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Volatility spillover between Bitcoin and financial stress index

Tuğba Nur[a], **Turhan Korkmaz**[b *]

[a] Sirnak University, Department of Health Management, e-mail address: nurtugba.91@gmail.com
[b] Mersin University, Department of Business Administration, e-mail address: tkorkmaz@mersin.edu.tr

ABSTRACT

Purpose: This paper aims to test the volatility models for Bitcoin (BTC) and the financial stress index (FSI) and examine the volatility spillover among them. This aim was reached by obtaining weekly data from the 7th of January 2011 and the 24th of December 2021.

Methodology: First, volatility modelling for the series is provided, and GARCH (1,1) for the BTC series and IGARC (1,2) for the FSI series are determined as the most appropriate volatility models. Then, residual volatility series are created for each variable over the IGARCH (1,2) and GARCH (1,1) models for the volatility spread between the series. The volatility spread between the series is examined with the diagonal VECH GARCH method. It is concluded that there is a positive volatility spillover effect from the FSI variable to the BTC variable. Then, impulse-response analysis is performed on the volatility residual series created for each variable. The empirical findings from impulse response analysis support a risk transfer between BTC and FSI series.

Results and Findings: Changes in the BTC return series and FSI series are caused mainly by themselves, and the series are most affected by their shocks. By comparing the variance decomposition of the volatility series with the analysis results, it can be said that the changes in the volatility series are caused mainly by each other.

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**Corresponding author:*
tkorkmaz@mersin.edu.tr
(Turhan Korkmaz)
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1. INTRODUCTION

Financial stress is defined as the force on financial markets and possible loss expectations. Financial stress and risk directly affect companies, financial markets, intermediary institutions and organizations, and the real economy. It arises because of the overvaluation of financial crises and causes disruptions in the functioning of financial markets (Hakkio and Keeton, 2009; cit. in Alsu, 2020). Although financial stress is often used as an indicator for predicting financial crises, it also adversely affects financial markets and economic growth and development (Barut et al., 2016). Financial stress has recently involved developing and developed financial markets and economies (Zhang and Wang, 2021).

There exists a vast literature on financial stress's effect on macroeconomics, financial markets, and the spillover among countries. [e.g., Sum (2012); Nazlıoğlu et al. (2015); Apostolakis (2016); MacDonald et al. (2018); Gil-Alana and Abakah (2019); Liu et al. (2021)]. However, the literature on the possible relationship between cryptocurrencies and financial stress is limited (Zhang and Wang, 2021). Attention to cryptocurrencies, considered risky investment instruments, is increasing daily. Therefore, it is essential to investigate whether the variance resulting from sudden changes in cryptocurrencies has a spillover relationship with the conflict resulting from sudden changes in the financial stress index, which shows the possible loss in financial markets. This paper examines the volatility modelling of Bitcoin, the financial stress index and the volatility spillover among them. The results are expected to have implications on investors' risk predictions.

This paper examines the volatility model of Bitcoin and the financial stress index for the period between the 7th of January 2011 and the 24th of December 2021 and consists of four sections. *The introduction* in the first section provides general information on the subject. The second section covers *the Literature Review*. The third section, *Methodology*, presents the research model and related empirical findings. Finally, the study is concluded by evaluating these empirical findings.

2. LITERATURE REVIEW

The literature review on the subject clearly shows a limited number of studies examining the volatility spillover among the financial stress index and cryptocurrencies. In contrast, the studies on the volatility spillover among macroeconomic variables, stock markets, financial stress index and cryptocurrencies are outnumbered, as given below.

Studies on volatility modelling and volatility spillover in the financial stress index:

Nazlıoğlu et al.'s (2015) paper examines the volatility spillover between WTI crude oil prices and Cleveland financial stress index for the pre-crisis, in-crisis, and post-crisis periods between 1991 and 2014, pointing to a causality relationship that was found in oil prices to financial stress index in the pre-crisis period and from financial stress to oil prices in the post-crisis period. Besides, the impulse response analysis concludes that the volatility spillover pattern has similar dynamics in the pre-and post-crisis periods. Apostolakis (2016) examines the spillover of financial stress in five Asian countries (China, South Korea, Malaysia, Thailand, and the Philippines), empirically finding that China impacts financial stress in other countries. In their study, MacDonald et al. (2018) examine the volatility spillover among Eurozone economies and financial markets using financial stress indices employing the GARCH model. Their findings reveal that financial stress spillover significantly affects the Eurozone banking and money markets. In their study, Gil-Alana and Abakah (2021) examine the stochastic characteristics of financial stress indices of 10 Asian countries and how they are transmitted among countries. They found that shocks will have temporary but long-term effects for all nations, and the spillover of financial stress among Japan and smaller economies is faster than in China. Zhang and Wang's (2021) study examines the volatility spillover of the financial stress index in China and the U.S. between gold and Bitcoin. They report that the financial stress index has a medium-term effect on gold prices in the U.S. during periods of uncertainty. It has a short-term impact on Bitcoin, while the financial stress index in China has a medium-term impact on Bitcoin. Apostolakis et al. (2021) examine~~d~~ the relationship between non-financial Brent oil market prices and financial stress and economic policy uncertainties in Group of Seven (G7) countries. Findings show that oil price volatility has a more significant spillover to financial stress and monetary policy uncertainty during COVID-19. Oil price uncertainty is associated with more financial stress for some G7 countries. In their study, Liu et al. (2021) examine~~d~~ the effects of different oil price shocks on China's financial stress index. They found that oil supply shocks have a significant positive impact on financial stress in case of low volatility, while demand shocks have a detrimental effect on financial stress.

Studies on volatility modelling and volatility spillover in cryptocurrencies:

Bouri et al. (2018) studied the volatility spillover among Bitcoin and stocks, commodities, foreign currency, and bonds from 2010 to 2017 under bear and bull market conditions. They reveal that the volatility spillover from stocks, commodities and exchange rates to Bitcoin is more significant than the volatility spillover from Bitcoin to stocks, commodities and exchange rates. Kumar and Anandarao (2019) examine the volatility spillover among Bitcoin, Ethereum, Ripple, and Litecoin for 2015-2018 using the dynamic conditional correlation-GARCH method. They identify a volatility spillover between Ethereum and Litecoin. In their study, Vardar and Aydoğan (2019) examine~~d~~ the volatility spillover between Bitcoin and conventional assets such as equities, bonds, and currencies between 2010 and 2018 using VAR-GARCH and BEKK methods. Their findings point out a one-way spillover effect from the bond market to Bitcoin. Katsiampa et al.'s (2019) study examine~~d~~ the volatility structure and the volatility spillover among Bitcoin, Litecoin, and Ethereum. They identify a two-way volatility spillover between Bitcoin and Ethereum and Bitcoin and Litecoin. Finally, Zhang and He (2021) examine~~d~~ the spillover effect among Bitcoin, gold, crude oil, and stock markets. They found that Bitcoin does not have a significant spillover effect compared to other assets, and there is a one-way volatility spillover between gold and stock markets.

3. EMPIRICAL ANALYSIS

3.1. Data

This paper aims to examine the volatility model of Bitcoin and the financial stress index for the period between the 7th of January 2011 and the 24th of December 2021 using weekly data and the volatility spillover among them.

Firstly, continuous returns are calculated using the formula in equation 1 using the Bitcoin weekly price series.

$$R_t = \ln\left(\frac{P_t}{P_{t-1}}\right) \tag{1}$$

St. Louis Fed Financial Stress Index is a proxy for the financial stress variable. St. Louis Fed Financial Stress Index is designed with an average zero value. Zero indicates normal market conditions, negative values indicate below-average financial market stress, and positive values indicate above-average financial market stress (fred.stlouisfed.org). Secondary data on the financial stress index and the Bitcoin price variables are obtained from *fred.stlouisfed.org* and *investing.com* websites.

3.2. Methodology

The stationarity of the series is checked by ADF and P.P. tests to examine the volatility spillover between the financial stress index and Bitcoin.

The equations for the ADF test are as follows:

$$\Delta y_t = \gamma\, y_{t-1} + \sum_{i=2}^{p} \beta_i \Delta y_{t-i+1} + e_t \varepsilon_t \sim WN(0, \sigma^2) \tag{2}$$

$$\Delta y_t = c + \gamma\, y_{t-1} + \sum_{i=2}^{p} \beta_i \Delta y_{t-i+1} + e_t \varepsilon_t \sim WN(0, \sigma^2) \tag{3}$$

$$\Delta y_t = c + \gamma\, y_{t-1} + \delta_2 t \sum_{i=2}^{p} \beta_i \Delta y_{t-i+1} + e_t \varepsilon_t \sim WN(0, \sigma^2) \tag{4}$$

The equation for the PP test is as follows:

$$\Delta Yt = \alpha + \rho Y_{T-1} + \mu_T \tag{5}$$

After checking the stationarity of the series, the best fitting ARMA model is determined according to the appropriate lag duration based on the Schwarz information criterion. Finally, the ARMA process is based on the assumption that the series is stationary, and A.R. (p), M.A. (q) and their combination ARMA (p,q) are applied to stationary processes.

The equation for the AR process is as follows:

$$Y_t - \delta = \alpha_t (Y_{t-1} - \delta) + \alpha + \delta + \mu_T \tag{6}$$

The equation for the MA process is as follows:

$$Y_t = \mu_T + \beta_0 \mu_T + \beta_1\, \mu_{T-1} \tag{7}$$

The equation is as follows when the Y time series fits both AR and MA processes:

$$X_t = e_t + \sum_{i=1}^{p} \Phi i\; X_{t-1} + \sum_{i=1}^{p} \Omega i\;\; e_{ti} \tag{8}$$

After determining the best fitting initial ARMA model, we examined whether heteroscedasticity and autocorrelation problems related to the model's error term and whether the series contained nonlinearity. Since the series have heteroscedasticity, autocorrelation problems, and nonlinearity, it is determined that the ARCH/GARCH models are required for volatility forecasting instead of the ARMA model. Various symmetric and asymmetric GARCH models select the most fitted model for volatility forecasting. The equations of the models that exceed only the significance and parameter constraints used in the study are provided below:

The equation for the GARCH (p, q) model is as follows:

$$h_t = \alpha_0 + \alpha_1\varepsilon_{t-1}^2 + \beta_1 h_{t-1} \quad (9)$$

The equation for the IGARCH (p, q) model is as follows:

$$h_t = \alpha_0 + \alpha_1\varepsilon_{t-1}^2 + (1-\beta_1)h_{t-1} \quad (10)$$

Following the forecasting of volatility for the series, residual volatility series (GARCH conditional variance series) is created for each variable through IGARCH (1,2), GARCH (1,1) models to identify the volatility spillover among series [Nazlıoğlu et al. (2015); Jan and Jebran (2015)]. Then, spillover, impulse-response, and variance decomposition analyses are performed on these series. First, the volatility spillover among series is examined using the Diagonal VECH method.

The equation for the diagonal VECH model is as follows:

$$\text{vech(ht)} = c + \sum_{j=1}^{q} A_J\, vech(\varepsilon_{t-j}\varepsilon'_{t-j}) + \sum_{j=1}^{q} G_J\, vech(h_{t-1}) \quad (11)$$

A standard VAR model is created to perform impulse-response and variance decomposition analyses among volatility series. The equations related to the VAR model are as follows:

$$\mathrm{BTCVOL_t} = a_1 + \sum_{i=1}^{p} b_{1i}\mathrm{BTCVOL_{t-i}} + \sum_{i=1}^{p} b_{2i}\mathrm{FSIVOL_{t-i}} + v_{1t} \quad (12)$$

$$\mathrm{FSIVOL_t} = c_1 + \sum_{i=1}^{p} d_{1i}\mathrm{FSIVOL_{t-i}} + \sum_{i=1}^{p} d_{2i}\mathrm{BTCVOL_{t-i}} + v_{2t} \quad (13)$$

An impulse-effect analysis is performed using the VAR model. The equation regarding to the impulse-effect analysis is as follows:

$$\begin{bmatrix}\mathrm{FSIVOL}_t\\ \mathrm{BTCVOL}_t\end{bmatrix} = \begin{bmatrix}a_{10}\\ a_{20}\end{bmatrix} + \begin{pmatrix}a_{11} & a_{12}\\ a_{21} & a_{22}\end{pmatrix}\begin{bmatrix}\mathrm{FSIVOL}_{t-1}\\ \mathrm{BTCVOL}_{t-1}\end{bmatrix} + \begin{bmatrix}e_{1t}\\ e_{2t}\end{bmatrix} \quad (14)$$

Following the impulse-response analysis, variance decomposition analysis determines which variables most affect a particular variable. The equation is represented as follows:

$$\frac{\sigma^2_{\mathrm{FSIVOL}}[\Phi^2_{11}(0)+\Phi^2_{11}(1)+\cdots+\Phi^2_{11}(n-1)]}{\sigma^2_{\mathrm{BTCVOL}}(n)} \quad (15)$$

$$\frac{\sigma^2_{\mathrm{BTCVOL}}[\Phi^2_{12}(1)+\Phi^2_{12}(1)+\cdots+\Phi^2_{12}(n-1)]}{\sigma^2_{\mathrm{FSIVOL}}(n)} \quad (16)$$

The empirical findings provided are given below in the following sections.

3.3. Volatility Forecasting Test Results

The descriptive statistics related to the Financial Stress Index (FSI) and Bitcoin (BTC) series are provided in Table 1 due to the analysis performed for volatility forecasting.

Table1. Descriptive statistics

	BTC	FSI
Average	1.878276	-0.297696
Median	1.365697	-0.404600
Maximum	82.29064	5.419600
Minimum	-71,56200	-1.131100
Std. Dev.	15.03587	0.595110
Skewness	0.460501	3.970257
Kurtosis	9.349392	32.15070

Jarque-Bera	974.1916	21603.29
Probability	0.000000	0.000000
Observation	568	568

Descriptive statistics show that the average value for the BTC series is 1.878 and -2.297 for the FSI series, and the standard deviation in the BTC series is higher than in the FSI series. The J-B probability of the series is less than 0.05, which is the critical value. Thus, the series is not normally distributed. Then, the stationarity of the series is checked. The graphs of BTC series return and FSI series index values are demonstrated in Figure 1.

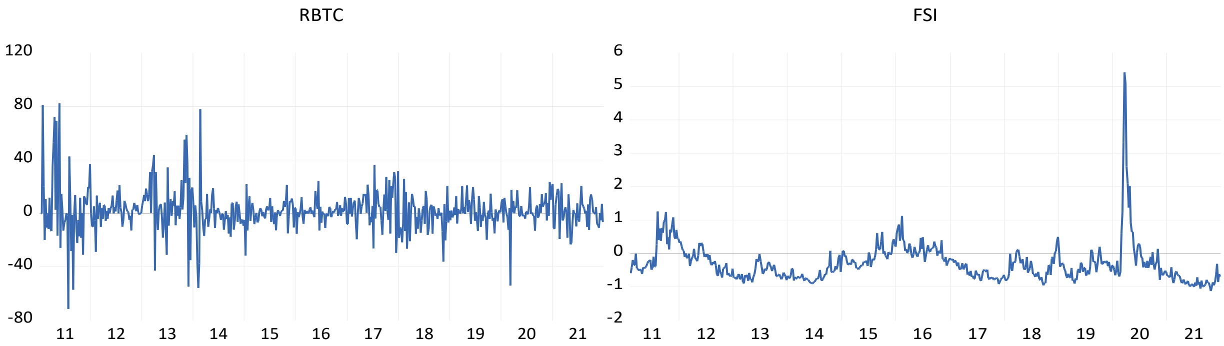


Figure1. Time-series graphs

Series graphs show an upward and downward trend and fluctuate around a fixed average value, and there is a deviation from the average in the FSI index only in 2020. Therefore, even though it can be deducted from the graphs that the series is stationary, this result needs to be supported by unit root tests. The unit root test results are shown in Table 2.

Table2. Unit root test results

BTC							
	Test	**Difference**	**%**	**Critical V.**	**t-sta.**	**Prob.**	**Decision**
Constant	ADF	Level	1% 5% 10%	-3.441 -2.866 -2.569	-23.255	0.000	I(0)
	PP	Level	1% 5% 10%	-3.441 -2.866 -2.569	-23.751	0.000	I(0)
	Test	**Difference**	**%**	**Critical V.**	**t-sta.**	**Prob.**	**Decision**
Constant and Trend	ADF	Level	1% 5% 10%	-3.974294 -3.417751 -3.131313	-23.285	0.000	I(0)
	PP	Level	1% 5% 10%	-3.974294 -3.417751 -3.131313	-23.751	0.000	I(0)
FSI							
	Test	**Difference**	**%**	**Critical V.**	**t-sta.**	**Prob.**	**Decision**
Constant	ADF	Level	1% 5%	-3.441573 -2.866383	-5.607164	0.000	I(0)

	Test	Difference	%	Critical V.	t-sta.	Prob.	Decision
			10%	-2.569409			
	PP	Level	1% 5% 10%	-3.441573 -2.866383 -2.569409	-5.618457	0.000	I(0)
Constant and Trend	**Test**	**Difference**	**%**	**Critical V.**	**t-sta.**	**Prob.**	**Decision**
	ADF	Level	1% 5% 10%	-3.974208 -3.417709 -3.131288	-5.648490	0.000	I(0)
	PP	Level	1% 5% 10%	-3.974208 -3.417709 -3.131288	-5.663060	0.000	I(0)

When ADF and P.P. test results for the BTC and FSI series are examined, it is observed that the probability values calculated for both tests, both in constant and inconstant and trend, are smaller than 0.05, which is the critical value. Therefore, the null hypothesis of "there is a unit root" in both series is rejected, and it is concluded that both sequences are stationary. As a result of the stationarity analyses, the most fitting initial ARMA model for the series was determined based on the Schwarz Information Criteria. Combinations calculated up to the fifth lag are shown in Table 3.

Table 3. Selection of ARMA (p/q) according to the Schwarz Information Criterion

BTC						
AR / MA	0	1	2	3	4	5
0	8.260514	8.266947	8.260446	8.255852	8.257992	8.247327
1	8.266829	8.258340	8.254330	8.249911	8.253265	8.248490
2	8.260588	8.254757	8.257759	8.250889	8.252859	8.251929
3	8.252045	8.249775	8.249349	8.251738	8.255259	8.250155
4	8.254118	8.250668	8.252472	8.255259	**8.233311**	8.255323
5	8.248009	8.250706	8.252441	8.253120	8.255088	8.254632
FSI						
AR / MA	0	1	2	3	4	5
0	1.801617	1.001182	0.555724	0.418303	0.352782	0.263038
1	0.200505	0.194335	0.196242	0.191618	0.194728	0.198176
2	0.193791	0.197266	0.192423	0.194831	0.198242	0.201031
3	0.197195	0.193227	**0.188459**	0.189322	0.191728	0.189706
4	0.194107	0.196079	0.189838	0.194135	0.193312	0.191365
5	0.196253	0.199480	0.191896	0.193444	0.196825	0.194647

According to the Schwarz Information Criterion, the ARMA (4,4) model with the lowest coefficient for the BTC series and the ARMA (3,2) model with the lowest coefficient for the FSI series are identified as the best fitting initial models. After determining the best appropriate ARMA model for the series, heteroscedasticity, autocorrelation problems, and whether the series include nonlinearity are examined using ARCH LM heteroscedasticity, error terms correlograms, and BDS linearity tests. The test results are shown in Table 4.

Table 4. ARCH LM Heteroscedasticity, Error Terms Correlograms, and BDS Linearity Test Results

BTC				
ARMA (4,4)	**Observed R^2**	**R^2 Significance**	**F Statistic**	**F Sta. Signf.**
1st Lag	48.07719	0.0000	52.34615	0.0000
5th Lag	80.75637	0.0000	18.65501	0.0000
10th Lag	92.62959	0.0000	10.88775	0.0000
20th Lag	122.2177	0.0000	7.563578	0.0000
30th Lag	119.2139	0.0000	4.810845	0.0000
ARMA (4,4)	**AC**	**PAC**	**Q-Statistics**	**Probability**
1st Lag	0.291	0.291	48.395	0.000
5th Lag	0.108	0.035	136.00	0.000
10th Lag	0.153	0.118	161.33	0.000
20th Lag	0.016	0.033	255.13	0.000
30th Lag	0.030	0.047	258.47	0.000
Size	**BDS Sta.**	**Std. Error**	**z- Statistics**	**Probability**
2	0.041107	0.004362	9.422850	0.0000
3	0.079230	0.006942	11.41387	0.0000
4	0.100859	0.008279	12.18270	0.0000
5	0.110233	0.008644	12.75311	0.0000
6	0.110657	0.008351	13.25117	0.0000
FSI				
ARMA (3,2)	**Observed R^2**	**R^2 Significance**	**F Statistic**	**F Sta. Signf.**
1st Lag	112.7465	0.0000	140.2340	0.0000
5th Lag	164.4355	0.0000	45.96022	0.0000
10th Lag	169.5418	0.0000	23.87371	0.0000
20th Lag	166.9276	0.0000	11.54254	0.0000
30th Lag	163.4979	0.0000	7.378104	0.0000
ARMA (3,2)	**AC**	**PAC**	**Q-Statistics**	**Probability**
1st Lag	0.446	0.446	113.53	0.000
5th Lag	0.116	0.085	258.92	0.000
10th Lag	0.006	0.013	265.15	0.000
20th Lag	-0.015	-0.005	266.06	0.000
30th Lag	0.002	0.000	266.28	0.000
Size	**BDS Sta.**	**Std. Error**	**z- Statistics**	**Probability**
2	0.131621	0.003439	38.26959	0.0000
3	0.222350	0.005454	40.76747	0.0000
4	0.279196	0.006481	43.08209	0.0000
5	0.312601	0.006740	46.38252	0.0000
6	0.328728	0.006485	50.68992	0.0000

When the ARCH LM heteroscedasticity test results for the BTC and FSI series are examined, it is observed that the probability value calculated for the 30th lag and following values is less than the critical value of 0.05. When the error terms correlograms of the series are examined, it is observed that the Q statistics probability values calculated for the 30th lag and the following ones are smaller than 0.05. These results indicate that both series have heteroscedasticity and autocorrelation problems. When the BDS test results of the series are examined, it is observed that the test probability value is less than the critical value of 0.05 in both series, and there is nonlinearity in both series. Since the series contained heteroscedasticity, autocorrelation problems, and nonlinearity, ARCH/GARCH models are needed for volatility forecasting instead of the ARMA model. To this end, various degrees of symmetric and asymmetrical GARCH models are tried for volatility forecasting, and models that fulfil significance and parameter constraints are selected. Only the GARC (1,1) model fulfilled the significance and parameter constraints for the BTC series. For the FSI series, the GARCH (1,1), GARCH (1,2), IGARCH (1,1), and IGARCH (1,2) models fulfil the significance and parameter constraints. For the FSI series, the IGARCH (1,2) model, which has the smallest Theil Inequality Coefficient, is the most fitting model. The models are presented in Table 5.

Table 5. Volatility forecasting models

Volatility Forecasting Models								
Index	**Models**	**Coefficients**						
		α_0	α_1	α_2	α_3	β_1	β_2	γ_1
FSI	IGARCH (p=1, q=2)	-	0.3165	-	-	0.2574	0.4259	-
BTC	GARCH (p=1, q=1)	10.198	0.2562	-	-	0.7180	-	-

The models shown in Table 5 fulfil the significance and parameter constraints. In this context, the GARCH (1,1) model is the most fitting model for the BTC series for volatility forecasting. For the model to be valid, the α_0 coefficient should have to be significant and positive, the $\alpha_1$ve β_1 coefficients should have to be substantially positive, and their sum must be smaller than one. The model fulfils these constraints. When the coefficients are examined, the α_1 coefficient is observed as 0.256, and it can be said that past shocks cause about 25% of the shocks affecting the BTC series. The β_1 coefficient is observed as 0.718, and it can be said that past shocks cause about 71% of the shocks affecting the BTC series. The most suitable model for the FSI series is IGARCH (1,2), and for the model to be valid, the α_1, β_1 and β_2 coefficients must be significant and positive, and their sum should have to be smaller than one. The model fulfils these restrictions, and the α_1 coefficient is 0.315, the β_1 coefficient is 0.257, and the β_2 coefficient is 0.425. Therefore, it can be said that about 31% of the shocks affecting the FSI index are caused by past shocks, and 67% are caused by previous shocks. In addition, it can be said that shocks that affect volatility in both indices have a short-term, lasting effect. Whether the models solve the problems of heteroscedasticity and autocorrelation is examined using ARCH-LM and error terms correlograms. The results of the tests are shown in Table 6.

Table 6. ARCH LM heteroscedasticity, error terms correlograms test results for the models

BTC				
GARCH (1,1)	**Observed R^2**	**R^2 Significance**	**F Statistic**	**F Sta. Signf.**
1st Lag	0.029167	0.8644	0.029066	0.8647
5th Lag	1.216701	0.9433	0.241268	0.9441
10th Lag	0.029167	0.8644	0.029066	0.8647
20th Lag	10.51065	0.9579	0.515277	0.9608
30th Lag	16.10626	0.9818	0.521554	0.9841
GARCH (1,1)	**AC**	**PAC**	**Q-Statistics**	**Probability**
1st Lag	0.007	0.007	0.0294	0.864

5th Lag	0.007	0.007	0.0294	0.864
10th Lag	-0.032	-0.032	4.5420	0.920
20th Lag	0.064	0.065	11.897	0.920
30th Lag	0.022	0.023	19.941	0.918
FSI				
IGARCH (1,2)	**Observed R^2**	**R^2 Significance**	**F Statistic**	**F Sta. Signf.**
1st Lag	1.373377	0.2412	1.371869	0.2420
5th Lag	5.315312	0.3786	1.061769	0.3806
10th Lag	8.461882	0.5838	0.842315	0.5879
20th Lag	18.01923	0.5861	0.895942	0.5927
30th Lag	22.57932	0.8322	0.740466	0.8416
IGARCH (1,2)	**AC**	**PAC**	**Q-Statistics**	**Probability**
1st Lag	0.049	0.049	1.3821	0.240
5th Lag	0.011	0.010	5.6401	0.343
10th Lag	0.015	0.022	9.1158	0.521
20th Lag	0.023	0.023	20.829	0.407
30th Lag	-0.022	-0.044	23.965	0.774

The F statistical and Q statistical probability values for the GARCH (1,1) and the IGARCH (1,2) models of the BTC and FSI series, respectively, are more significant than 0.05, the critical value. Therefore, it is determined that the models solve the problem of heteroscedasticity and autocorrelation. Following the volatility modelling, it is examined whether the asymmetric model is sufficient for volatility modelling of the series using the Engle-Ng (1993) Sign Bias test. The test results are shown in Table 7.

Table 7. Engle-Ng sign bias test

BTC	**t-statistics**	**Probability**
Sign Bias	-0.705466	0.4808
Negative Bias	-0.153208	0.8783
Negative Bias	-0.079100	0.9370
Common Bias	0.652125	0.8844
FSI	**t-statistics**	**Probability**
Sign Bias	-1.265190	0.2063
Negative Bias	1.124162	0.2614
Negative Bias	0.019689	0.9843
Common Bias	6.931624	0.0753

According to the Sign Bias test results, the test probability values of both indices are greater than 0.05, which is the critical value. Therefore, the null hypothesis that there is no leverage effect in the series cannot be rejected. In this context, it can be said that there is no leverage effect on the series and that the models selected for volatility forecasting are valid. The conditional heteroscedasticity graphs created for the GARCH (1,1) and IGARCH (1,2) models for the BTC series and the FSI series are shown in Figure 2.

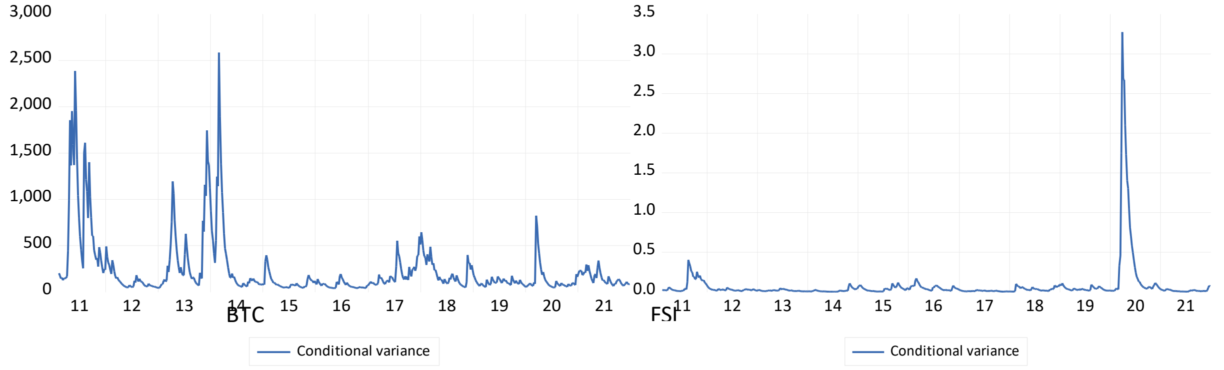
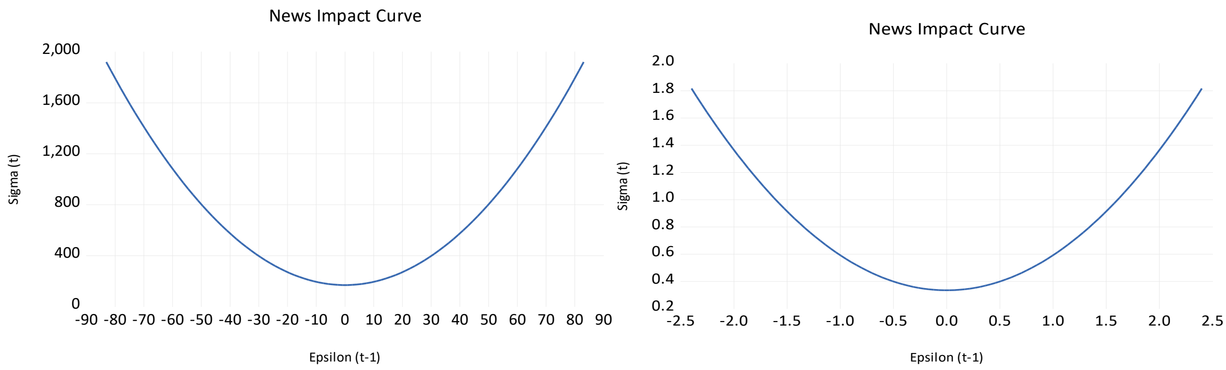


Figure 2. Conditional heteroscedasticity graphs for the series

According to the dependent heteroscedasticity graphs of the series, it can be said that volatility took place in the BTC series in 2011, 2013 and 2014 and in the FSI series in 2020. The news impact curve (NIC) for the GARCH (1,1) and IGARCH (1,2) models for the BTC series and the FSI series is shown in Figure 3.



BTC FSI

Figure 3. The news impact curve for the series

Figure 3 shows that the news impact curves for the GARCH (1,1) model for the BTC series and the IGARCH (1,2) model for the FSI series are symmetrical, so the time series are asymmetric.

3.4. Volatility Spillover Test Results

Following the forecasting of volatility for the series, residual volatility series (GARCH conditional variance series) are created for each variable through IGARCH (1,2), GARCH (1,1) models to identify the volatility spillover among series [Nazlıoğlu et al. (2015); Jan and Jebran (2015)]. Finally, the volatility spillover between the series is examined using the Diagonal VECH GARCH method through the generated sequence.

Table 8. Diagonal VECH GARCH analysis results

		Coefficient	Std. E.	z-Sta.	Prob.
Diagonal VECH FSI → BTC	M	0.0001	1.34E	7.8656	0.0000
	ARCH (FSI, FSI)	0.4965	0.0376	13.1812	0.0000
	ARCH (FSI, BTC)	0.5776	0.1454	3.9703	0.0001
	ARCH (BTC, BTC)	1.7693	0.1309	13.5138	0.0000
	GARCH (FSI, FSI)	0.7148	0.0060	118.2130	0.0000
	GARCH (FSI, BTC)	0.4040	0.0978	4.1288	0.0000
	GARCH (BTC, BTC)	0.2283	0.0427	5.3351	0.0000

The standard ARCH and GARCH parameters offer information about the shared variance among the variables. The fact that the sum of the coefficients for the parameters is less than 1, positive, and significant indicates volatility spillover among the variables (Yaman and Korkmaz, 2020: 697). According to the analysis results, the sum of the coefficients of the familiar ARCH and GARCH parameters is less than 1, positive and significant. Therefore, it can be said that there is a positive volatility spillover from the FSI variable to the BTC variable.

3.5. Impact-Response and Variance Decomposition Test Results

Impact-response and variance decomposition analyses are performed on residual volatility series created for each variable. In this context, the VAR model was created first. The VAR model lag duration test results are shown in Table 9.

Table 9. VAR lag duration determination criteria

Lag	LogL	LR	FPE	AIC	SC	HQ
0	-3855.152	NA	2987.198	13.67785	13.69322	13.68385
1	-2954.597	1791.531	124.3146	10.49857	10.54469	10.51657
2	-2927.810	53.09837	114.6647	10.41777	10.49463	10.44777
3	-2913.265	28.72830	110.4565	10.38037	10.48798	10.42238
4	-2883.757	58.07466	100.9040	10.28992	10.42827*	10.34392*
5	-2877.864	11.55649	100.2294	10.28321	10.45230	10.34921
6	-2876.492	2.680812	101.1684	10.29252	10.49237	10.37053
7	-2874.414	4.045924	101.8611	10.29934	10.52993	10.38935
8	-2864.758	18.72888*	99.83978*	10.27928*	10.54062	10.38130

The lag duration of the VAR model is determined to be eight according to the L.R., FPE, and AIC information criteria. VAR model results are shown in Table 10.

Table 10. VAR model results

	BTCVOL	FSIVOL
BTCVOL (-1)	0.915542	0.000178
	(0.04251)	(3.7E-05)
	[21.5375]	[4.86655]
BTCVOL (-2)	0.132976	-5.73E-05
	(0.05863)	(5.1E-05)
	[2.26786]	[-1.13373]
BTCVOL (-3)	-0.113078	-0.000201
	(0.05890)	(5.1E-05)

	[-1.91982]	[-3.95866]
BTCVOL (-4)	-0.097550	7.88E-05
	(0.05610)	(4.8E-05)
	[-1.73889]	[1.62976]
BTCVOL (-5)	0.061567	5.76E-06
	(0.05310)	(4.6E-05)
	[1.15942]	[0.12603]
BTCVOL (-6)	-0.053894	3.49E-05
	(0.05281)	(4.5E-05)
	[-1.02058]	[0.76688]
BTCVOL (-7)	0.067753	-2.40E-05
	(0.03917)	(3.4E-05)
	[1.72992]	[-0.71176]
FSIVOL (-1)	-39.70828	0.664330
	(49.4584)	(0.04260)
	[-0.80286]	[15.5938]
FSIVOL (-2)	7.082275	0.482801
	(59.0914)	(0.05090)
	[0.11985]	[9.48534]
FSIVOL (-3)	32.28929	-0.008939
	(63.4790)	(0.05468)
	[0.50866]	[-0.16347]
FSIVOL (-4)	14.26905	-0.401111
	(60.0300)	(0.05171)
	[0.23770]	[-7.75720]
FSIVOL (-5)	-21.80528	0.079577
	(62.6122)	(0.05393)
	[-0.34826]	[1.47550]
FSIVOL (-6)	-23.06539	0.087428
	(58.3333)	(0.05025)
	[-0.39541]	[1.73998]
FSIVOL (-7)	-0.935629	-0.026381
	(48.1244)	(0.04145)
	[-0.01944]	[-0.63640]
C	20.27381	0.005526
	(6.40429)	(0.00552)
	[3.16566]	[1.00171]

Before proceeding to the VAR model's impact-response and variance decomposition analysis, the autocorrelation assumption regarding the stationarity and error terms of the model was tested. The inverse roots of the A.R. characteristic polynomial for the stationarity of the model are shown in Figure 4.

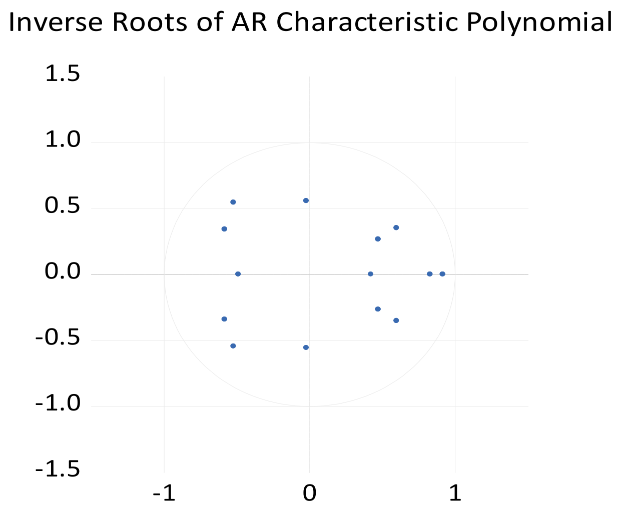


Figure 4. VAR model stationarity graph

The graph of the stationarity of the VAR model shows that the inverse A.R. roots are within the unit circle, and the model is stationary. The autocorrelation test results are shown in Table 11.

Table 11. Autocorrelation-LM test results

Lag	LRE* stat	df	Prob.	Rao F-stat	df	Prob.
1	15.57613	4	0.0036	3.918278	(4, 1094.0)	0.0036
5	2.720911	4	0.6056	0.680452	(4, 1094.0)	0.6056
10	2.122072	4	0.7133	0.530547	(4, 1094.0)	0.7133
20	0.675183	4	0.9544	0.168694	(4, 1094.0)	0.9544
30	0.290552	4	0.9904	0.072581	(4, 1094.0)	0.9904

According to the L.M. test results, the test probability values are more significant than the critical value of 0.05. Therefore, it was determined that there is no autocorrelation problem in the model. After examining the assumptions related to the model, the impulse-response analysis is carried out. The results are shown in Figure 5.

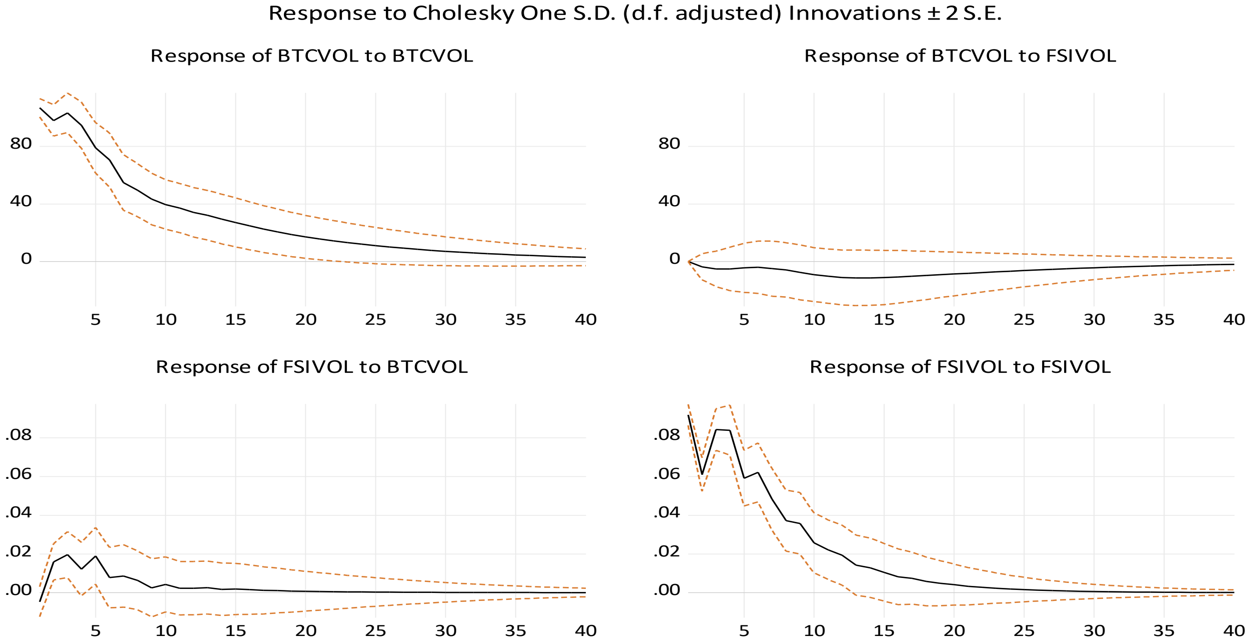


Figure 5. Impulse-Response analysis results

According to the results of the impulse-response analysis, a shock in the FSI volatility series ~~caused~~ a negative shock at week 5 in the BTC volatility series. This effect disappears as of week 35, coming close to zero. Conversely, a surprise in the BTC volatility series causes a positive shock at week 5 in the FSI volatility series. This effect disappears as of week 30, coming close to zero. Following the impulse-response analysis, the variance decomposition analysis is performed to determine what percentage of the changes in the BTC volatility series are caused by itself and the FSI volatility series, and what percentage of the changes in the FSI volatility series are driven by itself and the BTC volatility series. Analysis results are shown in Tables 12 and 13.

Table 12. Results of the variance decomposition test for the BTCVOL series

Period	S.E.	BTCVOL	FSIVOL
1	106.8260	100.0000	0.000000
2	145.0070	99.93667	0.063328
3	178.0852	99.87554	0.124461
4	201.7467	99.83876	0.161243
5	216.7084	99.81896	0.181036
6	227.9395	99.80643	0.193566
7	234.5004	99.77291	0.227088
8	239.7316	99.72291	0.277093
9	243.7445	99.63601	0.363988
10	247.1088	99.51006	0.489937
11	250.0936	99.35449	0.645511
12	252.6632	99.17490	0.825101
13	254.9538	98.99108	1.008917
14	256.9033	98.81137	1.188626
15	258.5698	98.64273	1.357266

16	259.9729	98.48972	1.510282
17	261.1473	98.35169	1.648309
18	262.1354	98.22859	1.771406
19	262.9629	98.11923	1.880771
20	263.6620	98.02214	1.977857

According to the variance decomposition analysis results, in the first period, all of the changes in the BTC volatility series are caused by themselves. In the second period, the variation outside the FSI volatility series, about 0.16%, is caused by the FSI volatility series. As of the 15th period, approximately 1% is caused by the FSI volatility series, and this rate increased. Therefore, it can be said that the changes in the BTC volatility series are caused mainly by itself, and the series is most affected by its shocks. The results of the variance decomposition test for the FSI volatility series are shown in Table 13.

Table 13. The results of the variance decomposition test for the FSIVOL series

Period	S.E.	BTCVOL	FSIVOL
1	0.092017	0.257980	99.74202
2	0.111571	2.214303	97.78570
3	0.141200	3.323359	96.67664
4	0.164713	2.984974	97.01503
5	0.176041	3.775534	96.22447
6	0.186851	3.524773	96.47523
7	0.193196	3.497625	96.50238
8	0.196848	3.472167	96.52783
9	0.200088	3.375976	96.62402
10	0.201788	3.364099	96.63590
11	0.203010	3.336664	96.66334
12	0.203940	3.319218	96.68078
13	0.204452	3.318948	96.68105
14	0.204864	3.312753	96.68725
15	0.205138	3.312278	96.68772
16	0.205309	3.312516	96.68748
17	0.205446	3.311338	96.68866
18	0.205531	3.311597	96.68840
19	0.205590	3.311425	96.68858
20	0.205634	3.311188	96.68881

According to the FSI volatility series analysis results, almost all of the changes in the FSI volatility series are caused by itself in the first period. During the second period, the variables outside the BTC volatility series, about 2%, are caused by the BTC volatility series. As of the 15th period, approximately 3% is caused by the BTC volatility series, which was found to increase. Therefore, it is safe to say that the FSI volatility series is also most affected by its shocks. Following the impulse-response and variance decomposition analyses of the residual series of the volatility models, examining the effect between Bitcoin return series and financial stress index values is thought to contribute to the findings. In this context, first, the VAR model is created for the Bitcoin return series and the financial stress index, and the results of the lag duration of the VAR model are shown in Table 14.

Table 14. VAR lag duration determination criteria

Lag	LogL	LR	FPE	AIC	SC	HQ
0	-2837.460	NA	80.90326	10.06901	10.08438	10.07501
1	-2376.957	916.1075	16.02979	8.450203	8.496320*	8.468205
2	-2366.554	20.62089*	15.66995*	8.427498*	8.504361	8.457502*
3	-2363.550	5.933953	15.72540	8.431029	8.538637	8.473034
4	-2359.928	7.128156	15.74655	8.432370	8.570723	8.486376
5	-2355.841	8.015556	15.74173	8.432060	8.601157	8.498067
6	-2354.957	1.727111	15.91675	8.443110	8.642952	8.521119
7	-2353.253	3.317867	16.04699	8.451250	8.681838	8.541261
8	-2352.550	1.363288	16.23590	8.462943	8.724276	8.564954

The lag duration of the VAR model is determined to be two according to the L.R., FPE, AIC, and H.Q. information criteria. VAR model results are shown in Table 15.

Table 15. VAR model results

	BTCVOL	FSIVOL
BTC (-1)	0.030434	-0.002277
	(0.04192)	(0.00072)
	[0.72597]	[-3.17108]
FSI (-1)	-1.276360	0.892868
	(1.08600)	(0.01860)
	[-1.17529]	[47.9928]
C	1.602597	-0.027735
	(0.72413)	(0.01241)
	[2.21312]	[-2.23577]

The inverse roots of the A.R. characteristic polynomial for the stationarity of the VAR model are shown in Figure 6.

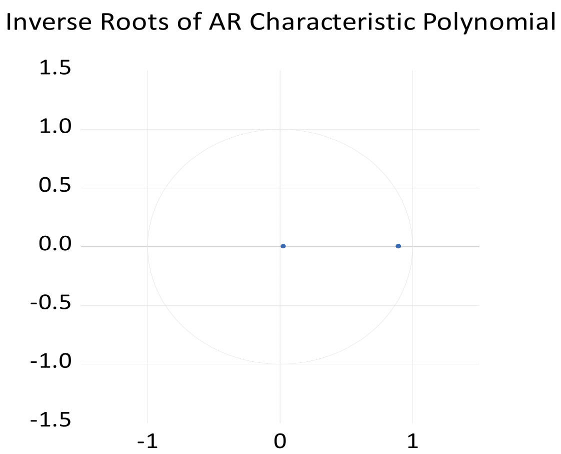


Figure 6. VAR model stationarity graph

The graph of the stationarity of the VAR model shows that the inverse A.R. roots are within the unit circle, and the model is stationary. The autocorrelation test results are shown in Table 16.

Table 16. Autocorrelation-LM test results

Lag	LRE* stat	df	Prob.	Rao F-stat	df	Prob.
1	18.45338	4	0.0010	4.647074	(4, 1130.0)	0.0010
5	9.150122	4	0.0575	2.294778	(4, 1130.0)	0.0575
10	2.332558	4	0.6748	0.583225	(4, 1130.0)	0.6748
20	2.622733	4	0.6228	0.655864	(4, 1130.0)	0.6228
30	1.341463	4	0.8543	0.335268	(4, 1130.0)	0.8543

L.M. test results show that the test probability values are more significant than 0.05, the critical value for the 10th lag and following lags. Therefore, it is determined that there is no autocorrelation problem in the model. After examining the assumptions related to the model, the impulse-response analysis is carried out. The results are shown in Figure 7.

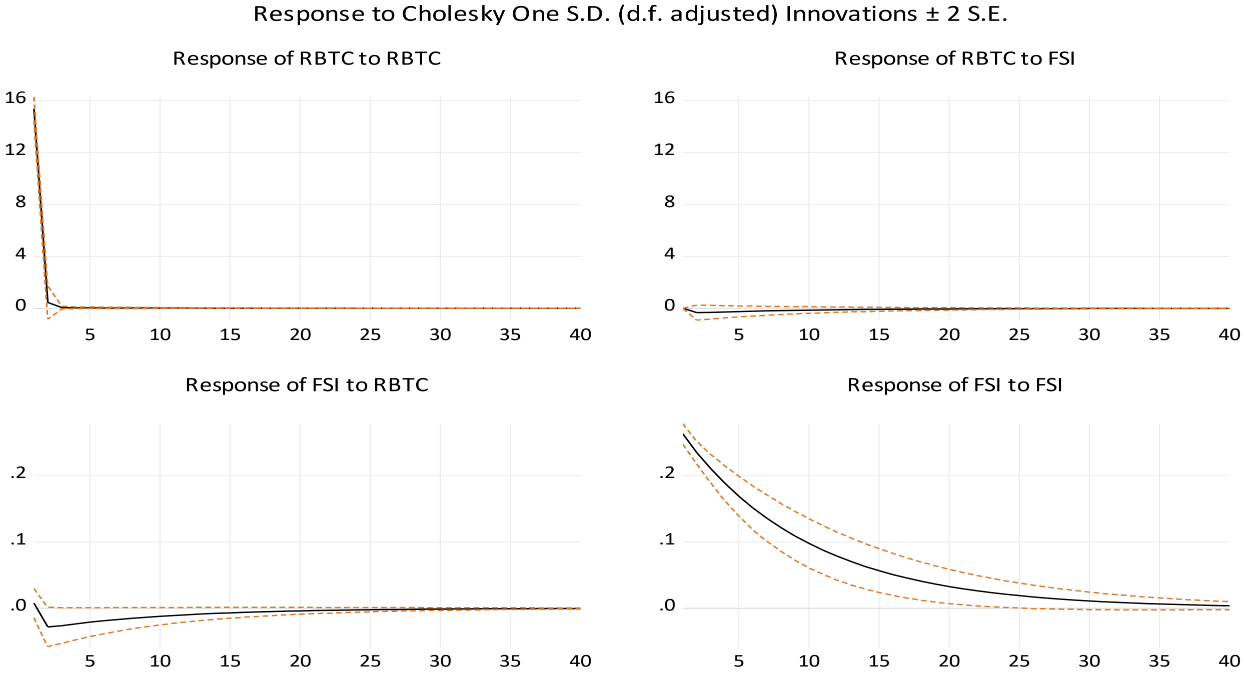


Figure7. Impulse-Response analysis results

The impact-response analysis results of the BTC return series and Financial Stress Index values show that a shock in the FSI series causes a negative surprise in week 5 in the BTC return series. However, this effect disappears as of week 10, coming close to zero. In contrast, a shock in the BTC return series caused a negative surprise in the FSI series in week 5. However, this effect disappeared as of week 20, coming close to zero. Therefore, it can be said that there is a longer-term effect among volatility series. Following the impulse-response analysis, the variance decomposition analysis is performed to determine what percentage of the changes in the BTC return series are caused by itself and the FSI series, and what percentage of the changes in the FSI series are caused by itself and the BTC return series. The analysis results on the BTC return series are shown in Table 17.

Table17. The Results of the variance decomposition test for the BTC series

Period	S.E.	BTCVOL	FSIVOL
1	15.37749	100.0000	0.000000
2	15.38800	99.95230	0.047705
3	15.39121	99.91166	0.088336
4	15.39376	99.87900	0.121005
5	15.39582	99.85277	0.147231
6	15.39747	99.83171	0.168286
7	15.39879	99.81481	0.185192
8	15.39985	99.80123	0.198766
9	15.40071	99.79033	0.209667
10	15.40139	99.78158	0.218421
11	15.40194	99.77455	0.225451
12	15.40239	99.76890	0.231097
13	15.40274	99.76437	0.235632
14	15.40303	99.76073	0.239274
15	15.40326	99.75780	0.242199
16	15.40344	99.75545	0.244548
17	15.40359	99.75356	0.246435
18	15.40371	99.75205	0.247951
19	15.40380	99.75083	0.249168
20	15.40388	99.74985	0.250146

According to the variance decomposition analysis results, in the first period, all of the changes in the BTC return series are caused by itself. However, the variables outside the FSI series, in the second period, about 0.04%, were caused by the FSI series. Finally, as of the 15^{th} period, approximately 0.24% is caused by the FSI series, and this rate was found to increase. The results of the variance decomposition test for the FSI series are shown in Table 18.

Table18. Results of the variance decomposition test for the FSI series

Period	S.E.	BTC	FSI
1	0.263431	0.081786	99.91821
2	0.354224	0.683237	99.31676
3	0.412986	0.908387	99.09161
4	0.454719	1.018712	98.98129
5	0.485650	1.082806	98.91719
6	0.509135	1.123871	98.87613
7	0.527242	1.151857	98.84814
8	0.541347	1.171740	98.82826
9	0.552416	1.186288	98.81371
10	0.561149	1.197163	98.80284
11	0.568066	1.205424	98.79458
12	0.573561	1.211775	98.78823

13	0.577937	1.216703	98.78330
14	0.581429	1.220555	98.77944
15	0.584218	1.223583	98.77642
16	0.586448	1.225974	98.77403
17	0.588234	1.227868	98.77213
18	0.589664	1.229373	98.77063
19	0.590811	1.230571	98.76943
20	0.591730	1.231527	98.76847

According to the results of the variance decomposition analysis of the FSI series, in the first period, 99% of the changes in the FSI series are caused by itself and the variables outside the BTC return series. In the second period, about 0.68% is caused by the BTC return series. As of the 15^{th} period, the BTC return series caused approximately 1%. This rate is found to be increasing. Therefore, it can be said that the changes in the BTC return series and FSI series are caused mainly by themselves, and the series are most affected by their shocks. By comparing the variance decomposition of the volatility series with the analysis results, it can be said that the changes in the volatility series are caused mainly by each other.

4. CONCLUSION

Financial stress refers to the changes that cause disruptions in financial markets that negatively impact financial markets and the entire economy. Recent studies on financial stress show that financial stress can reflect uncertainties and unexpected shocks in markets.

This paper aims to examine the volatility model of Bitcoin and the financial stress index for the period between the 7th of January 2011 and the 24th of December 2021. Firstly, a volatility model is employed for the series, and the most fitting volatility models are found to be GARCH (1,1) and IGARC (1,2) for the BTC and FSI series, respectively. Volatility is observed in 2011, 2013, and 2014 in the BTC series and 2020 in the FSI series. Following the forecasting of volatility for the series, residual volatility series (GARCH conditional variance series) are created for each variable through IGARCH (1,2) and GARCH (1,1) models to identify the volatility spillover among series (Nazlıoğlu et al., (2015); Jan and Jebran (2015)). Using the Diagonal VECH GARCH method, the volatility spillover between the series is examined through the series, and a positive volatility spillover effect from the FSI variable to the BTC variable was found. Then, impulse-response and variance decomposition analyses are performed on residual volatility series created for each variable. In this context, the VAR model is created first. According to the results of the impulse-response analysis performed on the VAR model, a shock in the FSI volatility series causes a negative shock at week 5 in the BTC volatility series. This effect disappears as of week 35, coming close to zero. A surprise in the BTC volatility series caused a positive shock at week 5 in the FSI volatility series. This effect disappeared as of week 30, coming close to zero. According to the results of the variance decomposition analysis performed after the impulse-response examination, it is found that the series are most affected by their shocks. Following the analyses of the volatility series, impulse-response and variance analysis analyses are performed on the BTC return series and Financial Stress Index values to render the findings comparable and supportable. Similar results are obtained with the analyses made on the volatility series.

The financial stress index and Bitcoin volatility's mutual influence show that an economic crisis may affect the cryptocurrency market, and the risks experienced in the cryptocurrency market may cause financial problems. Overall, it can be said that there is a relationship between the financial stress index and Bitcoin, and the findings are essential for investors using Bitcoin in their investment strategies, fund managers, and policymakers.

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