Bitcoin and traditional currencies during the Covid-19 pandemic period

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5 April 2021

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Abstract

The objective of this study is to examine the movement of Bitcoin and the traditional currencies (USD, EURO, GBP and CNY) and the Bitcoin's hedging of the traditional currencies. First, this paper observes the Bitcoin and four traditional currency exchange series: the USD, EURO, GBP and CNY. Second, it examines the fluctuation patterns of each series by using wavelet transform analysis, Third, a wavelet coherence analysis is applied to examine the interdependence between the Bitcoin and the four traditional currencies. The phase pattern analysis results indicate that the Bitcoin may not act as a hedging currency to replace the traditional currencies during the Covid-19 crisis. Another interesting result shows the rapid increasing number of the World Covid-19 Deaths (CovidDeaths) may not be the critical reason for the hyper price of the Bitcoin. The massive quantitative easing (QE) may be considered as the key reason for the soar-up of the Bitcoin price.

Keywords: Bitcoin, Traditional currencies, Covid-19, CovidDeaths, Hedging feature, Wavelet Analysis

1. Introduction

Bitcoin is launched as a digital currency in 2009. It can be used as an electronic payment instrument and can also be traded for traditional currencies. An increasing number of researchers are showing their interests in analyzing the Bitcoin movement and its correlation with the economy. Böhme *et al.* (2015) introduces the concept and technologies relating to the Bitcoin and discuss the governance of the bitcoin. Demir *et al.* (2020) analyzed the relationship between cryptocurrencies and Covid-19. They found that there is a negative relationship between the Bitcoin and the numbers of Covid-19 infection and death cases. Nadarajah and Chu (2017) tested the weak hypothesis on the Bitcoin returns. They found that the bitcoin returns are market efficient, which is inconsistent with other researchers' results.

Looking at the Bitcoin's price history, in 2011, the Bitcoin price firstly jumped from $1 in April to $32 in June. The sudden increase was 3.2 times within merely three months. The second large jump appeared in2013. The Bitcoin trading started at $13.40 and the price shot up to $220 by the beginning of April 2013, followed by a sudden decline in the middle of April to $70. The third historical jump was in early October of 2015, the cryptocurrency was trading at $123.20 however, unexpected it spiked to $1156.10 by December, resulting in an approximately 10 times increase.

Since the Covid-19 pandemic spread the world, the Bitcoin price rose from USD5,030 in March of 2020 to USD28868.27 in December of 2020. The soar-up of the Bitcoin price astonished many economists and policy makers. As seen from the figure, Moreover, the daily transactions of the Bitcoin jumped from 330,000 in December of 2020 to 400,000 in early January of 2021. The number of the Bitcoins processed daily reached historical high value at the beginning of 2021.

This unique and unprecedented rapid growing pattern of the Bitcoin motivates our research on the analysis the Bitcoin's movement characteristics and its co-movement with four traditional currencies during the Covid-19 period. This study tries to shed light on the Bitcoin time series during the covid-19 pandemic.

There have been various studies on the Bitcoin or cryptocurrency. Jiang *et al.* (2021) examined various studies related to the research trend of cryptocurrency and found that research interest has shifted from bitcoin technical issues to economic application. Zhu *el al.* (2021) analyzed the relationship between new investors' attention and the characteristics of Bitcoin. They found that investors' attention impacts the return of Bitcoin in an intense manner. Li *et al.* (2021) applied wavelet-based quantile Granger causality to understand the relation between investors' attention and cryptocurrency-return. Their results showed that in the short run, investors' attention impacts the return of cryptocurrency more strongly in bearish markets compared to the bullish counterparts. García-Monleón *et al.* (2021) established a theoretical valuation model for the cryptocurrency. Kim *et al.* (2020) investigated the investors of the Bitcoin from the perspective of psychological status. They concluded that Bitcoin investors were distinct since they possessed these aspects: a) they seek for higher novelty; b) they have higher gambling tendencies; and c) they follow unique investment patterns. Li *et al* (2020) compared the US and Chinese Bitcoin market. They concluded that the two markets were interacted with each other. The US market is more sensitive than the Chinese market; however, larger volume of Bitcoin transactions are conducted in the Chinese market.

Liu et al (2020) applied game theory under imperfect information to analyze how to block the bad coins successfully. Nazifi *et al.* (2021) firstly examined and found the effectiveness of cryptocurrencies as the next generation of recovery tool. They suggested that firms should consider crypto-compensation strategies. Martinazzi and Flori (2020) analyzed the sensitivity of Lightning Network (LN) to the market dynamics of the Bitcoin. They found that the market dynamics of Bitcoin are not the influence factors to the topological configuration of the LN. Guo and Donev (2020) investigated 833 papers and found that early studies on the intellectual bases provided only fundamental understandings of cryptocurrency. They stated that the current studies more focus on analysis of cryptocurrency market

Siu and Elliott (2020) studied the pricing of Bitcoin options using SETAR-GARCH model and conducted numerical studies on the Bitcoin option prices using real bitcoins data. Caporale *el al.* (2021) examined mean and volatility spillovers among the Bitcoin, Litecoin and Ethereum, and the influences by cyber-attacks. Cyber-attacks are supposed to strengthen cross-market linkages; consequently, it makes cryptocurrency investors lose some portfolio diversification opportunities.

Kyriazis (2020) found that Geopolitical Risk Index (GPR) is a powerful predictor of Bitcoin returns and is a major idea for determining the diversifying or hedging characteristics of the Bitcoin and other major cryptocurrencies. It is revealed that the innovative Geopolitical Risk Index coined by Caldara and Iacoviello (2019) exerts negative impacts on Bitcoin markets. Manavi *et al.* (2020) applied matrix correction method to compare 7 compare 7 cryptocurrencies. They conluded that the cryptocurrencies are not decentralized. Urom *el al.* (2020) quantified the spillovers and dependence between the Bitcoin to other assets. They found that the dependency is insignificant, which indicates that the Bitcoin may act as a safe-haven for other assets during unstable markets.

Baur and Dimpfl (2020) indicated that Bitcoin cannot work as a currency. Kleina *et al.* (2018) concluded that Bitcoin and Gold hold absolutely different properties as assets; Bitcoin is not new Gold. Dyhrberg (2016a) analyzed the Bitcoin, Gold and the US dollar. He found that Bitcoin is neither Gold nor a currency (US dollar); it is something in between. Dyhrberg (2016b) indicated that Bitcoin holds hedging abilities against stocks and the US dollar in the short run.

There is a clear lack of studies on the Bitcoin and its interdependence with traditional exchange rates over different timescales. This paper applies wavelet analysis to detect the characteristics of the Bitcoin and its dynamic interdependence maps with the USD, EURO, GBP, CNY and Covid Deaths as well, which can precisely examine the factors influencing the fluctuation of the Bitcoin.

The contributions of this study are as follows: First, this paper applies wavelet analysis to examine the dynamic characteristics of the Bitcoin and its dynamic interdependence with four traditional exchange rates. This style of analysis is a nonlinear approach widely applied in various fields. However, it has not been commonly employed in studying the Bitcoin. To my best knowledge, this is the first study to employ wavelet analysis to examine the relationship between the Bitcoin and the four traditional currencies (USD, EURO, GBP and CNY) during the Covid-19 period. Second, the empirical analysis is novel in the context of checking coherence between the Bitcoin and the four traditional currencies in the Covid 19 crisis, which examines whether the Bitcoin has a hedging feature. It is confirmed that the Bitcoin has no hedging feature by using the phase-difference analysis. Third, it discusses the reasons for the soar-up of the Bitcoin price and suggests that not the rapid increasing number of CovidDeaths but the massive quantitative easing (QE) might be the critical reason for the hyper price of Bitcoin.

The rest of this paper is organized as follows. Section 2 introduces the wavelet analysis. In section 3, the data set is described. The empirical analysis is applied in section 4. The conclusion as well as the directions for future research are depicted in the closing section.

2. Wavelet transform analysis

Wavelet transform theory was launched by famous French engineers Grossman and Morlet (Morlet et al. 1982a, 1982b; Grossmann and Morlet, 1985; Everson and Sirovich,1990). Before that, the Fourier transform theory was widely applied in field of signal processing. However, the Fourier transform theory had the limitation that can only capture frequency information but not time information. Wavelet transform theory has been proved that it can successfully detect both time and frequency information in a local period (Morlet *et al.* 1982a, 1982b; Mallat, 1998, 1999, 2008; Mandelbrot, 1982, 1999). Recently, the theory has been extended to be applied to different fields, such as engineering, medical science, and economics. Widely, it is applied to examine the correlation relationship between two time series. For example, Jeong *et al.* (2016) detected Parkinson's disease and Alzheimer's disease by using the wavelet transform theory. Karabulut *et al.* (2020) analyzed the movement of commodity price and applied the wavelet transform analysis to examine the correlation between commodity price and world uncertainty. Currently, Demir *et al.* (2020) applied wavelet analysis to detect whether there are close relationships between cryptocurrencies and COVID-19. They found the relationships between the Bitcoin and the reported infection and death cases of Covid-19 are negative.

Wavelet transform analysis theory can be explained as below (Mallat, 1998, 1999, 2008; Torrence and Compo, 1988; Aguiar-Conraria and Soares, 2011; Chu, 2007).

(1) Continuous Wavelet Transform (CWT): the following formula describes the Continuous Wavelet Transform:

$$Wf(u,s) = \int_{-\infty}^{\infty} \emptyset^{*}(\frac{t-u}{s})\, f(t)dt \tag{1}$$

S and u represent the scale and time shift. $\emptyset(t)$ is defined as a mother wavelet. $\emptyset(\frac{t-u}{s})$ is derived from the mother wavelet and called as a daughter wavelet and * represents the complex conjugation. $f(t)$ is a function which can be transformed into $Wf(u,s)$ by multiplying a wavelet function. $Wf(u,s)$ is called as the wavelet coefficient, which is a function of a and b. When scale a is shorter (or longer), it means the frequency is higher (or lower). Normally, the mother wavelet should meet the following condition:

$$\int_{-\infty}^{\infty} \emptyset(t)\, dt \; = 0 \tag{2}$$

(2) Wavelet power spectrum (WPS): the wavelet power spectrum (WPS), which is defined as follows:

$$(WPS)_t(s,u) = \; |W_t\,(s,u)|^2 \tag{3}$$

WPS can be plotted as scalogram, which gives a visual representation of a wavelet transform, showing the magnitude in a designed color. If the magnitude of the color is strong, it indicates high oscillation. If the magnitude of the color is weak, it means the oscillation is weak. The local oscillation power of a time series $f(t)$ is expressed by the wavelet power spectrum (WPS).

Wavelet transform theory is widely applied to examine the interdependence of two-time series by using wavelet coherence. The following formula defines a wavelet coherence R_{xy} of the time series $x(t)$ and time series $y(t)$.

$$R_{xy} \; = \frac{|S(W_{xy}\,(s,u))|}{[S(\,|W_x(s,u)|^2)\; S(|W_y(s,u)|^2\;\;)]^{\;1/2}} \tag{4}$$

Here, S is a smoothing operator. ${R_{xy}}^2$ is between zero and one. The closer the value of ${R_{xy}}^2$ is to 1, the stronger the interdependence between the two-time series $x(t)$ and $y(t)$. Further, phase-difference can be applied to examine interdependent patterns and lead-lag relationships between the different two time series. Another important concept is phase-difference. The phase-difference is defined as follows:

$$\varphi_{xy} \; = tan^{-1}\left(\frac{Im\{S(W_{xy}(s,u))\}}{Re\{S(W_{xy}(s,u))\}}\right), \quad \varphi_{xy} \; \in |-\pi, \pi\, | \tag{5}$$

According to different values of φ_{xy}, interdependent patterns of two time series can be examined. On wavelet coherence plots, the phase is represented by arrows which point to various directions. When two time series are examined to have the same frequency at the same observation, the two time series are defined as phase coherence. If one cycle is located slightly ahead of the other cycle in time, it means the ahead cycle leads the other one. If there is no phase difference between two time series, it means the two time series move together. When the arrows on the wavelet coherence plots are pointing to the right (left), it implies time series are positively (negatively) correlated without any series leading the other. The positive (negative) coherence is called in phase (out of phase). Furthermore, when arrows are pointing to the up right (up left) or the down left (down right), it means the series are in phase (out of phase) as well. Additionally, if the arrows are pointing vertically downward (upward), it means that the first (second) time series leads the second (first) one.

3. Data

The data used in this paper are the daily closing data from 2021.01.01 to 2021.02.22. Data were collected from the database provided by the Investment Com. Here, Bitcoin price and all the four currencies are expressed in Japanese Yen. Such that, we have five time series: Bitcoin, CovidDeaths, USD, EURO, POND and CNY.

Figure 1 displays the above six time series. It is clear that the Bitcoin is completely moving differently from the four currencies. The Bitcoin keeps increasing and reaches incredible high in the beginning of 2021. In fact, the Bitcoin soared up at the historical high point of 52993.2 on February 19, 2021.

Regarding the traditional four currencies, the USD, GBP and CNY show similar movement during the beginning of the breakout of Covid-19 from January 2020 to February 2020. Interestingly, the EURO displayed comparatively low fluctuation. This similar movement kept until June of 2020. Since July 2020, USD began to display a discrepant pattern of movement from other three currencies (USD, EURO and CNY). This implies that the USD was impacted by the Covid-19 pandemic since the USA reached the world's largest numbers of new cases and deaths of the Covid-19.

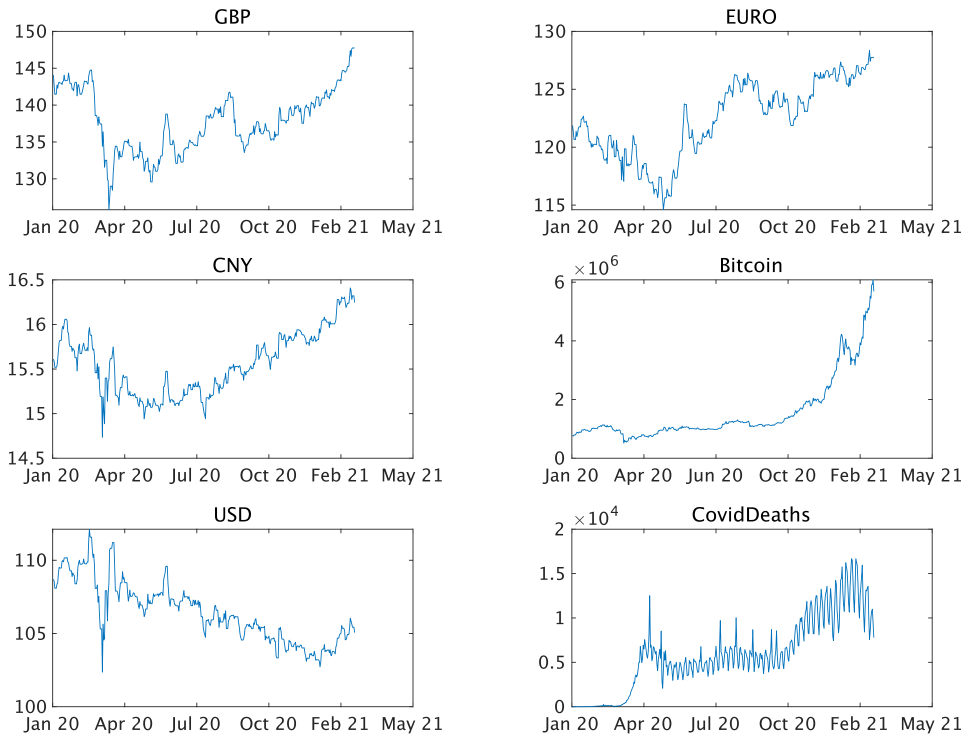


Figure 1. Time series of five exchange rates

Note: The data period is from 01 Jan 2020 to 22 Feb 2021. The data were extracted from the database provided by Investment Com (https://www.investing.com/currencies/).

4. Empirical results

4.1. Wavelet transform analysis results

Figure 2 to 7 plot the wavelet transforms of the Bitcoin, EURO, USD, GBP, CNY and CovidDeaths. It is interesting to note from the Figure 2 that there are no clear periodicals detected for Bitcoin price movement from Jan of 2020 to Dec of 2021. However, A periodicity centered at 45 days, appeared from 15 December 2020 to 22 February 2021, which explains that the Bitcoin price began to fluctuate fiercely and periodically since the end of 2020.

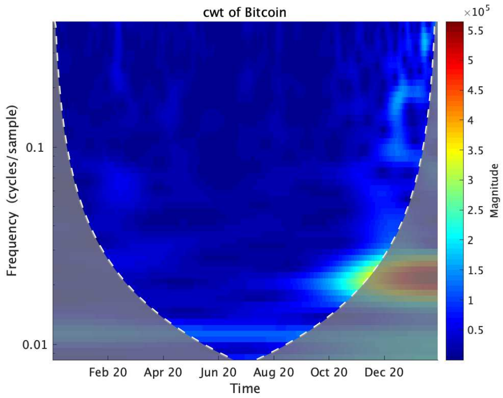


Figure 2. Wavelet Transform of Bitcoin

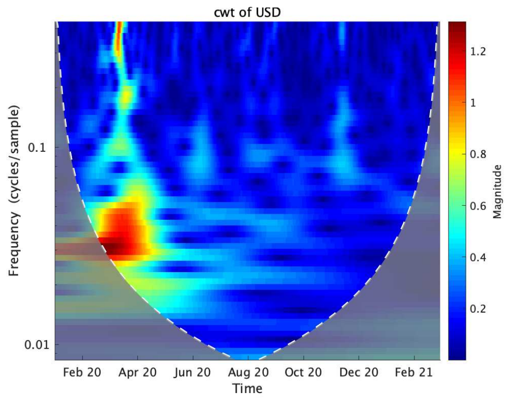
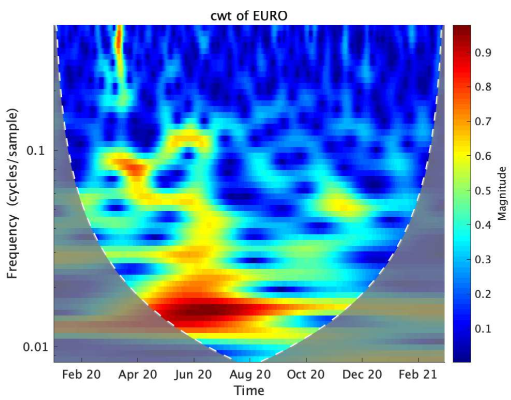


Figure 3. Wavelet Transform of USD

The USD displayed large fluctuations in several periodicity bands around 15 April 2020 (as seen in Figure 3). Short periodicity bands ranging from 1 day to 3 days appeared on 15 April 2020. And a long periodicity band which is centered around 33 days, from the beginning of January 2020 to the end of April 2020 was detected. Therefore, in April of 2020, both short and long periodicity bands are clearly confirmed. The results suggest that the USD fluctuated intensely and periodically in April of 2020 at which the Covid 19 pandemic spread to USA and all over the world. As noticed, on 6 April 2020 Japan make an emergency declaration.

As seen in Figure 4 and Figure 5, the EURO displays similar movement patterns with GBP. Both of them display more periodicity bands than USD from short to long periodicities. EURO had a clear 10 days periodicity band centered around 12 days, from 5 April 2020 to 25 April 2020. Further, EURO experienced a very strong periodicity band centered at 65 days from 25 April 2020 to 10 August 2020. GBP did not show a clear short periodicity as Euro did. However, it similarly experienced a longer strong periodicity although the periodicity band centered at 55 days is shorter than the EURO's at the same period. This suggests that the EURO and the GBP were closely comoved during April to August 2020.



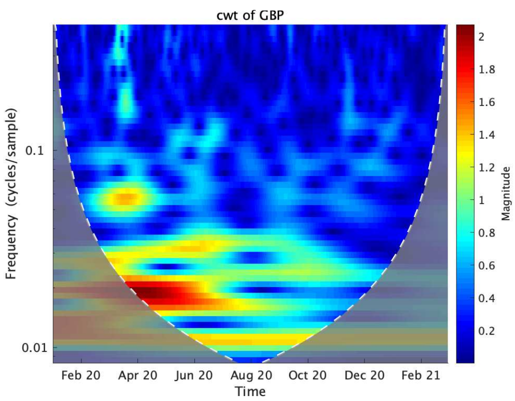


Figure 4. Wavelet Transform of EURO **Figure 5. Wavelet Transform of GBP**

On the other hand, as seen in Figure 6, CNY reveals no distinct periodicity bands during the whole period except one band in the beginning April 2020, which is centered at 32 days from February to the beginning of April 2020.

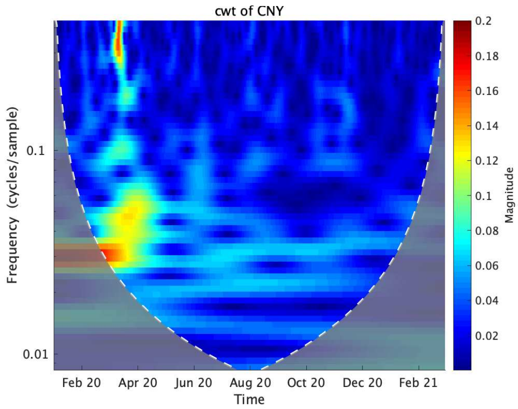


Figure 6. Wavelet Transform of CNY

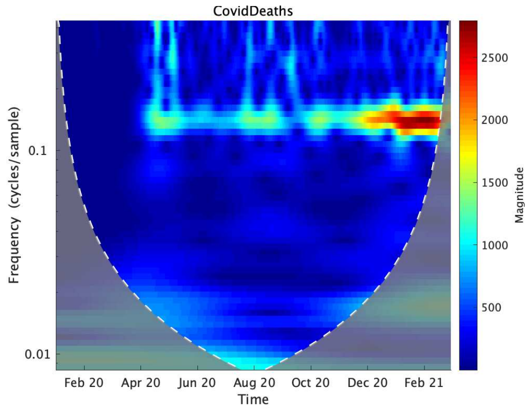


Figure 7. Wavelet Transform of CovidDeaths

Interestingly, the CovidDeaths only displays one periodicity band from December 2020 to February 2021. It implies that before the end of 2020, the number of CovidDeaths kept rising up with no sign of dropping downward. However, it displayed strong periodicity since the end of 2020, which means the situation of Coviddeaths has been relatively improved and has begun to show a strong periodicity. Nevertheless, the time series presented high vibration which explained the situation was still unstable till February of 2021.

4.2. Wavelet coherence analysis results

Seen from figures below, comparatively, the Bitcoin correlated with USD and GBP greater than with EURO and CNY. On the other hand, the Bitcoin has weak correlation with the EURO which is different from the GBP. We may suppose both UK and USA were influenced by the Covid 19 fiercely. And both countries were out of control. People may lose their confidence in USD and GBP so that they may invest more on the Bitcoin market.

Overall, weak correlations between Bitcoin and traditional currencies were examined except some long periodicity bands that are not significant. Interestingly, at a short band, negative interdependence was detected between the Bitcoin and USD. This implies that, during the crisis period, Bitcoin might act as a hedging currency instead of USD. Nevertheless, it is hard for Bitcoin replaces the USD and other traditional currencies to be an international currency. It is doubt that the Bitcoin could act as a hedging currency.

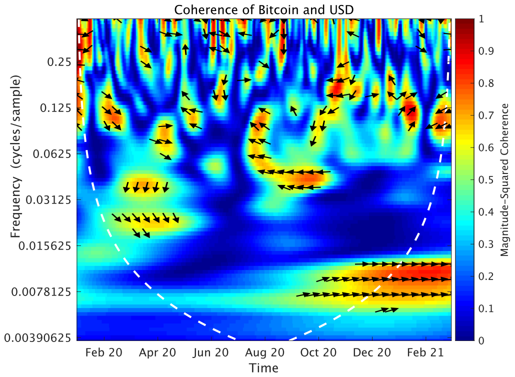


Figure 8

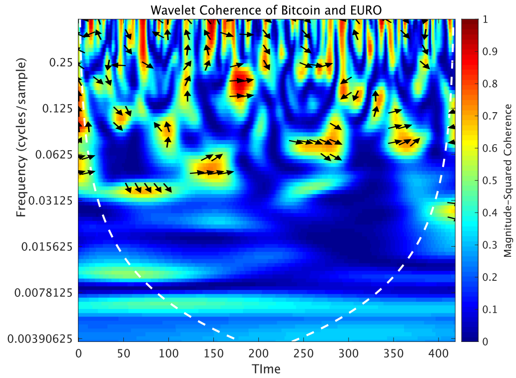


Figure 9

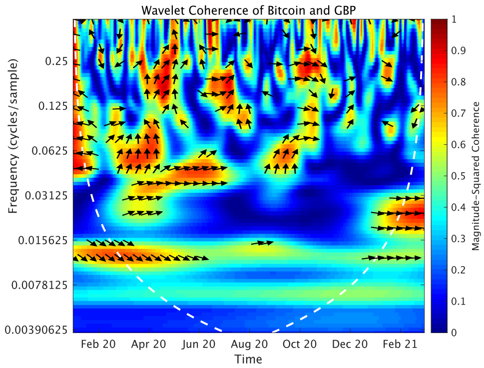


Figure 10

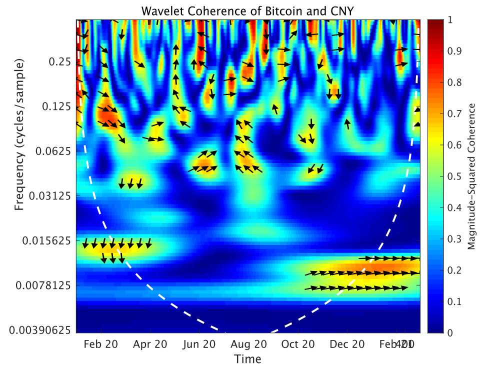


Figure 11

On the other hand, it is clear that Bitcoin has strong correlation with CovidDeaths during these four periods: January to February 2020, April to June 2020, July to August 2020, August to October 2020 and November 2020 to February 2021. Especially, from the end of 2020 to the beginning of 2021, Bitcoin was correlated with CovidDeaths with various periodicities ranging from 8 days to 3 months. This means that both the series move together displaying a tight comoving pattern. Moreover, the figure shows that most of the arrows are pointing from right to left denoting the CovidDeaths' co-movement with bitcoin. Both the number of CovidDeaths and the price of Bitcoin rise up fiercely.

Basically, there are positive relationships between the Bitcoin and the CovidDeaths. However, Aug 2020 to Oct 2020, negative correlation between Bitcoin and CovidDeaths was confirmed which suggests that the increasing number of Covid 19 caused decrease of Bitcoin price. Another negative coherence periodicity was detected from Nov of 2020 to Feb of 2021 but it was so strong. Positive correlations were examined at the two periods: one is at the beginning of 2020 and the other is from Nov of 2020 to Jan of 2021. Interestingly, from July to August of 2020, the arrows are pointing from bottom to top. This implies that the CovidDeaths led the Bitcoin. However, this did not last for a long time.

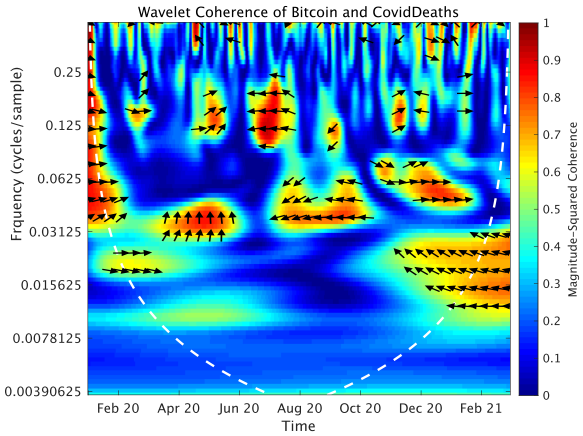


Figure 12

4.3. Reasons for the soar-up of the Bitcoin Price

During the period from March 2020 to June 2020, the arrows are pointing from bottom to top, which means the CovidDeaths lead the Bitcoin price. Surprisingly, during all the other periods, arrows are pointing from left to right or from right to left. We may suggest the rapid increasing number of CovidDeaths may not be the critical reason for the hyper price of Bitcoin.

Further, there are not strong negative or positive interdependence between the Bitcoin and the four traditional currencies. Thus, the fluctuation of the traditional currencies may not push the Bitcoin price skywards. The reasons why the Bitcoin soared up may be considered that the massive quantitative easing (QE) programmes were launched by central banks in the world, especially the Federal Reserve of USA. The Federal Reserve of USA has released trillions of dollars in stimulus to help saving US economy impacted by the Covid-19 crisis. Since people are holding much more cash in their hands and they may have lower belief in US dollars but high expectation on Bitcoin. This may be the critical reason to cause the Bitcoin price soar-up.

5. Conclusion

This study applies a nonlinear approach – wavelet analysis to examine the characteristics of the Bitcoin and its co-movement with four traditional currencies. The wavelet analysis is an effective tool in the study of the signal processing and recently widely applied in the engineering and medical sciences. However, wavelet analysis has rarely been applied to economics field. This study takes a challenge to use this nonlinear approach to study a new asset – Bitcoin.

The results show that the Bitcoin displays weak periodical vibration both in the short and long periodicity bands. It implies that the Bitcoin keeps going up without large fluctuation during the Covid-19 pandemic crisis. The results of the coherence between the Bitcoin and the four traditional currencies indicate that the Bitcoin has strong coherence relationships with USD, GBP and the CovidDeaths. This proves that the Bitcoin has a close interdependence with USD and GBP. Further the Bitcoin, USD and GBP were impacted largely by the Covid-19 pandemic. Meanwhile the correlation between the Bitcoin and EURO, the Bitcoin and the CNY were comparatively weak. This means that the EURO and CNY were less impacted by the Covid-19 pandemic. Nevertheless, the Bitcoin displays a long-term periodicity with CNY unexpectedly. Regarding a higher degree of correlation between the Bitcoin and USD, between the Bitcoin and GBP at long timescales during the end of 2020 and February of 2021, this implies that, in the long run, the Bitcoin may be considered to impact other traditional currencies, such as USD, GBP and CNY.

On the other hand, the phase patterns present that, the CovidDeaths leads the Bitcoin, and the Bitcoin leads the four traditional currencies. It implies that during the covid-19 pandemic crisis period, the Bitcoin became more significant, and it led the movement of traditional currencies.

Overall, the above results imply that, the Bitcoin, which is still under discussion whether it is an asset or currency, co-moves significantly with some of the USD, GBP and CNY. During the Covid-19 pandemic crisis, the Bitcoin became more important, however, it still could not act as a hedging currency to replace the traditional currencies. Further, the soar-up of the Bitcoin may result from governments' quantitative easing. These findings will be helpful for policymakers and foreign exchange market investors. In our further research we will conduct comparison analysis on the Bitcoin pre and post Covid-19 pandemic.

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