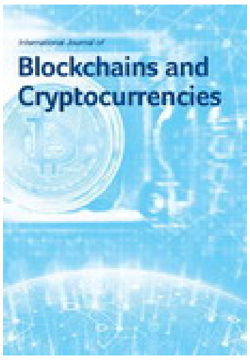

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Naeim Shokri, Amir Roshanfekr

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Investigating the spillover effects of Bitcoin's financial fluctuations on other digital currencies

Naeim Shokri*

Tarbiat Modares University,
Tehran, Iran
Email: n.shokri@modares.ac.ir
Email: naeimshokri@gmail.com
*Corresponding author

Amir Roshanfekr

Master of Information Technology Management,
Science and Research Branch,
Islamic Azad University,
Tehran, Iran
Email: amir.roshanfekr@gmail.com

Abstract: The purpose of this study is to investigate the effects of volatility spillover from Bitcoin as the largest digital currency on selected digital currencies. Volatility spillovers are a warning for risk management among cryptocurrencies and are especially instructive during periods of crisis. We investigate the effects of volatility spillover between digital currencies through the conditional covariance matrix. The findings show that Bitcoin had the highest volatility spillover on Dogecoin, Dash, and Ripple among digital currencies, respectively, and had the lowest volatility spillover on Ethereum. Bitcoin is used more as an asset than a currency and the Bitcoin market is more volatile than other currencies and prone to potential price bubbles. Based on the results, the bubbles in the digital currency market show that the market is irrational and due to the speculative behaviour of investors and the excitement of the Bitcoin market, it is causing economic instability.

Keywords: financial volatility spillover; digital currencies; multivariate GARCH approach.

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Biographical notes: Naeim Shokri obtained his degree of Doctor of Philosophy (PhD) at the Tarbiat Modares University, Tehran, Iran in July 2022 in the field of Health Economics. He received his MSc in Economic Science from the Razi University, Kermanshah, Iran in 2017. He is the author of more than 30 peer-reviewed articles. His research has been focused on the financial misalignment of social insurances, health economics, and the applicability of blockchain technology and digital currencies. He has been involved in industry projects as the project manager and works as an expert on budget integration at Tehran University's budget department.

Amir Roshanfekr received an MSc in Information Technology Management Science from the Azad University of Science and Research Branch, Tehran, Iran in 2020. His research has been focused on distributed systems of Blockchain. Currently, he has published several articles in the field of information technology management. His main research interests include management information systems, blockchain, and data mining. He is working as an information technology expert at Tarbiat Modares University.

1 Introduction

Bitcoin is one of the innovations in the field of e-commerce and finance that has expanded over the past nine years. Bitcoin is, in fact, an internet innovation with a function similar to 'unsupported money' whose value in global markets has increased from a few hundred dollars to thousands of dollars over the years (Chohan, 2017).

An examination of the fluctuations in the value of Bitcoin over one year in terms of the dollar shows that so far two main factors have been able to have a significant impact on Bitcoin. The first gender factor was the technological factor that had the least impact. The second factor or intervention of governments and reactions of world powers in the form of regulation in this area has been more important in the impact of this phenomenon and its evolutionary trajectory.

In any case, Bitcoin has been so influential in the nine years since its inception that monetary policy centres and executive bodies of countries have been studying and regulating it. The future of Bitcoin depends on the influence of the factors around it, but whether Bitcoin succeeds in achieving the desired future of its creators or whether it completely collapses, at present the influence of the world system on technological movements has taken historical evidence; Therefore, the research centres of the world should continuously monitor such technological changes by formulating regulations and policy measures, if necessary, to protect the interests of businesses. All of us have faced this emerging phenomenon of virtual finance in recent years, and at the same time as the spread of Bitcoin in the world, this phenomenon has also spread through virtual space, and various websites have been designed to create and sell it.

Because Bitcoin is used more as an asset than a currency, the Bitcoin market is now very risky and more volatile than other currencies and prone to potential price bubbles. Therefore, Bitcoin has a special place in the financial markets and portfolio management, which is why it is very important to study its volatility. Bitcoin price volatility modeling is an important factor in economic models. Therefore, proper modeling has attracted the attention of financial researchers and policymakers. Numerous articles in the monetary and financial literature section have used various generalised conditional variance (GARCH) models to model the instability of the digital currency market, including the studies of Huynh et al. (2020), Dyhrberg (2016), Katsiampa (2019), Baur and Dimpfl (2018) and Bouri et al. (2016).

The main issue of this study is to investigate the effect of fluctuations in large and small digital currencies in terms of investment using the multivariate GARCH approach (A-BEKK-GARCH) during the period 08/15/2015 to 05/21/2021. The purpose of this study is to investigate the effect of fluctuations from Bitcoin as the largest digital currency on other digital currencies. Finally, the novelty of the present article compared to similar works includes the following:

Therefore, the innovation of the present article includes the following:

1 Investigating the effect of Bitcoin fluctuations on other digital currencies.

2 Using the A-BEKK-GARCH approach with t-student distribution (t).

In the second part, theoretical foundations and a review of the research background are discussed and in the third part, the research method is presented. The fourth section is devoted to empirical findings and results, and the fifth and final section is devoted to conclusions, discussions, and policy proposals.

Unlike stocks or bonds, determining the underlying value of Bitcoin is difficult. The value of the Bitcoin cryptocurrency depends entirely on how people think and think about its value. Some analysts have claimed that the value of Bitcoin could rise to more than $ 400,000. Others, such as experts of Bank of America, have said that the current value of Bitcoin is a manifestation of the 'mother of bubbles' and that the price of this cryptocurrency will soon fall freely (Park et al., 2021). At present, Bitcoin does not have enough conditions to be considered a traditional form of money.

2 Literature review

Money has three basic functions in modern economics, it is a tool for trading and economic exchange, it is a tool for storing value, and it is used as a formal unit in accounts and financial books. Despite all the recent support from some financial systems for Bitcoin cryptocurrency, however, Bitcoin has not yet been able to find its place in the international financial system. Given the serious challenges of using Bitcoin in the context of day-to-day transactions, it is very difficult and unlikely that we can consider it a suitable tool for economic transactions and financial exchanges. In addition, deep fluctuations in the value of Bitcoin take it away from being an important tool for use in various economic relationships. With the advent of blockchain, a new method of money transfer was introduced, which based on the characteristics of the blockchain platform, established an emerging economy, with the development of blockchain-based platforms, in addition to money transfer, new needs also arose, some of them with a deeper look at blockchain technology and definitions New for its applications and another part were introduced by the developers based on the declaration of user needs (Roshanfekr, 2021). From the perspective of policymakers, considering financial spillover connectedness could help to develop forward-looking monitoring regulations and to facilitate financial stability (Kearney and Lucey, 2004).

Rehman et al. (2022), when analysing risk spillovers from Bitcoin to currencies, find that Bitcoin exercises significant power over most currencies, with the South African rand and Brazilian real holding both the highest downside and upside risk before and during the COVID-19 pandemic period, respectively.

Katsiampa et al. (2019) have investigated the spillover effects of fluctuations in digital currencies using daily data of Bitcoin, Ethereum, and Litecoin digital currencies during the period from August 7, 2015, to July 10, 2018, and have used multivariate GARCH (MGARCH) to do this. They concluded that past shocks and fluctuations of a digital currency significantly affect its current conditional variance. They have also stated that there are spillover effects of two-way fluctuations between Bitcoin and Ethereum and Bitcoin and Litecoin.

Katsiampa (2019) has studied the coordinated movement of volatility between Bitcoin and Ethereum using multivariate GARCH (MGARCH) under two normal and T-Student distributions. In his analysis, he used two digital currencies, Bitcoin and Ethereum, daily for the period of August 7, 2015, to January 15, 2018. The research results show that the multivariate GARCH model provides better results under the t-Student(t) distribution. Also, the findings of its research show that fluctuations between Bitcoin and Ethereum react to news and shocks simultaneously and have a high correlation.

Xu et al. (2021) have studied volatility series in digital currency markets using the value at risk (VaR) approach. In their analysis, they used 23 digital currencies daily from April 2016 to May 2019. They concluded that the volatility spillover increased in the final years of the study. They have also stated that the correlation of digital currencies has increased steadily over time and that Bitcoin and Ethereum have the most VaR in this market.

Moratis (2021) quantified the volatility spillover effect in digital currency markets using Bayesian self-explanatory vector relevancy (BVAR). In his work, he has used 30 major digital currencies (in terms of investment) daily during the period from October 1, 2016, to May 1, 2020. The results of that research show that the overflow of fluctuations in digital currencies is more during the crisis (such as in 2017) and reacts uniformly during the market crisis. It has also stated that Ripple is the biggest recipient of volatility from other major digital currencies such as Bitcoin.

Huynh et al. (2020) investigated the spillover effects of small digital currencies (in terms of investment) to large digital currencies from April 2013 to April 2019 and used the transfer entropy method in this study. They stated that there are spillover effects in the digital currency market and this transfer is more from the side of large currencies to smaller ones.

Pichl and Kaizoji (2017), in their article, analysing the time series fluctuations of Bitcoin price, have used the neural network model, which can model fluctuations. In this research, the daily data of Bitcoin from February 2012 to August 2017 is used. The results indicate that the price of bitcoin is more volatile than other common currencies such as the dollar and the euro.

Koutmos (2018), in his article, investigated the returns and volatility in digital currencies using vector autoregression (VAR). In his research, he used 18 digital currencies daily during the period from August 7, 2015, to July 17, 2018. The results of that research show that Bitcoin is the most important factor in volatility spillover among all digital currencies. It has also stated that this overflow has increased over time and shows a sudden increase due to the news.

In an article, Canh et al. (2019) investigated the systematic risk in the digital currency market using multivariate GARCH-dynamic conditional correlation (DCC-GARCH). In their research, they used the daily closing price of 7 major digital currencies from August 5, 2014, to December 31, 2018. The results of their research show that in large digital currencies such as Bitcoin and Ethereum, there is the most contagion of fluctuations to small digital currencies.

Also, Kim et al. (2020) and Cheikh et al. (2020) have stated that Bitcoin has the highest volatility among digital currencies and the most contagion to other digital currencies.

3 Research methodology

Given the widespread role of turbulence (variability) and its overflow effects in economic theories of quantification and numerical analysis of instability in the empirical field of economics is of particular importance. One approach in the field of econometrics to measure and quantify fluctuations and turbulence is the use of the conditional variance model of ARCH regression itself, which was first proposed by Engle (1982) and has expanded over time. After the introduction of this model by the parasitic modeling of turbulence in the financial time series, it attracted a lot of attention, and depending on the objectives of various studies, different types of GARCH models have been introduced, but one of the noteworthy and practical issues that are very focused on accurate modeling of turbulence The transfer and overflow of returns on financial assets to each other. To model such a phenomenon, we have to use an MGARCH model. MGARCH models model two or more variables simultaneously. MGARCH models use all the information available in the studied markets. According to the findings of Conrad et al. (1991), MGARCH models provide a more accurate and comprehensive estimate of parameters; because these models use the information of the entire variance matrix and covariance of the errors. In addition, it prevents correlation between the regressors obtained in the univariate model; because they estimate all the parameters together (Pegan, 1984). One of these models is BEKK presented by Engle and Kroner (1995). This BEKK model allows conditional variances and covariances of multiple time series. Among MGARCH models, the functions of the BEKK model are much deeper and more accurate than the DCC model form (Huang et al., 2010). In principle, the efficiency of the BEKK-GARCH model in detecting fluctuating transmission factors in financial markets has been proven in many related texts (Dai et al., 2014). It, therefore, allows us to identify the effects of oscillation transmission. In this paper, we examine the effects of oscillation transitions between digital currencies through a conditional covariance matrix. As a result, we use a simple methodological relation for the conditional mean equation. This is as follows:

$$y_t = c + \epsilon_t ; \epsilon_t \mid I_{t-1} \approx N\left(0, H_t\right) \tag{1}$$

where y_t is the price-return vector, c is the vector-estimating parameter, and ϵ_t is the residual vector with the conditional variance-covariance matrix H_t concerning the data set at the time I_{t-1}. The conditional variance-covariance matrix of BEKK is as follows:

$$H_t = W'W + A'\varepsilon_{t-1}\varepsilon'_{t-1}A + B'H_{t-1}B \tag{2}$$

where W, A and B are matrices of appropriate dimensions, W is the upper triangular matrix, and A and B are positive diagonal matrices (Bekiros, 2014). In addition, the original diameter elements H_t are $h_{ii.t}$, which represents the conditional variance of the residuals at time t, which are considered as fluctuations of the studied variables, while the elements outside the diameter are H_t, $h_{ij.t}$, That $i \neq j$ represents the conditional covariance. As a result, the diagonal elements of matrices A and B record the impact of asset shocks and past fluctuations, respectively, while the non-diameter elements of matrices A and B, a_{ij}, b_{ij}, in which $i \neq j$ are the inter-market effects of shocks, respectively (Li and Majerowska, 2008). These cross-market effects are also known as shock transfer effects and instability serial effects. The BEKK model without two-variable constraint should be expressed as follows:

$$\begin{pmatrix} h_{11.t} & h_{12.t} \\ h_{21,t} & h_{22.t} \end{pmatrix} = W'W + \begin{pmatrix} a_{11} & a_{12} \\ a_{21} & a_{22} \end{pmatrix} \begin{pmatrix} \varepsilon_{1.t-1}^2 & \varepsilon_{1.t-1}\varepsilon_{2.t-1} \\ \varepsilon_{1.t-1}\varepsilon_{2.t-1} & \varepsilon_{2.t-1}^2 \end{pmatrix} \begin{pmatrix} a_{11} & a_{12} \\ a_{21} & a_{22} \end{pmatrix} + \begin{pmatrix} b_{11} & b_{12} \\ b_{21} & b_{22} \end{pmatrix} \begin{pmatrix} h_{11.t-1} & h_{12.t-1} \\ h_{21.t-1} & h_{22.t-1} \end{pmatrix} \begin{pmatrix} b_{11} & b_{12} \\ b_{21} & b_{22} \end{pmatrix} \tag{3}$$

Accordingly, the BEKK diagonal model is represented by the following equations:

$$\begin{aligned} h_{11.t} &= w_{11}^2 + a_{11}^2\varepsilon_{1.t-1}^2 + 2a_{11}a_{21}\varepsilon_{1.t-1}\varepsilon_{2.t-1} + a_{21}^2\varepsilon_{2.t-1}^2 + b_{11}^2 h_{1.t-1} \\ &\quad + 2b_{11}b_{21}h_{1.2.t-1} + b_{21}^2 h_{2.t-1} \end{aligned} \tag{4}$$

$$\begin{aligned} h_{22.t} &= w_{12}^2 + w_{22}^2 + a_{12}^2\varepsilon_{1.t-1}^2 + 2a_{12}a_{22}\varepsilon_{1.t-1}\varepsilon_{2.t-1} + a_{22}^2\varepsilon_{2.t-1}^2 + b_{12}^2 h_{11.t-1} \\ &\quad + 2b_{12}b_{22}h_{1.2.t-1} + b_{22}^2 h_{22.t-1} \end{aligned} \tag{5}$$

$$\begin{aligned} h_{12.t} = h_{21.t} &= w_{12}w_{11} + a_{11}a_{12}\varepsilon_{1.t-1}^2 + (a_{12}a_{21} + a_{11}a_{22})\varepsilon_{1.t-1}\varepsilon_{2.t-1} \\ &\quad + a_{21}a_{22}\varepsilon_{2.t-1}^2 + b_{11}b_{12}h_{11.t-1} + (b_{12}b_{21} + b_{11}b_{22})h_{12.t-1} + b_{21}b_{22}h_{22.t-1} \end{aligned} \tag{6}$$

After estimating the model parameters, the conditional correlation between the two digital currencies can be estimated by the following equation:

$$r_{12.t} = \frac{h_{12.t}}{\sqrt{h_{11.t}}\sqrt{h_{22.t}}} \tag{7}$$

where $h_{11.t}$ and $h_{22.t}$ show the conditional variances of the two digitised currencies, while $h_{12.t}$ shows the corresponding conditional covariance.

4 Empirical result

It should be noted that Eviews12 software was used to estimate the effects of overflow between digital currencies in the BEKK-GARCH model. Statistical population and sampling the statistical population of this study includes the daily returns of digital currencies; Since the researchers of this study intend to study the series of fluctuations in digital currencies, so digital currencies in which the most investment was made between 08/15/2015 to 05/21/2021 and had high price fluctuations, in other words, we have seen a one-time increase and a one-time fall in their prices. Table 1 introduces these digital currencies.

Our sample contains 2106 views for each time series. The prices of the listed digital currencies are in US dollars and are collected from the data centre coinmarketcap.com and finance.yahoo.com. The returns of digital currencies are calculated using the formula (8).

$$y_{i,t} = \ln(p_{i,t}) - \ln(p_{i,t-1}) \tag{8}$$

where $p_{i,t}$ are the final prices of digital currencies i in period t.

Table 1 Introduction of research variables

Variable name	*Symbol*
Bitcoin return time series	RBTC
Ethereum return time series	RETH
Ripple return time series	RXRP
Lightcoin return time series	RLTC
Dash return time series	RDAS
Dogecoin return time series	RDOG

Source: Research findings

4.1 Unit root test of research variables

Unit root test is the main basis of time series analysis. If the assumption of the variability of the variables is rejected, or in other words, other research variables are unnamed; it will cause problems in the validity of statistical tests. Because the GARCH and MGARCH models require persistence over time, the unit root test was used to examine the variability of variables. Common tests of unit roots include time series such as Dickey and Fuller generalised (ADF) and Phillips and Peron (PP) tests. The results of unit root tests are given in Table 2.

Table 2 Results of unit root test on index returns

Variable	*Probability*	*Dickey-Fuller statistic*	*Phillips-Peron statistic*	*Critical value 1%*	*Critical value 5%*	*critical value 10%*
RBTC	0.0001	–47.0905	–47.08608	–3.4332	–2.8627	–2.5674
RETH	0.0001	–45.7566	–45.9574	–3.4332	–2.8627	–2.5674
RXRP	0.0001	–29.8253	–47.5126	–3.4332	–2.8627	–2.5674
RLTC	0.0001	–46.4307	–46.4666	–3.4332	–2.8627	–2.5674
RDAS	0.0001	–48.2922	–48.2734	–3.4332	–2.8627	–2.5674
RDOG	0.0001	–44.7026	–44.8691	–3.4332	–2.8627	–2.5674

Source: Research calculations

According to the results obtained from this test at the critical value of 1%, 5% and 10% of the absolute value of the calculated statistic is greater than the critical levels; it can be concluded that all the variables used in the research have no single root and are meaningful. Considering that in this study the logarithmic efficiency time series has been used, it can be concluded that the mentioned time series has been differentiated once, and most likely, the series of variables have remained.

4.2 Arch effect test (ARCH-LM)

The ARCH test is about whether the variance of the variance is constant or variable. Such a test must first be performed on the status of the variance of the error sentence. In this regard, to investigate the existence of the condition of heterogeneity of conditional variance, the conditional variance heterogeneity test of the parasite Lagrangian coefficient has been used. For the ARCH test, first, a linear regression model [such as (1) AR] is estimated for each of the research variables and then the Lagrangian coefficient test is performed on each of the variables. According to the results of this test in Table 3, the value of the calculated F statistic is greater than the critical value; Also, the probability value (P-value) of the obtained F-statistic, which is less than 0.05, indicates that the null hypothesis based on the variance homogeneity of the rejected variables and the one hypothesis based on the variance heterogeneity are accepted. As a result, the research variables have the effects of conditional variance heterogeneity, and GARCH models can be used to examine the research variables.

Table 3 ARCH effect test results

	RDOG	*RDAS*	*RLTC*	*RXRP*	*RETH*	*RBTC*
F-statistic	44.6367	8.8014	11.1779	33.3775	20.0715	6.2578
Prob	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
Obs*R-squared	202.2742	43.2253	54.5931	172.0731	96.0441	30.9170
Prob	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000

Source: Research calculations

4.3 Correlation of research variables

Unconditional correlations for returns are reported in Table 4. Although these correlations are inaccurate and have low accuracy, and relying on them creates problems in practice, this matrix can give us an overview of the correlations between the variables, which can be effective.

Table 4 ARCH effect test results

	RBTC
RETH	0.5471 (0.0000)
RXRP	0.3915 (0.0000)
RLTC	0.6786 (0.0000)
RDAS	0.5436 (0.0000)
RDOG	0.4395 (0.0000)

Source: Research calculations

According to Table 4, Bitcoin has positive correlations with digital currencies.

4.4 Estimation results of the BEKK-GARCH model

After performing the tests related to the statics of the variables and then the uncertainty test of the variables and observing the existence of uncertainty in the remainder of the model, we estimate the model. This study uses a multivariate GARCH model to simultaneously estimate the conditional mean, variance, and covariance of digital currencies. We used to estimate the parameters with t-student (t) distribution. Using the squared log correlation, the order p and q are equal to one. Also, the software used in this research is Eviews12. The following is a review of the Bitcoin series on other digital currencies. Firstly, we investigated the effect of Bitcoin fluctuation overflow on Ethereum.

Table 5 BEKK-GARCH results between pairs (Bitcoin and Ethereum)

	Coefficient	*Std. error*	*Prob.*
C(3)	0.0000139	0.00000426	0.0011
C(4)	0.0000302	0.00000833	0.0003
C(5)	0.0000985	0.0000248	0.0001
C(6)	0.481040	0.044108	0.0000
C(7)	0.493377	0.46945	0.0000
C(8)	0.934312	0.004676	0.0000
C(9)	0.923873	0.005772	0.0000
C(10)	0.64658	0.156007	0.0000

Source: Research calculations

In the study of the relationship between Bitcoin and Ethereum, because the value of the significant level C(4) related to the impact of Bitcoin on the Ethereum is equal to 0.0003 and less than 0.05. Therefore, we accept that Bitcoin yield fluctuations have a positive and significant effect on Ethereum yield fluctuations. We Investigated the effect of Bitcoin fluctuation overflow on Ripple.

Table 6 BEKK-GARCH results between pairs (Bitcoin and Ripple)

	Coefficient	*Std. error*	*Prob.*
C(3)	0.0000368	0.0000161	0.0022
C(4)	0.0000436	0.0000189	0.0211
C(5)	0.000131	0.0000512	0.0107
C(6)	0.638803	0.122382	0.0000
C(7)	0.674256	0.128729	0.0000
C(8)	0.937200	0.0005042	0.0000
C(9)	0.918171	0.0005709	0.0000
C(10)	2.2560	0.112487	0.0000

Source: Research calculations

In the research findings related to the relationship between Bitcoin and Ripple return fluctuations, since the value of the significant level of coefficient C(4) in Table 6 is equal to 0.02 and less than 0.05. It is concluded that Bitcoin return fluctuations have a positive and significant effect on Ripple return fluctuations. Then, we investigated the effect of Bitcoin fluctuation overflow on Lightcoin.

In the relationship between Bitcoin return fluctuations and Lightcoin return fluctuations, since the value of the significant level related to the effect of Bitcoin return fluctuations on Lightcoin return fluctuations is equal to 0.0509 and greater than 0.05. Therefore, it is not accepted that Bitcoin return fluctuations have a positive and significant effect on Lightcoin return fluctuations. The reason for this, according to the studies of Canh et al. (2019), is that Bitcoin affects Lightcoins through other digital currencies. Then, we investigated the effect of Bitcoin fluctuation overflow on Dash.

Table 7 BEKK-GARCH results between pairs (Bitcoin and Lightcoin)

	Coefficient	*Std. error*	*Prob.*
C(3)	0.0000191	0.00000655	0.0035
C(4)	0.000009	0.00000461	0.0509
C(5)	0.00000625	0.00000462	0.1755
C(6)	0.510358	0.059681	0.0000
C(7)	0.449356	0.052422	0.0000
C(8)	0.937730	0.004629	0.0000
C(9)	0.952337	0.003260	0.0000
C(10)	2.4595	0.128557	0.0000

Source: Research calculations

Table 8 BEKK-GARCH results between pairs (Bitcoin and Dash)

	Coefficient	*Std. error*	*Prob.*
C(3)	0.00002	0.00000561	0.0004
C(4)	0.0000329	0.00000894	0.0002
C(5)	0.000141	0.00000317	0.0000
C(6)	0.448812	0.037827	0.0000
C(7)	0.468126	0.040746	0.0000
C(8)	0.934744	0.005219	0.0000
C(9)	0.918878	0.006969	0.0000
C(10)	2.706829	0.153354	0.0000

Source: Research calculations

In the relationship between Bitcoin yield fluctuations and Dash yield fluctuations, since the level of significance is related to the effect of Bitcoin yield fluctuations on Dash yield fluctuations is 0.002 and less than 0.05, it is accepted that Bitcoin yield fluctuations have a positive and significant effect on Dash yield fluctuations. In the end, we investigated the effect of Bitcoin fluctuation overflow on Dogecoin.

Table 9 BEKK-GARCH results between pairs (Bitcoin and Dogecoin)

	Coefficient	*Std. error*	*Prob.*
C(3)	0.0000485	0.00000141	0.0006
C(4)	0.0000570	0.00000166	0.0006
C(5)	0.000140	0.00000367	0.0001
C(6)	0.554576	0.068496	0.0000
C(7)	0.769112	0.093756	0.0000
C(8)	0.926982	0.005805	0.0000
C(9)	0.859684	0.008197	0.0000
C(10)	2.424579	0.125938	0.0000

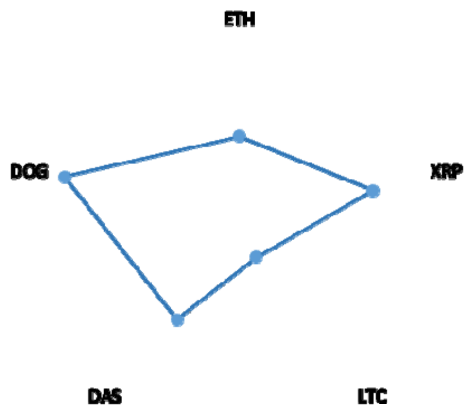
Source: Research calculations

In the relationship between Bitcoin return fluctuations and Dogecoin return fluctuations, since the value of the significant level related to the effect of Bitcoin return fluctuations on Dogecoin return fluctuations is 0.0006 and less than 0.05. Therefore, it is accepted that Bitcoin return fluctuations have a positive and significant effect on Dogecoin return fluctuations.

We concluded that the current fluctuations of a digital currency, except for Lightcoin, not only affect its past fluctuations but also depend on the past fluctuations of other digital currencies such as Bitcoin, which indicate the interrelationships between them.

Figure 1 shows the digital currencies that have received the most series from Bitcoin, as can be seen among the large Ripple digital currencies and the small Dogecoin digital currencies.

Figure 1 Comparison of the effect of bitcoin series on other digital currencies (see online version for colours)

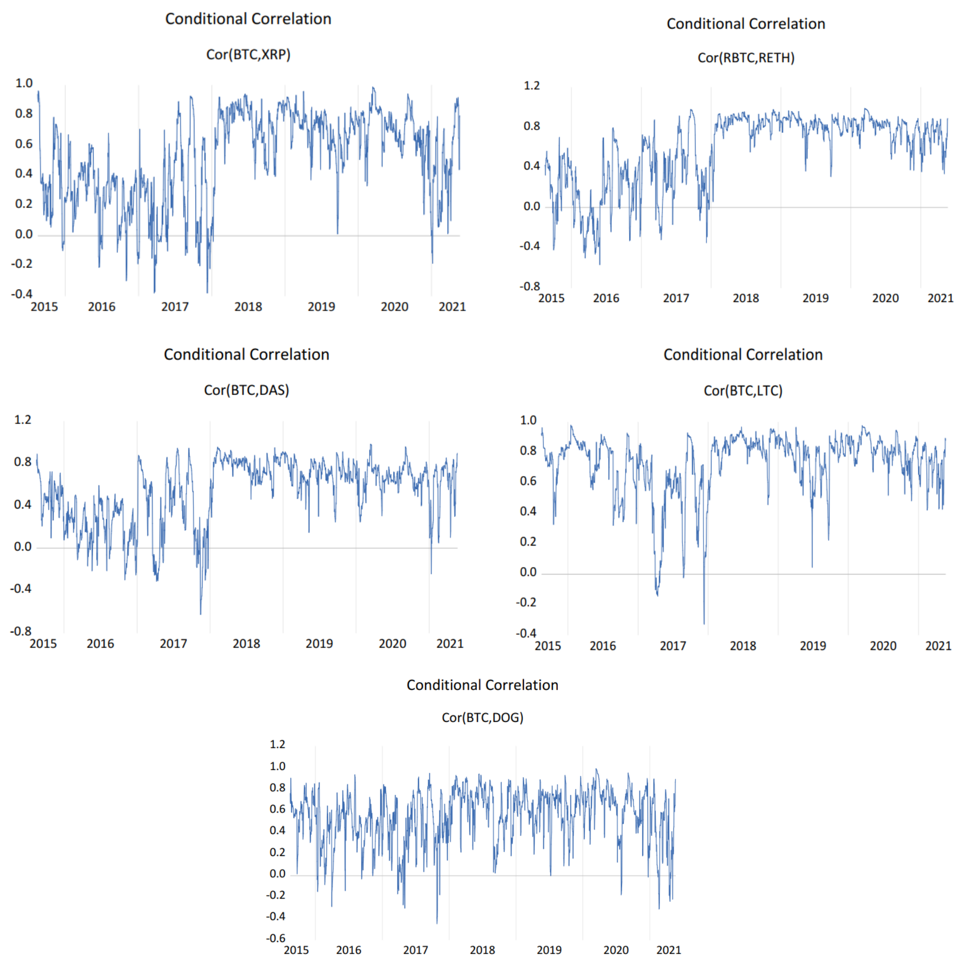


Source: Research calculations

Figure 2 shows the conditional covariance of digital currency pairs (such as Bitcoin-Ethereum, Bitcoin-Ripple, Bitcoin-Lightcoin, Bitcoin-Dash, and Bitcoin-Doge). These graphs confirm the dynamic conditional correlations between the mentioned digital currency pairs, and the correlations include positive and negative values, although positive correlations are mostly observed. In addition, the peak of the conditional solidarity that occurred in mid-or late-September 2017 seems to coincide with the time when China banned Bitcoin trading. As can be seen, the conditional correlations are significantly positive for all, which is consistent with the work of Katsiampa (2019) and Canh et al. (2019). Also, the correlation is higher during the corona crisis period than before the corona. This high correlation is justified during the Corona crisis due to fears and fluctuations and floral behavior in digital currency markets around the world. The latest developments in the value of Bitcoin indicate that the price of this cryptocurrency has increased by at least 300% by 2020. Since 2013, the recent fluctuations in the price of Bitcoin should be considered the third major period of increase in the price of this currency. The previous two periods, the staggering rise in Bitcoin prices, have fallen by a significant 80% each time.

These sharp fluctuations make it extremely difficult to use it as an effective economic tool in economic equations that require deep stability. In this regard, the instability of the value of Bitcoin is one of its most important negative points. In the current context, Bitcoin activism is a tool for storing value that has aroused great interest in it (due to its significant price increase) and has caused a great deal of debate about it. Bitcoin is not valuable in itself. What makes it attractive is that its supply is extremely limited (only 21 million Bitcoins are expected to be mined worldwide). However, critics believe that nothing can stop the creation of new currency cryptocurrencies using China's blockchain technology.

Figure 2 Conditional covariance of digital currency pairs (see online version for colours)



Source: Research calculations

With the price of gold rising 25% in 2020, Bitcoin has grown 300% over the same period. Gold is a tangible, durable, relatively rare item with intrinsic value (a precious metal used in the jewelry and electronics industry), and has a long history of preserving value. However, Bitcoin has emerged as an intangible and unproductive asset, with a lifespan of barely more than 12 years, and is trying to establish itself as a more effective means of storing value than gold, which has also seen significant growth. Has, introduce. This does not seem to be the case (Wang et al., 2021).

Concerning Bitcoin, the world is now in the midst of what former Nobel Prize-winning economist Robert Schiller calls an 'infectious narrative'. In this context, capitalists and economic activists sometimes tell stories and legends about a phenomenon such as Bitcoin to persuade people to move towards this phenomenon regardless of the facts. This leads to an attack on Bitcoin and a sudden increase in its price. Bitcoin is now the largest virtual currency in the world in terms of market value and has experienced heavy price fluctuations in recent months.

Bitcoin started the year 2021 very strong and broke the price record every day and every hour, but during May and April 2021, the price of Bitcoin fell below $30,000, despite rising to about $42,000 in a few days. Virtual currency market experts believe that there are various reasons for the recent and sudden fall in the price of Bitcoin. One of the reasons is that the value of this virtual currency decreased following the statements of Elon Musk about the sale or possible sale of Tesla's Bitcoin assets. Elon Musk's comments have caused the prices of virtual currencies, especially Bitcoin and Dogecoin, to fluctuate a lot over the past week. Musk said on Sunday following Tesla's announcement that the company would no longer use Bitcoin as an accepted payment method for his cars. Elon Musk attributed Tesla's decision to the negative effects of digital currency production on the environment and the high energy consumption for Bitcoin mining. On the other hand, they are one of the reasons other markets are rapidly growing. The first reason is that the market has faced resistance at $35,000, which Bitcoin has failed to break for the third time in recent days and reach stability around this price.

Experts believe that a significant portion of the sales queues formed in the Bitcoin market may have been due to short-term brokers' actions to identify profits, which has led to a domino trend in the market. However, large investors continue to view the fall in prices as an opportunity to enter the market, and more and more investors from Wall Street are turning to Bitcoin to protect the value of their assets against inflation and the US government's expansionary policies. Another consequence of observing a Bitcoin crash is that when Bitcoin crashes, other cryptocurrencies also crash. The reason for this is that other cryptocurrencies must first be converted to the equivalent of Bitcoin before it can be converted to USD. When the price of Bitcoin falls or rises against the dollar, all other cryptocurrencies usually work the same way. This is because the prices of other cryptocurrencies are based on their Bitcoin exchange rate and not their dollar exchange rate.

5 Conclusions and suggestions

Virtual money is a digital representation of value that can be traded digitally and acts as a medium of exchange and (or) unit of calculation and (or) storage of value and has no legislation and is accepted among members of a dedicated virtual community. Bitcoin was introduced as the first virtual currency and a successful example of previous operational plans. Because Bitcoin is used more as an asset than a currency, the Bitcoin market is now very risky and more volatile than other currencies and prone to potential price bubbles. Therefore, Bitcoin has a special place in the financial markets and portfolio management, which is why it is very important to study its volatility. The purpose of this study is to investigate the effect of fluctuations from Bitcoin as the largest digital currency on other digital currencies. One component of this analysis is the identification of digital currencies that have been most affected by the price bubbles and the free fall of Bitcoin prices, which has recently become an interesting topic for academics, researchers, and regulators.

The findings show that Bitcoin had the highest volatility spillover on Dogecoin, Dash, and Ripple among digital currencies, respectively, and had the lowest volatility spillover on Ethereum. Also, Lightcoin is not directly affected by the Bitcoin volatility spillover, because this digital currency is affected Intermediary by Bitcoin.

The results of the present study show that Bitcoin, due to the speculative behavior of investors in the asset markets, despite playing its role as money; Most follow the characteristics of the asset. The bubbles in the digital currency market indicate that the market is irrational, and the effects of the overflow are also due to the excitement of the Bitcoin market. The bubble in the digital currency market is causing economic instability, and due to the effects of the existing overflow, it may spread to domestic financial markets and cause a lot of fluctuations. Suggestions for future research: Researchers should investigate the impact of other financial markets such as stocks, gold, currency, etc., from the spillover effects of the digital currency market, the intelligent design of portfolio management in the digital currency market, and the design of a framework for the design of digital token valuation models, so that it is possible to have to Examine the relationship between different financial markets.

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