Research Article

Dynamic Connectedness of Major Digital Currencies: A Time-Varying Approach

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1. Introduction

With the rapid advancement of blockchain technology, the acceptance of digital currencies continues to grow, and digital currencies are gradually becoming a key element of public attention with their decentralized nature and positive stimulation of economic and social indicators [1]. The continuous increase in the market capitalization of digital currencies has determined them to be an essential force driving the development of global finance. The total market capitalization of digital currencies has reached 1.98 trillion, among which the market capitalization of Bitcoin (BTC) and Ethereum (ETH) has reached 21 billion and 11 billion, respectively, far surpassing the market capitalization of some national sovereign currencies (data were collected from CoinGecko on April 16, 2022). Digital currencies, represented by cryptocurrencies, are likely to become a mainstream financial asset in the future [2].

The continuous increase in the market capitalization of digital currencies has determined them to be an essential force driving global financial development. Research on digital currency connectedness has implications for the pricing of related financial products and the development of risk hedging strategies. This study aims to analyse the changing relationship among four prominent digital currencies over time. Our research period covers normal periods, outbreaks, and the post-epidemic phase. A refined TVP-VAR method was adopted to conduct this study, which ensures time-varying analysis and avoids errors caused by the rolling-window size and the calculation of the observation loss. It is found that the total connectedness of major digital currencies is in an upward trend in the majority of the time, which, however, dropped dramatically in 2020 as the epidemic spreads internationally. It is also found that ETH is a consistent spillover transmitter and that although BTC is often shown as a transmitter, its spillover initially declines considerably and then remains weak until recently. BNB and XRP are typically spillover recipients, with BNB’s spillover varying more greatly.
connection. Research on digital currency connectedness has implications for the pricing of related financial products and the planning of risk hedging strategies. The above is also the focus of our research in this paper.

The aim of this article is to investigate the connectedness among the major digital currencies. To be more precise, this study focuses on the four major digital currencies ranked by their market capitalization in March 2022 (i.e., BTC, ETH, BNB, and XRP; USDT and USDC, which have fixed exchange rates relative to the US dollar, were excluded). These currencies have different characteristics, with BTC being the earliest and currently the largest cryptocurrency in terms of market capitalization, ETH being more flexible due to the presence of smart contracts, BNB being developed on the basis of the largest cryptocurrency exchange, Binance, and XRP being the base currency of the Ripple network. These four digital currencies basically represent the mainstream digital currencies and are therefore the objects of this study.

A time-varying model was developed for the four currencies using the revised TVP-VAR method, and then the Diebold and Yilmaz’s [8] method was employed to measure their dynamic connectedness. This combined approach allows us to measure the time-varying relationships among these four digital currencies while avoiding the arbitrary setting of the rolling-window size.

Firstly, we find that the total connectedness has been moving higher for most of the time except for the year 2020 when the epidemic broke out but is significantly influenced by events and is very volatile from the beginning of the epidemic until now. We find that ETH and BTC generally have a positive spillover effect on other digital currencies, with ETH having the highest spillover effect and BTC having a higher spillover effect recently after a significant decline. The BNB and XRP have basically been influenced by other currencies, while the spillover effect of BNB is closer to zero recently. Through pairwise analysis, it is also proved that ETH has the most influence on other currencies and BNB is also influenced by its own related events significantly.

The layout of this study is as follows. Section 2 reports the data description and the methods of this study; data analysis results are described in Section 3, and Section 4 talks about the findings and conclusions of this study.

1.1. Literature Review. In addition to investigating the nature (e.g., protocol and architecture [9]) and function (e.g., currency substitution [10]) of digital currencies, there has been an emphasis on price-related research on digital currencies. Ample studies have been conducted to identify the patterns and characteristics of digital currency pricing. For example, Sirignano and Cont [11] used the deep learning method to find the universal features of digital currency pricing. Alessandretti et al. [12] and Fang and Chen [13] employed machine learning techniques to predict cryptocurrency prices and ascertain the price formation. The time-series characteristics of digital currency have also been explored. For example, Kyriazis [14] analysed the efficiency and profitable trading opportunities of digital currencies, and Livieris et al. [15] established a deep learning model to predict the time-series characteristics of digital currencies. Price-related risk has also attracted researchers’ attention. For example, Liu and Tsyvinski [16, 17] systematically analysed the risk components of cryptocurrencies and the corresponding benefits.

Time-varying parameter vector autoregression (TVP-VAR) has been widely used to study the dynamic connectedness between currencies or other financial instruments. For example, Wan and He [18] used this method to study the dynamic relationship among the currencies of G7 countries and found that the US dollar is a net transmitter. Primiceri [19] adopted this method to study monetary policy. Balcilar et al. [20] employed it to study the correlation between crude oil futures and commodity markets. Some scholars have also used this approach to analyse the association between digital currencies and other financial instruments, e.g., Dahir et al. [21] used it to study the interaction between Bitcoin and the stock market. For the connectedness of digital currencies, Balli et al. [22], Hasan et al. [23], and Ji et al. [24] adopted different methods to analyse the connectedness among multiple currencies in certain periods. However, it should be noted that these studies suffer from methodological limitations (e.g., the study of time varying is not precise enough, and it is difficult to avoid the errors caused by the manual setting of parameters), and that they mostly focused on the pre-COVID-19 periods.

1.2. Novelty. As for the novelty of our paper, first of all, our study covers a long period, which significantly improves the generalizability and soundness of the findings. To be specific, the situation of digital currencies in tight monetary environments has received little research. This is because during the fast development of digital currencies, national currencies were largely in a loose state. Our study spans the normal period, the epidemic outbreak period, the economic rescue period, and the recent post-epidemic period (i.e., inflation continues to increase and countries begin to tighten their monetary policies). The intensity of economic policies around the world, the dramatic changes in market value, and the characteristics of various digital currencies in recent years bring significance to our study. Second, a refined TVP-VAR method was adopted in our study, which ensures time-varying analysis and avoids errors caused by rolling-window size and the calculation of the observation loss. Third, the data analysed in this study come from the daily prices of four digital currencies that are the most popular and largest on the market. This helps make sure that our findings and conclusions are accurate and representative.

2. Data and Methodology

2.1. Data. The daily BTC, ETH, BNB, and XRP price data (in USD) were obtained from Yahoo Finance in the time period from January 1, 2018, to February 28, 2022. The log difference between the daily close price and the open price of the corresponding digital currency price is regarded as the daily price change which is denoted as $\Delta$. 

$\Delta$
As shown in Table 1, BTC, ETH, and BNB are in an appreciated state and XRP is in a depreciated state in the selected period. Their standard deviation reflects that they are all very volatile. The skewness of BTC, ETH, and XRP is negative, indicating that they are likely to depreciate significantly.

2.2. Methodology. We measure the dynamic connectedness by the refined method based on TVP-VAR, which is proposed by Antonakakis et al. [25]. This method is enhanced based on model proposed by Diebold and Yilmaz [8] in order to capture data changes in a more flexible and resilient manner. Additionally, it does not require setting the rolling-window size and calculating the observation loss.

The TVP-VAR model is as follows:

$$\Delta p_t = C_t \Delta p_{t-1} + \epsilon_t \sim N(0, \Sigma_t),$$
$$m(C_t) = m(C_{t-1}) + \text{vec}(\epsilon_t), \quad \text{vec}(\epsilon_t) \sim N(0, \Gamma_t),$$

(1)

where $C_t$ and $\Sigma_t$ denote the $k \times k$ dimensional matrices and $\Delta p_t, \Delta p_{t-1}$ and $\epsilon$ are $k \times 1$ dimensional vectors. $\Gamma_t$ is a $k^2 \times k^2$ dimensional matrix, while $m(C_t)$ and $\text{vec}(\epsilon_t)$ are $k^2 \times 1$ dimensional vectors. This model permits all parameters ($C_t$) to change over time. Furthermore, the variance-covariance matrices, $\Sigma_t$ and $\Gamma_t$, change over time. Then, using the Wold representation theorem, the model was transformed into a TVP-VMA model: $\Delta p_t = \sum_{i=0}^{\infty} A_i \epsilon_{t-1}$, where $A_i$ represents a $k \times k$ dimensional matrix of time-varying VMA coefficients.

Following Koop et al. [26] and Pesaran and Shin [27], we computed the H-step forward (scaled) generalized forecast error variance decomposition (GFEVD). The calculating process is as follows:

$$\phi_{ij,t}^{g} = \frac{\sum_{i=1}^{k} \sum_{t=1}^{H-1} (\epsilon_t A_{t,q} \epsilon_{t+1})^2}{\sum_{i=1}^{k} \sum_{t=1}^{H-1} (\epsilon_t A_{t,q} \epsilon_{t+1})^2},$$

$$\bar{\phi}_{ij,t}^{g} (H) = \frac{k \sum_{i=1}^{k} \phi_{ij,t}^{g} (H)}{\sum_{i=1}^{k} \phi_{ij,t}^{g} (H)},$$

(2)

where $\sum_{i=1}^{k} \phi_{ij,t}^{g} (H) = 1$ and $\sum_{i=1}^{k} \bar{\phi}_{ij,t}^{g} (H) = k$ hold, $\epsilon_{t}$ denotes a selection vector in the i-th place, and $\phi_{ij,t}^{g} (H)$ could be regarded as the pairwise directional connectedness from variable $j$ to $i$.

Based on GFEVD, we followed Diebold and Yilmaz [8] to measure the degree of connectedness. By calculating the average of all the directional connectedness, total connectedness ($TC_t$) indicates how tightly related the digital currencies are during the selected period, so

$$TC_t (H) = \frac{\sum_{i,j=1,i\neq j}^{k} \phi_{ij,t}^{g} (H)}{k} \times 100,$$

$$\bar{TC}_t (H) = \frac{\sum_{i,j=1,i\neq j}^{k} \bar{\phi}_{ij,t}^{g} (H)}{k} \times 100,$$

(3)

Directional connectedness is generally classified as either to-directional connectedness ($DC_{t\rightarrow j,t}$) or from-directional connectedness ($DC_{j\rightarrow t}$) based on the orientations involved.

Table 1: Description of our data (this table describes the main characteristics of the data we collected).

|                  | BTC       | ETH       | BNB       | XRP       |
|------------------|-----------|-----------|-----------|-----------|
| Mean             | 0.000674  | 0.000755  | 0.002261  | -0.000769 |
| Median           | 0.001220  | 0.001305  | 0.001009  | -0.001017 |
| Maximum          | 0.172248  | 0.230725  | 0.528936  | 0.444883  |
| Minimum          | -0.465006 | -0.550066 | -0.543173 | -0.549427 |
| Std. dev.        | 0.040060  | 0.051869  | 0.060278  | 0.062139  |
| Skewness         | -1.102441 | -1.079038 | 0.324479  | -0.076262 |
| Kurtosis         | 16.88042  | 13.64156  | 18.78201  | 15.45880  |

The to-directional connectedness of a digital currency is calculated by adding the pairwise directional connectedness from this digital currency to the other digital currencies, and the from-directional connectedness is calculated by adding the pairwise directional connectedness from the other digital currencies to this digital currency. So,

$$DC_{t\rightarrow j,t} = \frac{\sum_{i,j=1,i\neq j}^{k} \phi_{ij,t}^{g} (H)}{k} \times 100,$$

$$DC_{j\rightarrow t} = \frac{\sum_{i,j=1,i\neq j}^{k} \bar{\phi}_{ij,t}^{g} (H)}{k} \times 100.$$

Finally, we calculated the net connectedness ($NC_{ij,t}$), which refers to the net spillover of the specified digital currency, by reducing the to-directional connectedness by the from-directional connectedness. So,

$$NC_{ij,t} = DC_{i\rightarrow j,t} - DC_{j\rightarrow i,t}.$$

3. Analysis Results

3.1. Total Connectedness. The dynamics of the system’s overall connectedness are depicted in Figure 1. The total degree of connectedness fluctuates substantially across the given time period, with the data showing variations in the interval $[34.69, 71.46]$ and the mean value of 58.14. Also, Figure 1 shows that the second half of the period of total connectedness (i.e., after the outbreak of COVID-19) is more intense than the first half (i.e., before the outbreak of COVID-19). It is also shown by Figure 1 that the total connectedness is moving higher for the majority of the time except the year 2020. The year 2020 marks the global outbreak of COVID-19 when a significant decrease in total connectedness can be observed (Balli et al. [22] pointed out that economic uncertainty reduces the correlation of digital currencies, which supports this point sideways).

Some spikes and phases of fixed trends can be clearly observed in Figure 1 and Table 2, which correspond to some important economic nodes. The first peak occurred at the beginning of 2018 when various countries intensively released regulatory policies for digital currencies. The total connectedness first decreased rapidly, bottomed at the beginning of 2018, and then increased again. Meanwhile, connectedness among these four digital currencies was in a slow climb, but it topped out in early 2019 and then declined as the US continued to raise interest rates and trade wars took effect. The
decline did not end until the Libra White Paper was released in the cryptocurrency area in the middle of 2019, which significantly reversed the downward trend in connectedness and put it on a steady upward trend. In early 2020, with the outbreak of COVID-19 and its global spread, total connectedness experienced a rapid rise and reached its peak in March 2020. The connectedness was at the top from March to June 2020, when global stock markets, especially the US stock market, experienced several meltdowns, followed by bailouts, e.g., the announcement of unlimited QE in the US. Total connectedness then oscillated to the downside, with several bounces in the process, e.g., during the RCEP signing agreement. When the dollar index reached a new low in early 2021, total connectedness reached bottom. Then, the recovery of international economy and the continued rise in US treasury rates led to a rise in connectedness before entering a high shock phase in mid-2021, which continues to the present. The shock phase also has a slow upward trend, during which the world inflation level continues to move higher, e.g., in the US in late 2021 when it reached a new high.

The variation in the total connectedness indicates that international economic events as well as events in digital currencies exert a profound impact on the connections among digital currencies, while the impact varies from event to event.

3.2. Directional Connectedness and Net Connectedness. Table 3 shows that ETH is both the largest transmitter (i.e., the largest contribution to others) and the largest recipient (i.e., the largest connectedness from others). BTC follows in the second place, and there is not much difference between the two digital currencies. BNB is the smallest transmitter and recipient. Also, in terms of net connectedness value, BTC and ETH are both net transmitters, with ETH being the stronger one, and BNB and XRP are both net recipients, with BNB receiving more spillover.

Figure 2 shows that while BTC and ETH are net transmitters for most of the time, they also become net recipients sometimes. For BTC, it was a net transmitter until mid-2019, but net connectedness reached very close to zero in mid-2019, and it even became a net recipient for a while in late 2019. But net connectedness moved rapidly higher again in early 2021 and reached a high point in mid-2021. It was also at this point that El Salvador made bitcoin a national legal tender, the first country to make a virtual currency a national legal tender. However, BTC’s net connectedness then fell back down again and was very close to zero, followed by a slow increase recently. For the majority of the history, ETH has been a net transmitter, with only a brief period of being a net recipient in early 2018. It is worth noting that ETH went through a period of volatility from late
2020, due to improvements in late 2020 when ETH started to enter the ETH 2.0 era.

Similarly, BNB and XRP, as net recipients, have witnessed a brief role change. Specifically, BNB briefly became a net transmitter in early 2018 and then as a net recipient until 2020, after which net connectedness came very close to zero. For XRP, it became a net transmitter in mid-to-late 2018 and late 2020 and remained a net recipient for the remaining years.

It is also found that the directional connectedness and net connectedness of all four digital currencies experienced huge fluctuations in early 2018 and in the first half of 2021. This is because the prices of many digital currencies hit a record high in the beginning of 2018, but the frequently released regulatory policies on digital currencies in many countries caused the prices of digital currencies to fall rapidly. The net connectedness of digital currencies showed different changes during this phase, with the indicators of BTC and BNB first rising sharply and then falling back quickly, while the indicators of ETH and XRP exhibited the opposite patterns, first falling rapidly and then moving quickly higher. The first half of 2021 was the period when market liquidity reached a historic high, while global inflation became a very serious problem. At this time, the net connectedness of BTC and ETH was always in a positive state, and the net connectedness of BNB and XRP was always in a negative state.

The above analysis shows that ETH is typically in the transmitter role, while XRP is typically in the recipient role. Although BTC is for most of the time in the role of transmitter, its net connectedness remained extremely near to zero of an extended period following a major decline and has just recovered recently. Additionally, although BNB is mostly a recipient, its net connectedness has been near to zero in recent periods.

### 3.3. Pairwise Analysis

Table 3 also describes the average pairwise directional connectedness. As can be observed, the most influential factor for each currency is ETH, except for its own influence on itself, and the second most influential is BTC, while BNB is always the least influential factor for other remaining digital currencies.

Figure 3 illustrates the dynamics of pairwise connectedness between these currencies. First, it can be seen that ETH, BNB, and XRP had all been significantly in the recipient position of BTC until mid-2018. Then, their pairwise connectedness to BTC all climbed significantly, with ETH remaining in transmitter status almost ever since, and BNB reaching a pairwise connectedness very close to zero. It is
worth noting that their pairwise connectedness both declined significantly in mid-2020 and then reached a new high in late 2020. It is believed that the former is most likely due to the halving of developer rewards in BTC in mid-2020, while BTC’s price reached a historic high in late 2020, thus triggering investors’ concerns about its price decline. Furthermore, the impact of these three currencies on BTC has again declined significantly from the end of 2021, suggesting an upward trend in BTC’s impact status in the last half year. As suggested in Figures 3(d) and 3(f), BNB’s impact on ETH and XRP rose significantly and peaked in early 2018, most likely due to the release of Binance Smart Chain by the Binance Exchange that BNB was associated with in early 2018, which raised investors’ expectations for BNB. The latter half of 2020 also saw a significant decline and then a significant rise in BNB’s influence on ETH and XRP shortly afterwards, most likely due to the impact of several focused projects launched by Binance Exchange during this time. It is observable in Figure 3(e) that XRP is relatively stable compared with ETH and has basically been the recipient of the connectedness of ETH.

The above analysis suggests that ETH has been exerting a significant influence on other currencies. The influence of BTC on other currencies was still relatively strong in 2018, which rapidly diminished, but tended to recover in the recent period. BNB’s influence on other currencies is more variable and is mainly influenced by its own related events. XRP is mainly receiving influence from other currencies.

4. Conclusions and Future Work

Using a time-varying analysis of the major digital currencies, it is found that ETH is by far the largest transmitter of spillover, whereas BTC’s impact on other currencies has only recently picked up after a significant decline. BNB and XRP have been acting as recipients of spillover and BNB is more variable. It is also found that the total connectedness among these four digital currencies was significantly less volatile.
before the epidemic outbreak than after it, which we speculate is due to frequent monetary policies and economic changes after the epidemic. As digital currencies continue to influence the world as emerging assets, our research provides insights into the pricing of related assets, the development of related risk hedging strategies, and the risk management by digital currency platforms.

It is noteworthy that this paper just ties the connectedness of digital currencies to economic events, and it does not explain how these economic events had influenced the pricing of digital currencies or the interrelationship among these currencies. This transmission mechanism is the direction of future research. To this end, the research by Sirignano and Cont [11] and Alessandretti et al. [12] is a valuable reference, since it inspires us that machine learning-related approaches are quite promising in examining the link between digital currencies and investigating the interrelationship between factors in the transmission mechanism.

Data Availability

The data can be collected from official website.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

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