



Full length article

Return spillover analysis across central bank digital currency attention and cryptocurrency markets[☆]Yizhi Wang^{a,1}, Yu Wei^{b,*,1}, Brian M. Lucey^{c,d,e,f,1}, Yang Su^{c,1}^a Cardiff Business School, Cardiff University, Aberconway Building, Cardiff CF10 3EU, United Kingdom^b School of Finance, Yunnan University of Finance and Economics, Kunming, China^c Trinity Business School, Trinity College Dublin, Dublin 2, Ireland^d Institute of Business Research, University of Economics Ho Chi Minh City, 59C Nguyen Dinh Chieu, Ward 6, District 3, Ho Chi Minh City, Viet Nam^e Institute for Industrial Economics, Jiangxi University of Economics and Finance, 169, East Shuanggang Road, Xialuo, Changbei District 330013 Nanchang, Jiangxi, China^f University of Abu Dhabi, Zayed City, Abu Dhabi, United Arab Emirates

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ABSTRACT

Many central banks have now developed their digital currencies in response to the challenges posed by the proliferation of decentralised digital cryptocurrencies. However, little is known about the effects of the introduction of central bank digital currencies (CBDCs) on extant digital cryptocurrencies. This paper, therefore, aims to identify both the time- and frequency-domain spillover effects among cryptocurrency markets and a newly developed central bank digital currencies attention index (CBDCAI) by using two TVP-VAR-based spillover models. Our results demonstrate that CBDC attention significantly impacts cryptocurrency markets. Also, most investors in cryptocurrency markets are more likely to trade in the short term. The results of this study contribute to helping investors and investment institutions effectively avoid investment risks, reduce losses, and predict the return of some cryptocurrencies. Also help policymakers better understand the impact of markets and policies, and provide a reference for them to formulate policies.

1. Introduction

With the development of technology and finance, people's lifestyles are gradually turning digital. As a medium of economic exchange, money has also gradually undergone a revolution, from the old shells, ordinary metal money, precious metal money, paper money, and now the latest digital currency (Davies, 2010; Wang et al., 2022c). The need for physical cash is diminishing as the digital age dawns. Technological advances make it possible for digital payments to gradually become one of the significant trends of the future (Gomber et al., 2018; Kuehnlenz et al., 2023).

Digital currencies, or encrypted tokens, including cryptocurrency, virtual currency and central bank digital currency, are virtual products with money features, offering a unit of account and a store of value (Gans and Halaburda, 2015). As of August 2022, there are more than 20,000 cryptocurrencies in the world, and their market capitalisation exceeds US\$980 Billion, with Bitcoin

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and Ethereum having the largest market share, accounting for 38% and 20% of the market share, respectively.² The huge usage of cryptocurrencies now means that there is a growing demand for them, representing a promising future for cryptocurrencies and other forms of digital currency in the future (Goodell et al., 2022).

Some studies argue that the financial instability of cryptocurrencies is obvious and is prone to large price fluctuations, which can lead to significant losses for investors (Griffin and Shams, 2020; Gao et al., 2021; Wang et al., 2022b,d; Lucey et al., 2022). For example, Bitcoin, which currently has the largest market share, rose to \$12,000 in December 2017 and then fell to \$3,000 eleven months later. Bitcoin rose again from \$10,000 in September 2020 to nearly \$60,000 in about six months, six times the original price. Then, it quickly plummeted by 40% in just three months. So, cryptocurrencies are a financial asset with high financial instability (Balvers and McDonald, 2021; Allen et al., 2022; Letho et al., 2022). Another widely discussed topic about cryptocurrency is that they are difficult to be regulated. Bitcoin, for example, is a huge challenge in terms of regulation (Nabilou, 2019; Marobhe, 2021). Bhaskar et al. (2022) claim that it is essential to monitor the flow of funds, so that is the reason why central banks of many countries have introduced their own central bank digital currencies (CBDCs).

Some researchers hold similar views about why the government started to work on CBDCs. Cryptocurrency performs poorly in terms of financial stability and sustainability, so the government tries to develop their own CBDCs to anti the negative impacts of cryptocurrencies (Sinelnikova-Muryleva, 2020; Ward and Rochemont, 2019). It is also believed that many governments may not be willing to give up their monopoly on currency, so they are starting to work on their own CBDCs (Laboure et al., 2021; Ngo et al., 2022; Jabbar et al., 2023).

In summary, academics agree that CBDCs are created to resist the future impact of the cryptocurrency markets. CBDC also called Digital Fiat Currency or Digital Base Money, which is inspired by Bitcoin and similar blockchain-based cryptocurrencies (Wang et al., 2022a). CBDCs have many benefits for the community. First, CBDCs could reduce the costs of cash, including the cost of making cash, and the cost of cross-border transactions, especially in some underdeveloped countries (Morgan, 2022; Ozili, 2022). Likewise, reducing the manufacture of banknotes helps to save energy and improve financial sustainability. Second, CBDCs are inclusive and can conduct transactions without the need for an identity or account, or even an Internet connection (Lee et al., 2021; Ozili, 2022). It is argued that the existence of CBDCs may prevent tax evasion by taxpayers in cash transactions, so the existence of CBDCs may indirectly benefit social welfare (Minesso et al., 2022). Third, CBDCs could help the monetary supervision and regulation. For example, it has an impact on money laundering, especially token-based options that could combat financial crime (Dupuis et al., 2021; Fernández-Villaverde et al., 2021). As more and more central banks in different countries are becoming interested in CBDC, the influence of geopolitics is causing more countries to join in Laboure et al. (2021) and Li et al. (2023).

Based on these benefits, many countries around the world have started CBDCs. There are 105 countries around the world exploring CBDCs by the end of August 2022, representing over 95% of global GDP³.

The relationship between CBDCs and the cryptocurrency market is one of the current trends in research. The existing literature establishes that there are various aspects of the dynamics of cryptocurrencies that interact with the policies of central bank digital currencies (Allen et al., 2022; Jagtiani et al., 2021; Pompella and Matousek, 2021; Mzoughi et al., 2022). The studies find that public interest in CBDCs increases and cryptocurrency prices rise more sharply when the central bank makes a positive statement (Marmora, 2022; Scharnowski, 2022). Researchers have widely used a new type of index named Attention index" recently, which could measure the intensity and change of public interest because they believe that the attention of investors may affect market returns and volatility (Vozlyublennaya, 2014; Wang, 2022). Using attention as an indicator has high accuracy and a certain comprehensiveness when it is applied to different econometric models and when it is used to predict returns related to financial markets based on previous research. Therefore, this paper uses CBDC attention to represent the public's interest in CBDC to study its relationship with the cryptocurrency market.

Overall, there seems to be some evidence indicating inter-linkages between CBDC attention and the cryptocurrency markets. The development of CBDCs and public attention on the development of CBDCs could affect the cryptocurrency market and cause volatility. However, many of the studies are keen on qualitative, without any quantitative experiments to comprehensively evaluate the interconnections between the CBDCs and cryptocurrency markets, especially their volatility transmission channels. In order to address this research gap, this study proposes quantifying the interconnections of the CBDC attention and the cryptocurrency markets. Utilise CBDCAI and the TVP-VAR spillover model from two domains: time and frequency, to make an in-depth analysis of cryptocurrency investors' attitudes towards CBDC attention using a quantitative approach, which could help public and regulators get more information in this area (Antonakakis et al., 2020; Barunik et al., 2020; Wang et al., 2022a).

There are four main findings in this research. Firstly, as the finds are based on both time domain and frequency domains, including short-term (i.e. 1 to 4 weeks) and long-term (i.e. longer than 4 weeks), CBDC attention is a majority return information transmitter to cryptocurrency markets. Bitcoins, Ethereum, and CBDC attention are the only three factors that could keep stable positive net pairwise directional spillover. Secondly, in the time domain, Bitcoin and Ethereum are the key spillover transmitters, as Binance, Tether, and USD coin are the key spillover receivers for return transmission in the system. Thirdly, we find that most of the investors in cryptocurrency markets are more likely to trade in the short term than in the long term. Finally, by using linear regression models, we confirm that TSI and NET spillover could have impacts on cryptocurrency markets and CBDCAI has significant predictive power on the return of Bitcoin and Ethereum from a fixed-effect perspective.

This study firstly contributes to fleshing out the intrinsic link between CBDCs and the cryptocurrency market. A quantitative approach is used to provide an in-depth analysis of the impacts of public attention on cryptocurrency markets. Secondly, for investors

² Today's cryptocurrency prices by market cap. <https://coinmarketcap.com/>.

³ <https://www.atlanticcouncil.org/cbdctracker/>

and investment institutions, the findings of this study could facilitate investors to understand better the market patterns and the inducing factors of price instability in cryptocurrency markets. With the variation of the CBDCAI, investors could use this index to forecast the fluctuations in cryptocurrency markets. The volatility of financial markets could have effects on investor psychology. Especially for risk-averse investors, this result will be of great interest to them to reasonably avoid risks to reduce losses and increase returns in future investments. At the same time, it provides useful information for investment institutions to be able to predict price fluctuations and collect variations from cryptocurrency markets by using CBDCAI. Thirdly, for policymakers and regulators, it could help them understand the spillover effects of CBDC attention on cryptocurrency markets, to provide new insights into how CBDC policy adjustments and public interest in CBDCs can significantly influence the cryptocurrency markets. It also allows them to understand the importance of CBDCs and their roles in the future. Moreover, our research results also could help the market regulators to understand better that the regulation of digital assets should be on short-term trading to minimise any policy issues or regulatory inadequacies.

This research is composed of five sections. Section 2 explains the frameworks of TVP-VAR-DY and TVP-VAR-BK models, while Section 3 introduces the data used. Section 4 presents the empirical results and Section 5 summarises the main findings.

2. Methodology

Recently, the spillover index method proposed by Diebold and Yilmaz (2009) and Diebold and Yilmaz (2012) are widely used in investigating the spillover effects among financial and commodity markets in the time domain. Then Baruník and Křehlík (2018) further extend this method by considering the possible heterogeneous responses of the financial systems to exogenous shocks in different time frequencies. These two approaches, however, are designed mainly to depict the static spillover effects within a system. To obtain the time-varying spillover measurements, they have to employ a rolling-window technique, which is found to have several clear drawbacks by Antonakakis et al. (2020) as follows: firstly, the choice of rolling-window size can be very arbitrary, which may influence the measurement of spillover effect. Secondly, when using this rolling-window method, researchers will lose some dynamic measurement results over the first rolling window, a problem that can be very serious for small sample studies. Lastly, Antonakakis et al. (2020) further argue that the empirical results based on a rolling-window approach are very sensitive to extreme observations. Estimates of the spillover effects are prone to significant jumps or drops when extreme observations are first included or excluded from the rolling window sample, making it difficult to capture market interactions in times of crisis accurately.

This model, which calculates two spillover effects, visualises the spillover returns in the form of figures to help people understand more clearly about how CBDC affects the cryptocurrency market. Therefore, in this paper, we employ two TVP-VAR-based spillover methods proposed by Antonakakis et al. (2020) and Baruník et al. (2020), which are two natural extensions of the static spillover methods of Diebold and Yilmaz (2012) and Baruník and Křehlík (2018), which we labelled as TVP-VAR-DY and TVP-VAR-BK model, respectively, hereafter.

2.1. TVP-VAR-DY approach in time domain

The TVP-VAR version of Diebold and Yilmaz (2012) spillover index method is proposed by Antonakakis et al. (2020), which is designed to quantify the dynamics of spillover effects in a N -variable TVP-VAR (p) model. This model has a good performance in the time domain when studying spillover effects, and it can accurately measure the total spillover effect and the net spillover effect. It is able to show both the total spillover effect with CBDC and the cryptocurrency market and the spillover effect between CBDC and the ten cryptocurrencies, showing who are the information transmitter and receivers in the whole system, respectively. Therefore, this study chooses the TVP-VAR-DY model to study the spillover effects of CBDC attention and the cryptocurrency market in this static system in the time domain from the net and total.

This method can estimate the time-varying directional spillover index without losing the initial estimation sample results in a rolling-window method and is not sensitive to extreme observations in the data sample. A N -variable TVP-VAR(p) model is defined as:

$$Y_t = A_t X_{t-1} + \varepsilon_t, \varepsilon_t | \Omega_{t-1} \sim N(0, \Sigma_t), \quad (1)$$

$$vec(A_t) = vec(A_{t-1}) + \xi_t, \xi_t | \Omega_{t-1} \sim N(0, \Xi_t), \quad (2)$$

where $Y_t = (y_{1,t}, y_{2,t}, \dots, y_{N-1,t}, y_{N,t})'$ is a $N \times 1$ vector of interested variables at time t and $X_{t-1} = (Y_{t-1}, Y_{t-2}, \dots, Y_{t-p})'$, where the lag order p is chosen by using the AIC or BIC information criterion. Then $A_t = (A_{1t}, A_{2t}, \dots, A_{pt})$ is a $N \times N$ parameter matrix, and $vec(A_t)$ denotes the vectorisation of A_t . Moreover, ε_t and ξ_t are the error vectors, and Ω_{t-1} is the information set available until $t-1$. Finally, Σ_t and Ξ_t time-varying variance-covariance matrixes for ε_t and ξ_t , respectively. Then this TVP-VAR (p) model is estimated through the Kalman filter algorithm with both forgetting and decay factor to be set as 0.99 in the following empirical estimation. The key idea of spillover index method is to measure the generalised forecast error variance decomposition (GFEVD) at H -step-ahead by this TVP-VAR (p) model as follows:

$$Y_t = A_t X_{t-1} + \varepsilon_t = \sum_{i=0}^{\infty} B_{t,i} \varepsilon_{t-i}, \quad (3)$$

where $B_{i,t} = \sum_{l=1}^p A_{l,t} B_{i-l,t}$ denotes the response function, $B_{0,t}$ is a unit matrix, and $B_{i,t} = 0$ when $i < 0$. Based on Eq. (3), the H -step-ahead GFEVD is then calculated as:

$$\Phi_{jk,t}(H) = \frac{\sum_{k=1}^{N-1} \sum_{h=0}^{H-1} (\theta'_j B_{h,t} \Sigma_t \theta_k)^2}{\sum_{h=0}^{H-1} (\theta'_j B_{h,t} \Sigma_t B'_{h,t} \theta_j)}, \quad (4)$$

where $\theta_j(\theta_k)$ is a $N \times 1$ vector with the j th (k -th) element being 1, and 0 otherwise. When $j \neq k$, $\Phi_{jk,t}(H)$ indicates the share of H -step-ahead forecast error variance in j caused by the shocks of k . To ensure the sum of the elements in each row to be to 1, i.e., all variables together contribute 100% forecast error variance of variable j , we normalise each entry by the row sum as:

$$\hat{\Phi}_{jk,t}(H) = \frac{\Phi_{jk,t}(H)}{\sum_{j=1,k=1}^N \Phi_{jk,t}(H)} \times 100, \quad (5)$$

with $\sum_{k=1}^N \hat{\Phi}_{jk,t}(H) = 1$ and $\sum_{j=1,k=1}^N \hat{\Phi}_{jk,t}(H) = N$. Therefore, we may define the time-varying total spillover index (TSI) in this TVP-VAR system as:

$$TSI_t(H) = \frac{\sum_{k=1,j \neq k}^N \hat{\Phi}_{jk,t}(H)}{\sum_{j=1,k=1}^N \hat{\Phi}_{jk,t}(H)} \times 100. \quad (6)$$

It is used to quantify the total intensity of spillover effects among all variables in this system. Based on these definitions, we, therefore can compute the directional spillover effect received by j from all the other variables as:

$$FROM_{j \leftarrow *,t}(H) = \frac{\sum_{k=1,j \neq k}^N \hat{\Phi}_{jk,t}(H)}{\sum_{j=1,k=1}^N \hat{\Phi}_{jk,t}(H)} \times 100, \quad (7)$$

and then a natural way to measure the directional spillover of variable j transmitting to all the other variables is as follows:

$$TO_{j \rightarrow *,t}(H) = \frac{\sum_{k=1,k \neq j}^N \hat{\Phi}_{kj,t}(H)}{\sum_{j=1,k=1}^N \hat{\Phi}_{jk,t}(H)} \times 100, \quad (8)$$

Furthermore, to assess the net directional spillover of variable j , i.e., the difference in directional TO and FROM spillover effects, we calculate it as:

$$NET_{j,t}(H) = TO_{j \rightarrow *,t}(H) - FROM_{j \leftarrow *,t}(H). \quad (9)$$

From Eq. (9), we can see that a positive NET spillover index shows that variable j is a net transmitter of spillover effects to others, otherwise it is a net spillover receiver. Lastly, to evaluate the spillover effect between two specific variables, we define the net pairwise directional spillover index (NPDS) between j and k as:

$$NPDC_{jk,t}(H) = \left(\frac{\hat{\Phi}_{kj,t}(H)}{\sum_{j=1,k=1}^N \hat{\Phi}_{jk}(H)} - \frac{\hat{\Phi}_{jk,t}(H)}{\sum_{j=1,k=1}^N \hat{\Phi}_{jk}(H)} \right) \times 100. \quad (10)$$

Similarly, it is easy to understand that a positive NPDC reveals that the spillover effect of j to k is stronger than that of k to j , indicating that variable j dominates the change of k , and vice versa.

2.2. TVP-VAR-BK approach in frequency domain

As noted above, for the reason that financial and economic systems respond heterogeneously to exogenous shocks at various time frequencies (Dew-Becker and Giglio, 2016; Li and Meng, 2022; Umar et al., 2022; Wei et al., 2020, 2022), it is extremely significant for policymakers and investors to understand the time-varying spillover effects not only in time domain, but also in the frequency domain (e.g., from short- and long-term horizons). Barunik et al. (2020) then extend the static spillover index method of citetbarunik2018measuring to a TVP-VAR based version. This new tool not only gains the benefits of the time-varying spillover index of Antonakakis et al. (2020), but also captures these spillover effects at different time frequencies, i.e., from short- to long-term horizons, allowing us to improve our view of the heterogeneous responses of different variables to exogenous shocks.

Similar to Eq. (3), the TVP-VAR-BK method of Barunik et al. (2020) constructs a time-varying response function of $B_t(e^{-i\omega h})$ at frequency ω like this:

$$B_t(e^{-i\omega}) = \sum_{h=0}^{H-1} e^{-i\omega h} B_{h,t}, \quad (11)$$

with $i = \sqrt{-1}$, and the generalised causal spectrum over the frequencies $\omega \in (-\pi, \pi)$ is defined as:

$$(f_t(\omega))_{jk} = \frac{\sum_{k=1}^{N-1} |\theta'_j B_t(e^{-i\omega}) \Sigma_t \theta_k|^2}{\theta'_j B_t(e^{-i\omega}) \Sigma_t B'_t(e^{+i\omega}) \theta_j}. \quad (12)$$

This equation computes the spillover effect of the j th variable at frequency ω due to the shocks from the k th variable. Then, after defining a frequency band of $d = (s, l)$, and $s < l$, $s, l \in (-\pi, \pi)$, we can calculate the generalised forecast error variance decomposition (GFEVD) on frequency band d as:

$$\Phi_{jk,t}(d) = \frac{1}{2\pi} \int_d W_{j,t}(\omega)(f_t(\omega))_{jk} d\omega, \quad (13)$$

and

$$W_{j,t}(\omega) = \frac{\theta'_j B_t(e^{-i\omega}) \sum_t B'_t(e^{+i\omega}) \theta_j}{\frac{1}{2\pi} \int_{-\pi}^{\pi} (\theta'_j B_t(e^{-i\lambda}) \sum_t B'_t(e^{+i\lambda}) \theta_j) d\lambda} \quad (14)$$

Similarly, the normalised GFEVD on the frequency band d are then calculated as:

$$\hat{\Phi}_{jk,t}(d) = \frac{\Phi_{jk,t}(d)}{\sum_{k=1}^N \Phi_{jk,t}(\infty)}, \quad (15)$$

with

$$\Phi_{jk,t}(\infty) = \frac{1}{2\pi} \int_{-\pi}^{\pi} W_{j,t}(\omega)(f_t(\omega))_{jk} d\omega. \quad (16)$$

Based on the above definitions, the total, from, to, net and net pairwise directional spillover (NPDS) indices on frequency band d are computed as follows:

$$TSI_t(d) = \left(\frac{\sum_{j=1,k=1}^n \hat{\Phi}_{jk,t}(d)}{\sum_{j=1,k=1}^n \hat{\Phi}_{jk,t}(\infty)} - \frac{Tr\{\hat{\Phi}_{jk,t}(d)\}}{\sum_{j=1,k=1}^n \hat{\Phi}_{jk,t}(\infty)} \right) \times 100, \quad (17)$$

$$FROM_{j \leftarrow *,t}(d) = \left(\left(\sum_{k=1,j \neq k}^n \hat{\Phi}_{jk,t}(d) \right) \frac{\sum_{j=1,k=1}^n \hat{\Phi}_{jk,t}(d)}{\sum_{j=1,k=1}^n \hat{\Phi}_{jk,t}(\infty)} \right) \times 100, \quad (18)$$

$$TO_{j \rightarrow *,t}(d) = \left(\left(\sum_{k=1,j \neq k}^n \hat{\Phi}_{kj,t}(d) \right) \frac{\sum_{j=1,k=1}^n \hat{\Phi}_{jk,t}(d)}{\sum_{j=1,k=1}^n \hat{\Phi}_{jk,t}(\infty)} \right) \times 100, \quad (19)$$

$$NET_{j,t}(d) = TO_{j \rightarrow *,t}(d) - FROM_{j \leftarrow *,t}(d), \quad (20)$$

$$NPDS_{jk,t} = (\hat{\Phi}_{kj,t}(d) \frac{\sum_{j=1,k=1}^n \hat{\Phi}_{kj,t}(d)}{\sum_{j=1,k=1}^n \hat{\Phi}_{jk,t}(\infty)}) - (\hat{\Phi}_{jk,t}(d) \frac{\sum_{j=1,k=1}^n \hat{\Phi}_{jk,t}(d)}{\sum_{j=1,k=1}^n \hat{\Phi}_{jk,t}(\infty)}) \times 100. \quad (21)$$

where $Tr\{\cdot\}$ is the trace operator. According to the methods of Li and Meng (2022), Umar et al. (2022), and many others, we mainly focus on two frequency bands d (i.e., 1 to 4 weeks, and longer than 4 weeks) in the following empirical results, which correspond to short- and long-term time horizon, respectively.

3. Data

The purpose of this paper is to identify the impacts of Central Bank Digital Currency attention on cryptocurrency markets. Thus, we choose one new digital asset index, CBDC attention proposed by Wang et al. (2022a), as the proxy of public attention on Central Bank Digital Currency, which has been recorded in weekly frequency since January 2, 2015.⁴ In terms of cryptocurrency markets, according to the statistics by coinmarketcap.com, we select cryptocurrencies with the top 10 largest market capitalisation by the end of July 2022 in our empirical analysis. They are Bitcoin, Ethereum, Tether, USD coin, BNB, XPR, Binance, Cardano, Solana, and Dogecoin.⁵ For data availability, we choose weekly data of CBDC attention and the ten cryptocurrencies from April 6, 2020, to July 18, 2022. All these weekly data are transferred to logarithm returns for stationarity, and Table 1 reports the descriptive statistics of these returns.

Table 1 shows that, firstly, the mean weekly returns for various cryptocurrencies are quite different. For example, Bitcoin, Ethereum, BNB, Cardano, Solana, and Dogecoin have positive mean returns over 1%, where Solana gets the biggest one of 3.269%. While Tether, USD coin and Binance obtain very small negative mean weekly returns. Secondly, the standard deviations for these cryptocurrencies also demonstrate quite discrepancies, e.g., Dogecoin has the largest standard deviation of 25.209%, yet USD coin has only this statistic of 0.12%, indicating the significantly distinct market risks in different cryptocurrencies. Thirdly, the skewness, kurtosis, and Jarque–Bera statistics reveal that all these returns are not normally distributed. Furthermore, the Ljung–Box Q statistics show that some cryptocurrencies have significant autocorrelations for up to 8 weeks, while others have not, suggesting the heterogeneous price persistent patterns in different cryptocurrency markets again. Finally, the Augmented Dickey–Fuller and Phillips–Perron unit root tests demonstrate the stationarity in all these time series.

⁴ <https://sites.google.com/view/cryptocurrency-indices/home?authuser=0>

⁵ The cryptocurrency prices are downloaded from <https://finance.yahoo.com/>.

Table 1

Descriptive statistic of weekly returns for the ten cryptocurrencies and CBDC attention.

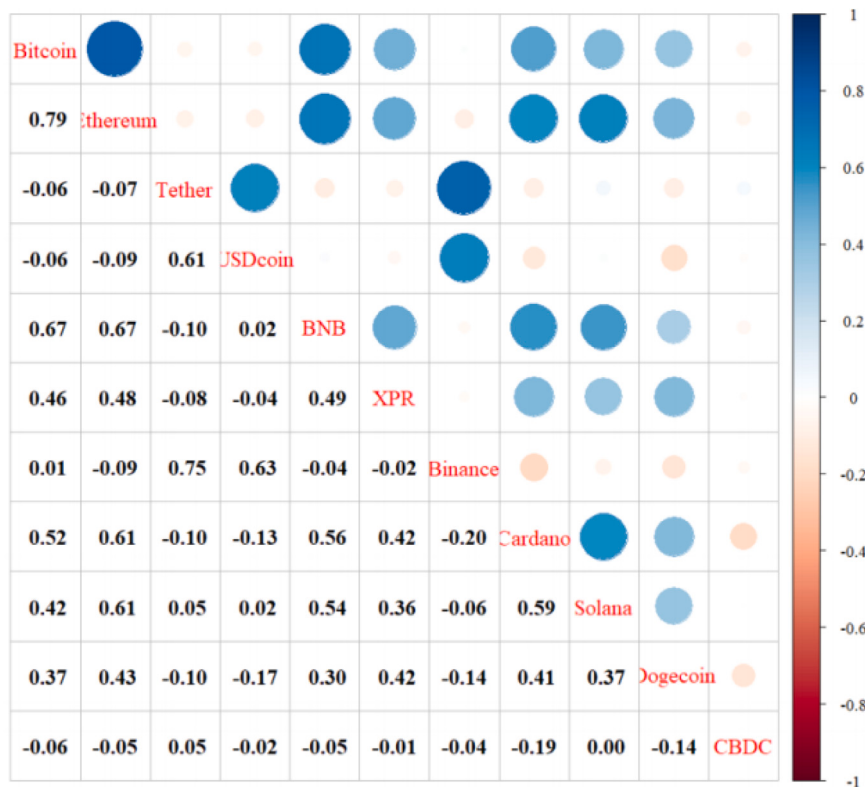
	Bitcoin	Ethereum	Tether	USD coin	BNB	XPR	Binance	Cardano	Solana	Dogecoin	CBDC
Obs.	119	119	119	119	119	119	119	119	119	119	119
Mean	1.012	1.886	-0.007	-0.003	2.428	0.553	-0.007	2.264	3.269	2.991	0.017
Std. dev.	9.671	12.856	0.149	0.120	16.548	18.153	0.156	15.815	20.332	25.209	0.744
Skewness	-0.447	-0.624	-0.451	-1.841	0.521	0.544	-1.426	0.629	0.072	3.427	0.907
Kurtosis	3.567	5.246	9.588	15.839	11.232	7.804	11.442	5.481	3.404	19.071	7.789
Jarque-Bera	5.560**	32.734***	219.226***	884.530***	341.403***	120.287***	393.753***	38.365***	0.911	1513.572***	130.018***
Q (4)	8.053*	5.3104	23.992***	14.765***	3.298	4.377	14.864***	4.510	11.344**	4.995	7.389
Q (8)	13.974*	8.846	42.806***	27.880***	12.119	15.303*	25.788***	9.881	12.612	5.885	14.092*
ADF	-8.761***	-9.696***	-16.917***	-15.694***	-9.244***	-10.727***	-14.903***	-8.917***	-9.211***	-9.364***	-13.234***
P-P	-8.803***	-9.828***	-16.903***	-15.661***	-9.364***	-10.691***	-14.870***	-9.030***	-9.434***	-9.440***	-13.186***

Notes: The Jarque-Bera statistic tests for the null hypothesis of normality in the distribution. Q (n) is the Ljung-Box Q statistics with lag length of n. ADF and P-P are statistics of Augmented Dickey-Fuller and Phillips-Perron unit root test.

*Indicate rejection at the 10% significant level.

**Indicate rejection at the 5% significant level.

***Indicate rejection at the 1% significant level.

**Fig. 1.** Pearson correlation coefficient matrix of the ten cryptocurrencies and CBDC attention.

Notes: This table shows correlation coefficients between ten cryptocurrencies and CBDC attention. If the coefficient value lies between ± 0.50 and ± 1 , then it is said to be a strong correlation. If the value lies between ± 0.30 and ± 0.49 , then it is said to be a medium correlation. When the value lies below ± 0.29 , then it is said to be a small correlation.

Then Fig. 1 visually reveals the Pearson correlation matrix among the ten cryptocurrencies and CBDC attention index. On the one hand, we can find in Fig. 1 that various cryptocurrencies show quite different correlations. For instance, Bitcoin and Ethereum have a very large positive correlation coefficient of 0.79, but this number between Binance and Cardano is -0.20 . These correlation coefficients, either positive or negative, suggest that it is possible for investors to utilise these assets to allocate optimal portfolios in cryptocurrency markets. On the other hand, we can see that CBDC attention has small but negative correlations (i.e., ranging from -0.19 to -0.01) with almost all the ten cryptocurrencies, implying that high levels of CBDC attention may dampen price increases in the digital cryptocurrency markets.

Table 2
Mean spillover measurements among the ten cryptocurrencies and CBDC attention in time domain.

	Bitcoin	Ethereum	Tether	USD coin	BNB	XPR	Binance	Cardano	Solana	Dogecoin	CBDC	FROM
Bitcoin	35.85	20.33	0.54	0.16	14.86	8.18	0.31	7.64	5.33	5.75	1.05	64.15
Ethereum	18.26	30.37	0.33	0.23	12.61	7.92	0.29	10.59	11.48	6.97	0.95	69.63
Tether	1.12	1.25	43.42	16.62	1.61	2.94	22.69	4.42	3.02	0.83	2.09	56.58
USD coin	3.85	1.49	14.05	39.23	3.40	3.72	22.93	2.25	2.46	1.39	5.22	60.77
BNB	15.84	14.48	0.61	0.14	35.06	10.29	0.20	8.81	9.08	3.82	1.67	64.94
XPR	9.11	11.41	1.23	0.11	11.21	38.23	0.27	9.28	8.18	6.08	4.89	61.77
Binance	1.35	1.40	22.33	22.4	1.93	1.91	38.31	3.31	4.09	1.16	1.81	61.69
Cardano	11.06	12.92	0.82	0.91	9.69	8.81	1.34	32.92	10.61	8.30	2.61	67.08
Solana	7.25	15.06	0.34	0.41	9.94	7.09	0.52	12.55	37.92	8.36	0.56	62.08
Dogecoin	7.61	10.09	0.93	1.13	4.23	9.03	0.62	6.98	6.80	48.14	4.45	51.86
CBDC	0.53	0.56	0.16	0.22	0.29	0.24	0.85	2.72	3.05	2.41	88.96	11.04
TO	75.98	88.99	41.33	42.33	69.78	60.14	50.01	68.56	64.1	45.06	25.29	TSI
NET	11.83	19.36	-15.25	-18.44	4.83	-1.63	-11.67	1.48	2.02	-6.79	14.25	57.42

Notes: This table reports the directional spillover among crude oil, carbon and agriculture futures markets by the method of [Diebold and Yilmaz \(2012\)](#) in time domain. The rightmost column (FROM) of this table indicates the directional spillover from all others to a specific futures market. The penultimate row (TO) of this table indicates the directional spillover to all others from a specific futures market. The bottom row (NET) shows the net spillover, i.e., the difference between TO and FROM spillover of a specific futures market. The number in the bottom right corner of this table (indicated in bold face) is the TOTAL spillover index (TSI) of all the futures markets.

4. Empirical results

4.1. Time-domain spillover evidence by TVP-VAR-DY method

In this section, to get an overall view of the spillover effects among cryptocurrency markets and CBDC attention in the time domain, we first report the mean return spillover indices based on TVP-VAR-DY method proposed by [Antonakakis et al. \(2020\)](#).

[Table 2](#) shows that, firstly, the total spillover index (TSI) is 57.42%, indicating a relatively high degree of spillover effects among the ten cryptocurrencies and CBDC attention. Secondly, regarding pairwise directional spillover measures, we find that the spillover effects between Bitcoin and Ethereum, as well as the ones between Binance and Tether (USD coin) are some of the largest among all the pairwise directional spillover indices. These findings are in line with those revealed in [Fig. 1](#), which shows the Pearson correlation coefficient matrix. Thus, we think that Bitcoin, Ethereum, Binance, Tether, and USD coins may be the major nodes for information transmission in the system. Furthermore, although the pairwise directional spillover measurements between CBDC attention and the ten cryptocurrencies are relatively small (smaller than 5%), the spillover indices from CBDC attention to cryptocurrencies (the numbers in CBDC column in [Table 2](#)) are mostly larger than those from cryptocurrencies to CBDC (the numbers in CBDC row in [Table 2](#)). This evidence may suggest that CBDC attention, as an exogenous variable for cryptocurrency markets, has greater impacts on the cryptocurrency markets than the cryptocurrency markets have on itself. Thirdly, in terms of TO and FROM spillover measurements, we find that Ethereum is both the strongest spillover transmitter and receiver in this system, while CBDC attention again is the weakest spillover transmitter and receiver. Finally, the NET indices shown in the bottom row of [Table 2](#) confirm that Ethereum, CBDC attention, and Bitcoin are the top three biggest return spillover senders, whereas USD coin, Tether, and Binance are the three largest acceptors. These results imply that besides Bitcoin and Ethereum, the two well-recognised leading assets in cryptocurrency markets, CBDC attention can serve as an additional important impactor on cryptocurrency markets. The public attention on CBDCs may help to understand the dependence and spillover effects across cryptocurrency markets, and thus may contribute to better risk management and portfolio allocation strategies for cryptocurrency markets.

After the mean evidence of time-domain spillover effects among cryptocurrency markets and CBDC attention, we further report the time-vary results of total spillovers in [Fig. 2](#). It indicates that the total spillover index (TSI) among cryptocurrency markets and CBDC attention fluctuates up and down around about 60%, suggesting that the system maintains a relatively strong spillover effect. In particular, we find that the TSI increases significantly from about April 2020 to July 2020, reaching a very high level of over 70%. After that, it decreases gradually to lower than 60% till May 2021. Then the TSI rises to greater than 60% and thereafter maintains a moderate upward trend until July 2022. When we analyse from a time domain, it can be confirmed that the cryptocurrency markets and CBDC attention are intrinsically linked. As a whole, a spillover of no less than 60% proves that the spillover effect of CBDC attention is strong and that CBDC attention could influence the price volatility of the cryptocurrency market to a large extent. It is clear from the results that the Dynamic total spillover index has remained at a high level, with a sharp rise, especially during the period from April 2020 to July 2020. Relating the indicator to reality, we find that the bull market started in April 2020, and cryptocurrency prices rose during the period. It may therefore be concluded that the sharp rise in the TSI over the period strongly connects with the bull market's start. This finding has significant practical implications. We find that the spillover effect of CBDC is very strong, which is very helpful for investors and investment institutions. When public interest in CBDCs increases obviously, a certain degree of volatility may be imminent in the cryptocurrency market. This can provide an important signal to investors and investment institutions, which can help market participants to be more sensitive to the cryptocurrency market and avoid possible risks to a certain extent.

Then, [Fig. 3](#) demonstrates the time-varying net spillover effects estimated by TVP-VAR-DY method of [Antonakakis et al. \(2020\)](#). We can see in [Fig. 3](#) that, Bitcoin, Ethereum, and CBDC attention are three major net spillover senders across the data sample from

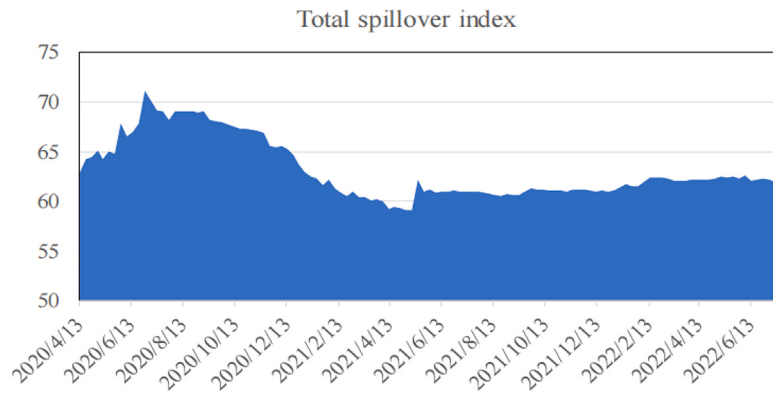


Fig. 2. Dynamic total spillover index (TSI) in time domain.

Notes: The total spillover index (TSI) measures the spillover effect of ten cryptocurrencies and CBDC attention in time domain.

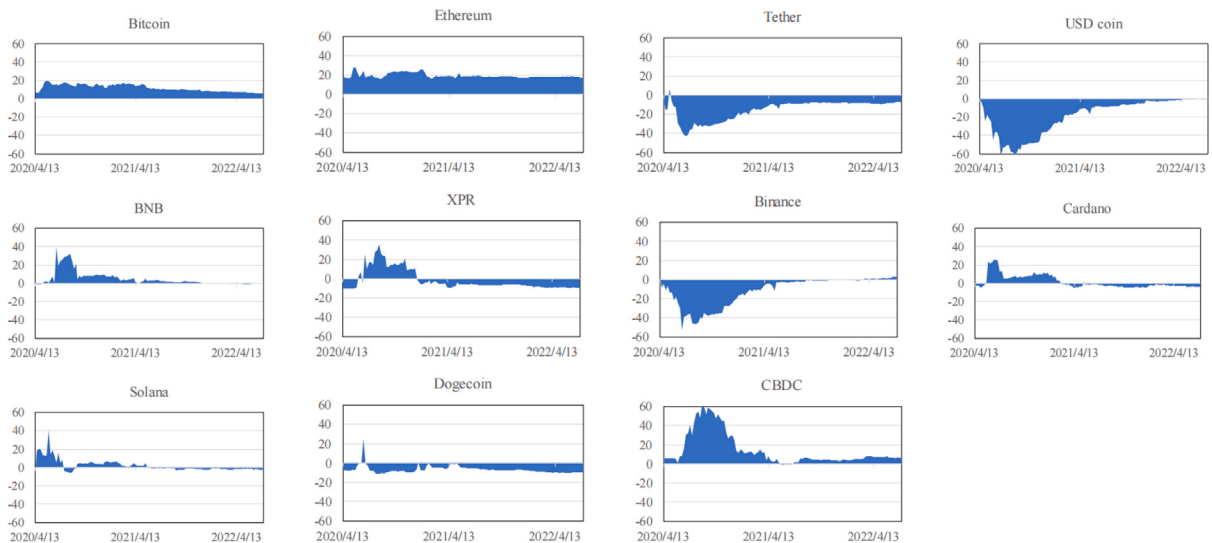


Fig. 3. Dynamic net spillover in time domain estimated by TVP-VAR-DY method.

Notes: The Dynamic net spillover shows the net spillover effect of individual variables in the whole system in time domain. Positive values imply that the variable acts as a transmitter of systemic shocks, while negative values indicate that the role of the variable is a receiver in terms of systemic risk shocks.

April, 2020 to July, 2022, whereas Tether, USD coin, and Binance are three main net spillover receivers. In other words, the price fluctuations in Tether, USD coin, and Binance are mainly driven by Bitcoin, Ethereum, and CBDC attention. In special, we can see that in the first half of the sample (roughly from April 2020 to April 2021), CBDC attention is the largest net spillover transmitter to others, while Tether, USD coin, and Binance are primary spillover recipients. This finding can provide more information to investors and policymakers. According to this finding, when CBDC attention, Bitcoin, and Ethereum fluctuate, Tether, USD coin and Binance may also fluctuate. For risk averse, they can use the findings to better hedge their risks. For policymakers, it provides valuable information on how the cryptocurrency market will likely be affected when public attention to CBDC fluctuates. This can help them better understand the intrinsic connection between CBDC and the cryptocurrency market and help them better formulate appropriate financial policies.

Moreover, we illustrate the network of net pairwise directional spillover index (NPDS) in the time domain in Fig. 4. Consistent with the findings in Fig. 2 and Fig. 3, Fig. 4 shows that, on the one hand, Ethereum, Bitcoin, and CBDC attention are the three strongest NPDS transmitters, while USD coin, Tether, and Binance are three major NPDS receivers. More importantly, we can see that CBDC is NPDS transmitter to both Ethereum and Bitcoin, indicating its dominant role in information spillover among these cryptocurrency markets.

In summary, the time-domain spillover evidence reveals that although Bitcoin and Ethereum are two leaders in information transmissions among cryptocurrency markets, CBDC attention is also a very important factor that has significant impacts on cryptocurrency prices, especially it has positive NPDS to Bitcoin and Ethereum markets.

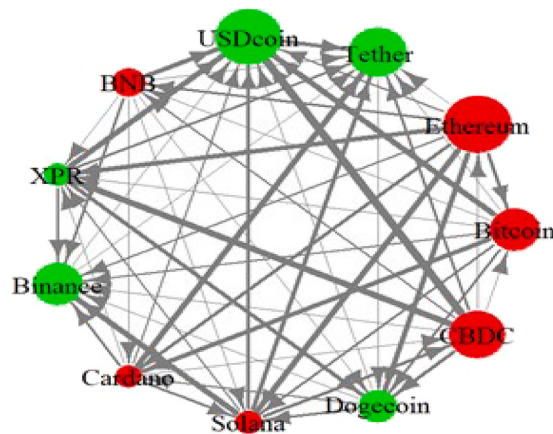


Fig. 4. Network of net pairwise directional spillover index (NPDS) in time domain.

Measured by TVP-VAR-DY method. The red (green) nodes denote the transmitters (receivers) of NPDS. The size of one node represents the net spillover effects this node has. The arrow indicates the direction of NPDS, and the width of the line indicates the spillover intensity. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

Table 3

Mean spillover measurements among the ten cryptocurrencies and CBDC attention in frequency domain at short-term frequency (1 to 4 weeks).

	Bitcoin	Ethereum	Tether	USD coin	BNB	XPR	Binance	Cardano	Solana	Dogecoin	CBDC	FROM
Bitcoin	23.7	14.25	0.3	0.1	10.86	6.31	0.26	6.16	3.79	3.57	1.01	46.62
Ethereum	12.19	21.8	0.19	0.17	9.97	6.25	0.21	8.66	8.47	4.13	0.88	51.12
Tether	1.04	1.16	39.67	15.62	1.57	2.9	20.67	4.2	2.46	0.73	2.07	52.42
USD coin	3.21	1.34	11.91	34.1	3.1	3.62	18.45	2.2	2.07	1.27	5.1	52.27
BNB	9.92	9.97	0.45	0.08	23.68	6.9	0.19	6.33	5.68	1.65	1.18	42.35
XPR	6.76	6.78	1.2	0.09	8.57	28.94	0.18	6.61	4.67	4.49	4.12	43.46
Binance	0.98	1.27	19.68	20.18	1.59	1.7	33	3.24	3.74	0.99	1.64	55.02
Cardano	5.4	7.3	0.44	0.65	5.38	4.95	0.96	23.13	7.73	3.87	2.34	39.02
Solana	4.14	9.66	0.3	0.26	6.51	4.79	0.37	9.12	26.32	3.98	0.42	39.55
Dogecoin	6.04	6.47	0.79	0.87	2.91	5.58	0.48	5.93	4.71	34.34	3.99	37.77
CBDC	0.37	0.5	0.15	0.15	0.24	0.16	0.66	2.44	2.44	2.31	73.27	9.43
TO	50.05	58.7	35.4	38.17	50.72	43.16	42.43	54.88	45.76	26.99	22.76	TSI
NET	3.43	7.58	-17.02	-14.1	8.37	-0.3	-12.58	15.86	6.21	-10.78	13.33	42.64

Notes: This table reports the directional spillover among crude oil, carbon and agriculture futures markets by the method of Baruník and Křehlík (2018) in frequency domain. The rightmost column (FROM) of this table indicates the directional spillover from all others to a specific futures market. The penultimate row (TO) of this table indicates the directional spillover to all others from a specific futures market. The bottom row (NET) shows the net spillover, i.e., the difference between TO and FROM spillover of a specific futures market. The number in the bottom right corner of this table (indicated in bold face) is the TOTAL spillover index (TSI) of all the futures markets.

4.2. Frequency-domain spillover evidence by TVP-VAR-BK method

In Section 4.1, we present the time-domain spillover effects across ten cryptocurrency markets and CBDC attention. However, as noted by Baruník and Křehlík (2018), to better understand the sources of spillover effects in economic systems, it is crucial to realise the frequency dynamics of these spillover effects, since shocks to economic activity affect economic variables with different frequencies and intensities. We should believe that the main reason why economic agents operate at different investment horizons represented by various time frequencies (from short to long term) lies in the formation of their preferences at different time horizons. A financial system in which asset prices are driven by consumption growth with different cyclical components will naturally generate shocks with heterogeneous frequency responses. Thus, various sources of impacts generate an overall spillover effect in this system containing the short-, medium-, and long-run components (Dew-Becker and Giglio, 2016). Therefore, when quantifying spillover effects, we should carefully consider the different degrees of persistence of the relationships behind such overall spillovers (i.e., the spillover effects reveal in the time domain). Similarly, we should consider the frequency domain as a natural way to measure spillover effects in cryptocurrency markets (Li and Meng, 2022).

As a consequence, in this subsection, we employ the TVP-VAR-BK method to investigate further the frequency spillover effects among the ten cryptocurrencies and CBDC attention. Following the suggestions of Li and Meng (2022) and Umar et al. (2022), we divide the overall frequency band into two parts, one for short term (i.e., 1 to 4 weeks) and the other for long term (i.e., longer than 4 weeks). Then Tables 3 and 4 report the empirical measurements.

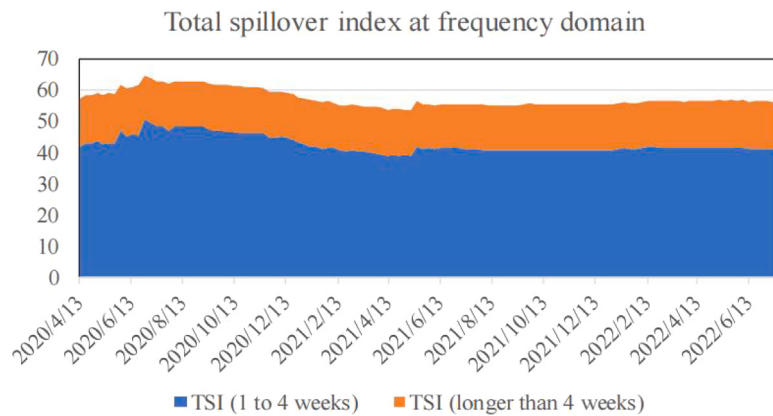
First of all, the major results of pairwise directional spillover, TO, FROM, NET, and TSI spillover indices are found to concentrate at a short-term frequency (i.e., 1 to 4 weeks). For example, the total spillover index (TSI) at the short term is measured to be

Table 4

Mean spillover measurements among the ten cryptocurrencies and CBDC attention in frequency domain at long-term frequency (longer than 4 weeks).

	Bitcoin	Ethereum	Tether	USD coin	BNB	XPR	Binance	Cardano	Solana	Dogecoin	CBDC	FROM
Bitcoin	12.15	6.08	0.24	0.06	3.99	1.87	0.05	1.48	1.53	2.18	0.04	17.53
Ethereum	6.07	8.57	0.14	0.06	2.64	1.67	0.09	1.94	3.01	2.84	0.06	18.51
Tether	0.08	0.09	3.75	1	0.04	0.05	2.01	0.22	0.56	0.1	0.01	4.17
USD coin	0.64	0.15	2.15	5.13	0.3	0.1	4.48	0.06	0.39	0.12	0.12	8.5
BNB	5.91	4.51	0.16	0.06	11.38	3.39	0.01	2.48	3.41	2.16	0.5	22.59
XPR	2.35	4.63	0.03	0.02	2.64	9.29	0.08	2.68	3.51	1.58	0.77	18.31
Binance	0.37	0.13	2.65	2.23	0.34	0.21	5.31	0.07	0.35	0.17	0.16	6.67
Cardano	5.66	5.62	0.39	0.26	4.31	3.85	0.38	9.79	2.89	4.43	0.27	28.06
Solana	3.11	5.4	0.04	0.16	3.43	2.3	0.15	3.43	11.6	4.38	0.14	22.53
Dogecoin	1.57	3.62	0.13	0.26	1.32	3.46	0.14	1.04	2.09	13.8	0.46	14.09
CBDC	0.16	0.06	0.01	0.07	0.05	0.07	0.19	0.28	0.61	0.1	15.7	1.61
TO	25.93	30.29	5.93	4.17	19.06	16.98	7.58	13.68	18.34	18.07	2.53	TSI
NET	8.4	11.78	1.77	-4.33	-3.53	-1.33	0.91	-14.37	-4.19	3.99	0.93	14.78

Notes: This table reports the directional spillover among crude oil, carbon and agriculture futures markets by the method of Baruník and Křehlík (2018) in frequency domain. The rightmost column (FROM) of this table indicates the directional spillover from all others to a specific futures market. The penultimate row (TO) of this table indicates the directional spillover to all others from a specific futures market. The bottom row (NET) shows the net spillover, i.e., the difference between TO and FROM spillover of a specific futures market. The number in the bottom right corner of this table (indicated in bold face) is the TOTAL spillover index (TSI) of all the futures mark.

**Fig. 5.** Dynamic total spillover index (TSI) in frequency domain.

Notes: The total spillover index(TSI) measures the spillover effect of ten cryptocurrencies and CBDC attention in frequency domain. This figure shows the stacked area map for total spillover, where the blue and orange parts indicate short-term and long-term net spillover indices, respectively.

42.64%, while this index at long-term frequency is only 14.78%. These findings suggest that investors in cryptocurrency markets are more likely to do their trading activities in the short term (1 to 4 weeks) than in the long term (longer than 4 weeks), and thus policymakers and portfolio managers should pay closer attention to short-term market movements and knowing that formulate short-term regulatory and risk management strategies in cryptocurrency markets may be more effective than those made for long term programme. Secondly, we also find in Tables 3 and 4 that, the pairwise directional spillover indices between Bitcoin and Ethereum, as well as those between Binance and Tether (USD coin) are larger than the others, further proving that Bitcoin, Ethereum, Binance, Tether, and USD coin are the key markets in information exchange in this system. Finally, regarding net spillover effects, Table 2, Tables 3 and 4 show some different evidence. For example, in both time domain (Table 2) and in short-term frequency (Table 3), Bitcoin, Ethereum, BNB, Cardano, Solana, and CBDC attention are net spillover senders, while in long-term frequency Bitcoin, Ethereum, Tether, Binance, Dogecoin, and CBDC attention are net spillover transmitters. In other words, only Bitcoin, Ethereum, and CBDC attention are always the net spillover emitters in both time and frequency domains, implying that the CBDC attention is really an important exogenous impactor on cryptocurrency markets, and it can be used to design better regulatory, risk management and portfolio allocation tools for policymakers and portfolio managers.

Then Figs. 5 and 6 present the stacked area maps for total spillover (TSI) and net spillover indices of the ten cryptocurrencies and CBDC attention, respectively. On the one hand, Fig. 5 reveals that short-term (i.e., 1 to 4 weeks) total spillover of this system dominates the long-term one (i.e., longer than 4 weeks), further confirming the fact that these ten cryptocurrency markets and CBDC attention interact with each other mainly at short time horizon. Investors are more likely to trade cryptocurrencies and pay attention to the information from the central bank's digital currency in the short term. On the other hand, we find in Fig. 6 that, most net spillover effects of the ten cryptocurrencies and CBDC attention centred at short term, with exceptions for Bitcoin, Ethereum, and Cardano, indicating that Bitcoin and Ethereum are long-term information leaders in cryptocurrency markets. Moreover, CBDC attention is a very powerful net spillover sender over other markets, and its net spillover effects on other markets are almost entirely

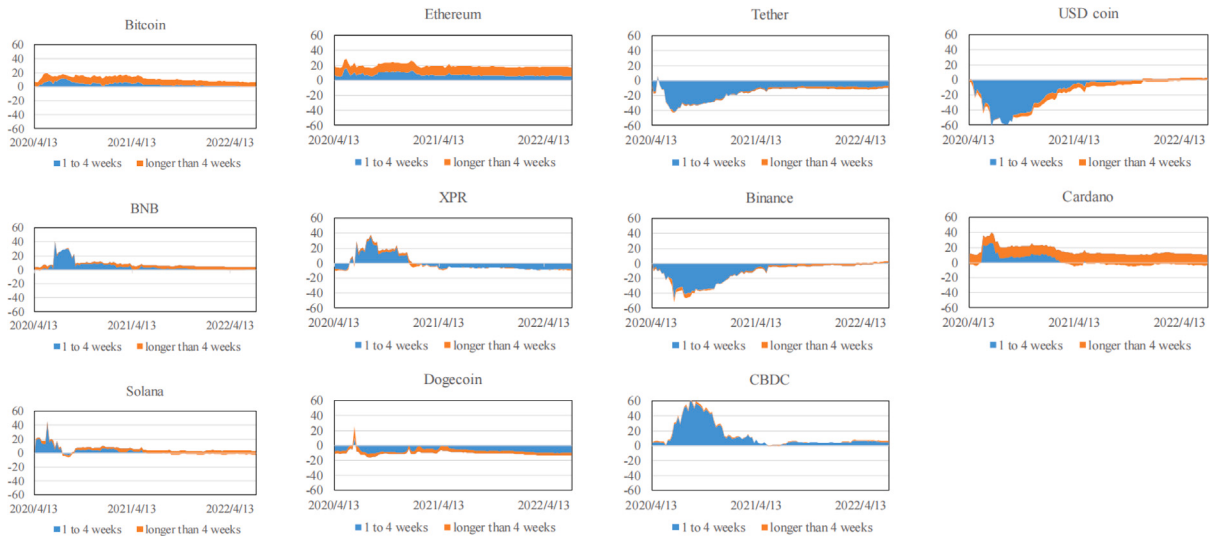


Fig. 6. Dynamic net spillover in frequency domain estimated by TVP-VAR-BK method.

Notes: The Dynamic net spillover shows the net spillover effect of individual variables in the whole system in frequency domain. Positive values imply that the variable acts as a transmitter of systemic shocks, while negative values indicate that the role of the variable is a receiver in terms of systemic risk shocks, where the blue and orange parts indicate short-term and long-term net spillover indices, respectively. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

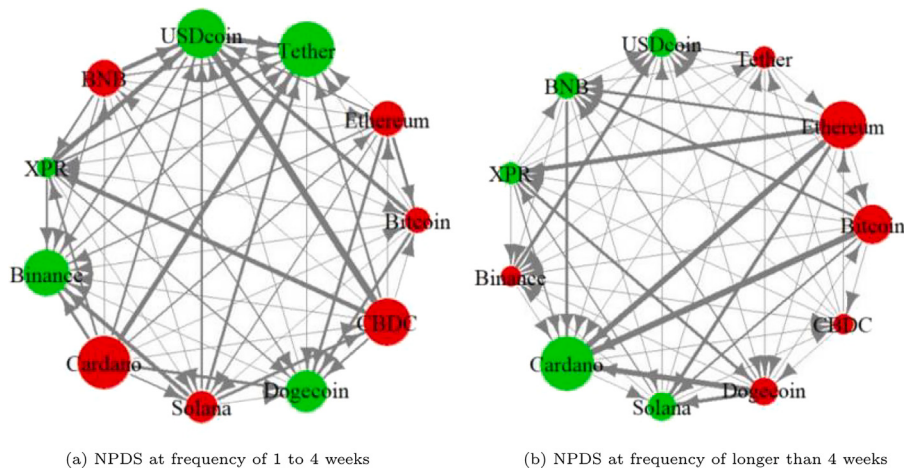


Fig. 7. Networks of net pairwise directional spillover index (NPDS) in frequency domain.

Panels (a) and (b) show the NPDS by TVP-VAR-BK approach at time frequencies of 1 to 4 weeks and longer than 4 weeks, respectively. The red (green) nodes denote the transmitters (receivers) of NPDS. The size of one node represents the net spillover effects this node has. The arrow indicates the direction of NPDS, and the width of the line indicates the spillover intensity. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

concentrated in the short-term component, implying its short-term dominant role in information transmission among cryptocurrency markets. Furthermore, we can see that, in both the short and long term Tether, USD coin, and Binance is the three major net spillover receivers in the system, especially in the first half of the data sample (i.e., roughly from April 2020 to April 2021). In summary, both Fig. 5 and Fig. 6 CBDC attention concentrate on short-term frequency (i.e., 1 to 4 weeks), and CBDC attention, as well as Bitcoin and Ethereum, are the major net spillover transmitters to other cryptocurrency markets.

Moreover, we illustrate the networks of net pairwise directional spillover index (NPDS) in Fig. 7 to investigate the changing roles of various cryptocurrency markets and CBDC attention at different time frequencies. Fig. 7 shows that three nodes (i.e., Bitcoin, Ethereum, and CBDC attention) do not change their characteristics as net pairwise spillover senders from short-term (1 to 4 weeks) to long-term (longer than 4 weeks) frequencies, proving their stable roles as information emitters to other markets. Taking it a step further, we can see that in Panel (a) of Fig. 7, CBDC attention is a net spillover sender to both Bitcoin and Ethereum markets within 1 to 4 weeks, although in the longer-term its role decreases as shown in Panel (b) of Fig. 7. Then we find that only USD coin and

Table 5
Regression results of Bitcoin and Ethereum returns on spillover indices.

	TSI impact		NET impact		TSI and NET impacts	
	Bitcoin	Ethereum	Bitcoin	Ethereum	Bitcoin	Ethereum
Constant	−27.618* (16.410)	−20.634 (23.820)	−10.058 (7.654)	−14.846* (8.804)	−26.842 (20.513)	−7.994 (26.843)
Bitcoin(−1)	0.145 (0.099)		0.167 (0.112)		0.125 (0.101)	
Ethereum(−1)		0.068 (0.091)		0.021 (0.091)		−0.004 (0.083)
TSI	−3.257** (1.577)	−5.381* (3.172)			−3.659*** (1.326)	−6.320** (2.651)
TSI(−1)	3.753** (1.599)	5.769* (3.228)			3.988*** (1.378)	6.177** (2.808)
$NET_{Bitcoin}$			0.283 (0.808)	2.125* (1.192)	0.485 (0.758)	2.523** (1.090)
$NET_{Bitcoin}(−1)$			−0.14 (0.781)	−1.664 (1.206)	−0.444 (0.708)	−2.057* (1.062)
$NET_{Ethereum}$			−0.553 (0.602)	−1.075 (−0.966)	−0.747 (0.474)	−1.320* (0.78)
$NET_{Ethereum}(−1)$			1.027 (0.657)	1.650* (0.953)	1.176** (0.555)	1.964*** (0.759)
Adjusted R^2	0.076	0.056	0.035	0.049	0.079	0.119

Notes: The linear regression estimation is made by Least Squares with heteroscedasticity-consistent (Eicker–White) standard errors. TSI and NET are total spillover and net spillover index, respectively. (−1) after one regressor indicates the one-order lag of this series. The numbers in parentheses are the standard errors of the estimates.

*Denote significance at 10% level.

**Denote significance at 5% level.

***Denote significance at 1% level.

XPR are always the spillover recipients in both short- and long-term frequencies, and the roles of other markets reserve from short- to long-term frequencies. This result confirms the view put forward by Wang et al. (2022a) that CBDC attention has a positive correlation relationship with the cryptocurrency market's volatility. At the same time, this analysis further expands his research and clearly shows the path of information fluctuation overflow. The simplified system nodes and spillover arrows show certain critical paths and causal relationships. It shows regulators how a CBDC could affect the cryptocurrency market and highlights the importance of Bitcoin and Ethereum. In this way, they better understand that when conducting regulation, they should pay more attention to the volatility overflow of Bitcoin and Ethereum. These outcomes further prove that, although Bitcoin and Ethereum are two major leaders in information exchanges among cryptocurrency markets, CBDC attention is also a key information transmitter for cryptocurrency markets, and should be considered as an important impactor on cryptocurrency prices.

4.3. The impacts of spillover effects on cryptocurrency returns

In this sub-section, to understand what we can learn from the spillover effects among cryptocurrency markets and CBDC attention, we further investigate the impacts of total and net spillover effects on cryptocurrency market returns. As noted in Section 4.1 and Section 4.2, since Bitcoin and Ethereum are the two dominant markets over other cryptocurrency markets, we, therefore, focus on the impacts of total and net spillover effects on these two markets by using the commonly used multiple regression approach. The left part of Table 5 firstly shows the impacts of the total spillover index (TSI) on the returns of Bitcoin and Ethereum. We use constant, one-order lagged Bitcoin and Ethereum returns, TSI and one-order lagged TSI as regressors. It shows that, lagged Bitcoin and Ethereum returns do not have significant effects on the present returns of Bitcoin and Ethereum, suggesting that Bitcoin and Ethereum markets are efficient enough for impossibilities in speculation from their past performances. However, we find that both TSI and one-order lagged TSI have significant impacts on the returns of Bitcoin and Ethereum, which indicates that the total spillover effects among cryptocurrency markets and CBDC attention really help to explain and predict Bitcoin and Ethereum market returns. Moreover, the one-order lag of TSI has a positive influence on both Bitcoin and Ethereum returns, while the present TSI negatively affects their returns.

The middle part of Table 5 then demonstrates the impacts of net spillover effects (NET) on the Bitcoin and Ethereum returns. Similarly, we adopt constant, one-order lagged Bitcoin and Ethereum returns, NET and one-order lagged NET spillover indices of Bitcoin and Ethereum as regressors in this part. The estimation results present that most of the regressors have no significant effects on the Bitcoin and Ethereum returns, indicating the poor explanatory and predictive abilities of NET spillover effects on these markets. Finally, the right part of Table 5 investigates the impacts of both TSI and NET spillover indices on the Bitcoin and Ethereum returns. It reveals that again both TSI and lagged TSI have significant effects on the two returns, and also the NET spillover indices generally contribute to explaining and predicting them, especially for the Ethereum return. These results confirm that TSI and NET spillover effects among cryptocurrency markets and CBDC attention can significantly help to understand the price fluctuations in Bitcoin and Ethereum markets and offer us a new perspective to develop more effective predictive and risk management tools for cryptocurrency markets.

5. Conclusions

This paper utilises the TVP-VAR-DY and TVP-VAR-BK spillover models to study the spillover connectedness between cryptocurrency markets and CBDC attention from two domains: time and frequency. To achieve this aim, we select the top ten cryptocurrencies and CBDCAI to represent the cryptocurrency markets and CBDC attention, separately.

The empirical results of this study show that there are four main findings in this research. Firstly, CBDCAI has a great impact on cryptocurrency markets, which could affect the price of cryptocurrencies. Moreover, Bitcoin and Ethereum could also serve as main risk volatility spillover transmitters. CBDC attention, Bitcoin, and Ethereum are the only three factors that keep stable positive net pairwise directional spillover. Secondly, from the time domain, Binance, Tether, and USD coin are primary spillover receivers that play a significant role in information transmission in the variable system. Third, from a frequency perspective, we find that the short-term TSI is smaller than that of the long-term TSI, which means investors prefer short-term transactions. Finally, through a linear regression analysis, our study can verify that TSI and NET spillover effects exist among cryptocurrency markets and CBDCAI has the predictive power for the price fluctuation in Bitcoin and Ethereum markets from a fixed-effect perspective.

From a social perspective, this paper could help investors, especially risk-averse investors, hedge their risks or predict the returns of Bitcoin and Ethereum promptly based on the new proxy of CBDCAI. Furthermore, because this paper indicates that investors tend to make more short-term investment decisions in cryptocurrency markets than long-term decisions, investment institutions can increase the net short positions of cryptocurrency assets in their portfolio, which could help them improve investment returns. This study also has several benefits for policymakers and financial market regulators. Through this study, they will be able to understand better how public attention to CBDCs can influence the fluctuations of cryptocurrency markets. So, when developing new policies, policymakers can predict the repercussions of their newly issued policies more accurately.

We believe it pertinent to mention two research pathways for future investigation of CBDCs. Firstly, the index used in this article is CBDCAI, Wang et al. (2022a) also developed the Central Bank Digital Currency Uncertainty Index (CBDCUI). Therefore, it would be interesting to analyse further the risk transmission channels between the CBDC uncertainty and cryptocurrency markets. Secondly, a linear regression model could only examine the predictive power of CBDCAI from a fixed-effect perspective. The following researchers could employ other classic forecasting detecting models to explore the predictive power of CBDC indices on financial markets.

As CBDCs continue to evolve, their influence in financial sectors will grow in the future. Because money will always be used, there would be many benefits to further research into CBDCs. As the digital currency continues to develop and the way of individual payments is changing, more and more countries are exploring the CBDC, which could definitely become one of the key pillars in the financial system. However, CBDCs are still in their infancy, and their roles in the monetary system are still untapped, and we can still explore the potential impacts of CBDCs.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

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