256 days. During these periods of significant fluctuations in Bitcoin price, several events occurred that had important impacts on Bitcoin, including the outbreak of COVID-19 [35], changes in Bitcoin supply [36], and the strengthening of Chinese government regulatory policies [37, 38]. For details, in March 2020, the global spread of COVID-19 pandemic dealt a heavy blow to financial assets, including Bitcoin. Consequently, the price of Bitcoin dropped from nearly \$10,000 to a minimum of \$4,000. In May 2020, Bitcoin underwent its third reward halving, after which the price of Bitcoin once again exceeded \$10,000. In May 2021, three associations announced strengthening Bitcoin regulations, which caused the price of Bitcoin to plummet by 40%. Finally, in September 2021, the Chinese government issued a document deeming virtual currency-related business activities as illegal financial activities, which largely prevented the flow of domestic funds to the Bitcoin market and exacerbated Bitcoin's price volatility.

From Fig. 2(b), it can be observed that the fluctuations of the RMB exchange rate against USD are concentrated mainly from the beginning of 2018 to the end of 2020. Three significant higher-energy areas can be identified in the bottom middle of the figure (marked with red circles), with fluctuation periods of approximately 128, 128 and 256. During these periods, there were some significant events such as the Sino-US trade friction and the US interest rate hike, which could be the reasons for the dramatic fluctuations in the RMB exchange rate [39, 40]. Specifically, in March and June 2018, the Federal Reserve raised interest rates twice in a row and announced measures to escalate Sino-US trade frictions, causing the RMB to depreciate rapidly. In August 2018, the People's Bank of China restarted two policies of foreign exchange reserve risk requirement and counter-cyclical adjustment factor, which stabilized the RMB exchange rate. In December 2018, China and the United States reached a brief ceasefire agreement in the trade war, and the RMB exchange rate temporarily rebounded. In May and August 2019, the United States announced tariffs on goods shipped from China, causing the RMB to depreciate sharply. The spread of the COVID-19 pandemic in 2020 also resulted in financial market turbulence, which exacerbated the inherent fluctuations of the RMB exchange rate during that period.

Figure 3 illustrates the wavelet coherence and phase difference between Bitcoin price and RMB exchange rate. The color in the figure represents the strength of coherence between the two, while the arrow depicts the lead–lag relationship and phase difference between them. An arrow pointing to the right or left ($\rightarrow$ and $\leftarrow$) indicate that Bitcoin and RMB are in phase or out of phase, respectively. In-phase and out-of-phase relationships imply positive and negative correlations between the fluctuations of Bitcoin and RMB, respectively. An upward-pointing arrow ($\uparrow$) signifies that the first time series (Bitcoin) leads the second time series (RMB), while a

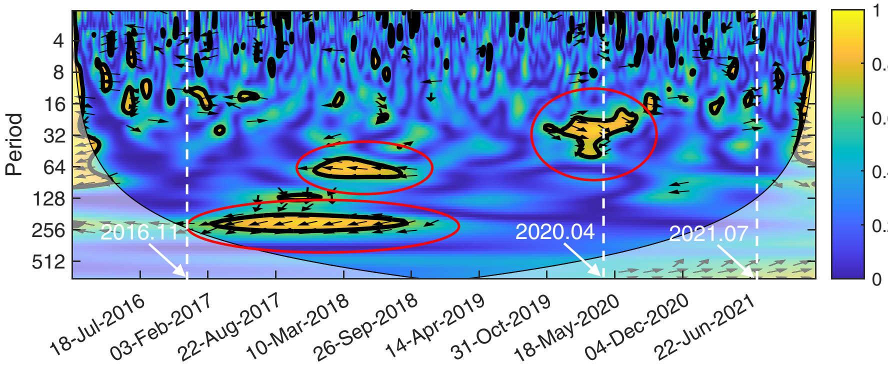


Fig. 3. Wavelet coherence spectrum of Bitcoin price and RMB exchange rate.

downward-pointing arrow (↓) indicates that the first time series (Bitcoin) lags the second time series (RMB). Thus, the arrow ↙ indicates that the first time series (Bitcoin) lags the second time series (RMB) and the two fluctuations are negatively correlated, and the same for the arrow ↘.

There are three significant high-energy areas marked with red circles in Fig. 3. These areas are denoted as Area 1 (February 2017 to September 2018), Area 2 (December 2017 to September 2018) and Area 3 (November 2019 to July 2020). Area 1 exhibits a long-term negative co-movement between Bitcoin and RMB, with a period of approximately 256 days and a majority of arrows pointing ↙, indicating that Bitcoin lags behind RMB. Area 2 has a shorter period of approximately 64 days, with mostly ←arrows indicating a negative linkage between the two fluctuations. These two high-energy areas occur between Events 1 and 2 (November 2016 and April 2020) and are not due to the trial operation of DCEP. It is worth noting that the wavelet power spectrum of RMB exchange rate also shows that there is a significant fluctuation area in this time range, which is likely caused by the combined effects of Sino-US trade frictions and US dollar interest rate hikes. We believe that the continuous combined effects contribute to the long-term negative co-movement led by RMB in Area 1, which may reflect capital flows from RMB to Bitcoin in certain time intervals. In December 2017, Bitcoin futures trading in CBOE and CME caused a price collapse in Bitcoin, while the RMB exchange rate continued to rise. These trends reinforce their inherent fluctuations in opposite directions and cause a shorter-term (64 days) negative co-movement in Area 2.

The high-energy Area 3, marked by red circles in Fig. 3, exhibits mostly bottom-right-pointing(↘) arrows with periods of 16–32 days, indicating that Bitcoin lags behind RMB, but there is a positive co-movement between the two. The COVID-19 pandemic broke out at the end of December 2019, coinciding with this time range, as well as with the occurrence of Event 2 of DCEP trial operation in April 2020. This short-term positive co-movement is likely due to the pandemic, as noted in [41], which found that Bitcoin could not serve as a safe haven during the outbreak and its

Table 1. Stationarity and Granger causality tests.

Test name	Null hypothesis	Statistics
ADF test	Bitcoin return series has unit root	-12.2570^{***}
	RMB return series has unit root	-11.8130^{***}
PP test	Bitcoin return series has unit root	-49.1960^{***}
	RMB return series has unit root	-46.6610^{***}
Granger test	RMB does not Granger cause Bitcoin	8.2143^{***}
	Bitcoin does not Granger cause RMB	0.2193

Notes: *** denotes the rejection of null hypothesis at the 1% significance level.

price fell alongside the S&P index. Both Bitcoin and RMB exhibited a similar downward trend after the pandemic until the latter half of 2020. As China controlled the pandemic and it spread to other countries, China's economy recovered, and investors from other countries began to view Bitcoin as a safe-haven asset, causing both Bitcoin and RMB to rise. The two trends strengthen the inherent fluctuations of Bitcoin and RMB in the same direction, leading to the short-term positive co-movement led by RMB shown in Area 3. Additionally, the news of DCEP pilot tests (Event 2) in April 2020 may have increased attention on both Bitcoin and RMB and strengthened the short-term positive co-movement led by RMB.

To further validate the lead–lag relationship between Bitcoin and RMB, we can also apply the Granger causality test which requires stationary time series. Thus the daily log-returns $\{r_t\}$ of Bitcoin and RMB are used for Granger causality test.

$$r_t = 100 \times \ln(P_t/P_{t-1}),$$

where P_t denotes the price at time t. The stationarity of two return series is tested via Augmented Dickey & Fuller (ADF) test [42] and Phillips & Perron (PP) test [43] for unit root. Results of stationarity tests are shown in Table 1, which suggest that both return series are stationary. Additionally, Table 1 presents results of Granger causality tests. As shown in Table 1, the RMB is the one-way Granger reason for Bitcoin, indicating that the RMB has a significant impact on Bitcoin, while Bitcoin has no significant impact on the RMB. This result is consistent with findings of the wavelet coherence analysis, which show that the exchange rate of RMB leads the price of Bitcoin in all significant co-movement areas.

5. Conclusion Remarks

Given Bitcoin's unique features of decentralization, transaction anonymity and irrevocability, it presents a challenge for tracking transactions and enables capital flows without proper oversight. In this study, we employed wavelet coherence analysis to investigate the co-movement between Bitcoin and RMB in the time-frequency domain, aiming to identify potential capital flows between them. Additionally, we examined the impact of DCEP on their co-movement, which to our knowledge, has not been considered in prior research. Our findings can serve as a valuable reference for further research in the field of digital currency.

The findings of this study revealed that the price of Bitcoin lagged behind the exchange rate of RMB in all significant co-movement areas, indicating that the fluctuations in the price of Bitcoin had less impact on the exchange rate of RMB, while the fluctuations in the exchange rate of RMB had an impact on the price of Bitcoin. The long-term negative co-movement between February 2017 and September 2018 could be attributed to the combined effects of Sino-US trade frictions and US dollar interest rate hikes, reflecting capital flows from RMB to Bitcoin. The short-term positive co-movement between November 2019 and July 2020 might be due to the COVID-19 pandemic, and the DCEP trial event could have strengthened this short-term positive co-movement led by RMB. Notably, this study is the first to consider the effects of DCEP when studying the co-movement between Bitcoin and RMB, making it an important reference for future research in the digital currency field.

All results are consistent with previous studies on the relationship between Bitcoin and RMB [26, 27]. However, we showed more new details. Baumöhl found that RMB and Bitcoin were negatively correlated in both long and short terms before December 2017 [26]. We confirmed this result and further detected a recent positive co-movement between them (from November 2019 to July 2020). Palazzi *et al.* concluded that the RMB affected Bitcoin based on daily log-returns from July 2010 to April 2020 [27]. We further gave two detailed intervals of effects (from February 2017 to September 2018 and from November 2019 to July 2020).

The detection of DCEP effects is our initial attempt. As analyzed in our work, they weren't detected effectively via wavelet coherence analysis since we could not exclude the effects of other key factors such as the COVID-19 pandemic. At the end of 2022, China has released an updated policy on COVID-19, which will definitely affect the co-movement between RMB and Bitcoin. It makes the study on effects of COVID-19 pandemic more interesting. Since both prices of Bitcoin and RMB are in USD, the USD index (not including RMB) may have impacts on both Bitcoin and RMB, which may produce spurious co-movement. we couldn't also exclude these effects. The two problems will be our future work. Besides, it is also interesting to integrate the detection of DCEP effects into wavelet coherence in future work.

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