Journal of Money and Economy
Vol. 18, No. 2, Spring 2023
pp.263-284
DOI: 10.61186/jme.18.2.263

Original Research Article

Modeling the Dynamic Correlations among Cryptocurrencies: New Evidence from Multivariate Factor Stochastic Volatility Model

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Received: 27 Nov 2023 Approved: 8 May 2024

This paper intends to model the volatilities of returns of 20 different cryptocurrencies using daily data from 08/03/2018 to 09/20/2022. The multivariate factor stochastic volatility model (MFSV) within the framework of the nonlinear space-state approach is used. In this method, the cryptocurrency return volatility is decomposed into volatility rooted in latent factors and idiosyncratic volatility, and the time-varying pairwise correlation and dynamic covariance matrix are estimated in four sub-periods. The MFSV model's results revealed that each sub-period contains a distinct number of latent factors, 2, 5, 4 and 2, which generally have a favorable impact on all cryptocurrency volatilities. The time-varying positive correlations between the return volatility of all cryptocurrencies are confirmed. Indeed, the strongest pairwise correlations belong to Ethereum, Litcoin, EOS, and VET in each sub-period, respectively. The DOGE, DOGE, Filecoin, and XRP, on the other hand, showed the weakest correlations. As the pairwise correlations of cryptocurrency volatilities get stronger, especially during descending periods, it seems that the benefits of diversifying a crypto portfolio are getting less and less over time.

Keywords: Factor Stochastic Volatility, Cryptocurrencies, Bayesian Approach, Heteroskedasticity, Dynamic Correlation
JEL Classification: C11, C32, C58, G17

1 Introduction

Recently, cryptocurrencies have attracted significant attention. The cryptocurrency market has experienced rapid growth, with market capitalization rising from $18 billion in January 2017 to $950 billion in September 20, 2022 (Coinmarket Cap, 2022). Despite the exponential growth of cryptocurrencies, this phenomenon is still new and almost unidentified.

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However, the academic world has not overlooked the importance of this theme; the number of studies containing the “cryptocurrency,” “blockchain,” “Bitcoin,” and “electronic money” on the Scopus database has increased from 666 in 2017 to 1513, and 1122 in 2021 and the first nine months of 2022, respectively. A wide range of topics, especially in computer science, engineering, management and accounting, mathematics, economics, and legal concerns, has covered about 10800 published studies, with a 14% share of economics. Evaluating the spillover effects within cryptocurrencies and other financial markets is among the most critical issues (Scopus Database, 2022). Indeed, identifying the relations between cryptocurrency volatilities provides helpful information for market participants (miners and investors) by improving the knowledge of information transmission mechanisms.

Over the period, numerous studies have been conducted regarding different aspects of cryptocurrencies, such as the Bitcoin capabilities of hedging against other assets (Samah, 2020; Kyriazis, 2019; Stensås et al., 2019; Chan et al., 2019; Ji et al., 2018; Klein et al., 2018; Bouri et al., 2017; Baur & Dimpfl, 2018; Dyhrberg, 2016a; Dyhrberg, 2016b); the existence of bubbles in cryptocurrencies (Choi & Jarrow, 2020; Agosto & Cafferata, 2020; Hafner, 2020; Fendi et al., 2019; Chu et al., 2017; Cheah & Fry, 2015); the market efficiency of cryptocurrencies (Le Tran & Leirvik, 2020; Kyriazis, 2019; Sensoy, 2019; Nadarajah & Chu, 2017; Urquhart, 2016); the price volatility of cryptocurrencies (Cebrián-Hernández & Jiménez-Rodríguez, 2021; Guizani & Nafti, 2019; Phillip et al., 2018; Katsiampa, 2019); the relationship between cryptocurrencies and conventional assets (Taleblou & Mohajeri, 2023; Jaroenwiriyakul & Tanomchat, 2020; Kim et al., 2020; Corbet et al., 2018; Chuen et al., 2017), using different specifications and methodologies. Therefore, the literature on investigating the interdependencies between the cryptocurrency markets is insufficient. Moreover, despite the capability of multivariate factor stochastic volatility (MFSV) models, developed by Kastner et al., 2017, in modeling the cryptocurrency volatility correlations has been neglected except the study of Shi et al., 2020.

Consequently, this study aims to model the volatility correlations of 20 cryptocurrencies. Followed by Shi et al., 2020, who applied the MFSV model to analyze the six cryptocurrency correlations, this research employs the MFSV model, which is superior to generalized autoregressive conditional heteroscedasticity (GARCH) class models. The essential advantages can be listed as considering the latent stochastic process in modeling the volatility of financial time series, providing accurate estimations of dynamic correlations between cryptocurrencies, and its high flexibility in explaining the stylized facts (e.g., clustering behavior time-varying volatility co-movement (Bollerslev, 1986). This study contributes to the literature in three ways: (1). Modeling the daily dynamic correlations of 20 cryptocurrencies with a total market capitalization of over $ 660 billion, accounting for approximately 70% of the global crypto market capitalization; (2). Extending the period to September 20, 2022, due to the incredible volatility of cryptocurrencies; and (3). Dividing the period into four sub-periods to examine the degree of pairwise correlations of the crypto volatilities in ascending and descending periods.

The remainder of this paper is organized as follows. Section 2 reviews the related literature; Section 3 explains the research method focusing on MFSV models; Section 4 describes the statistical foundations and empirical results. Finally, the research ends up with conclusions and policy implications in Section 5.

2 Literature Review

The most recent topics studied are evaluating the co-movements between cryptocurrencies, their co-movements with the conventional assets, and modeling their volatilizations.

The first strand investigates the co-movements between cryptocurrencies. Huynh et al., 2018 demonstrated a risk of contagion among various cryptocurrencies and suggested that investors carefully diversify their portfolios to avoid a contagious phenomenon. Cagli, 2019, discovered that all cryptocurrencies have explosive behavior and significant pairwise co-movement links. Luu Duc Huynh, 2019, concluded that based on the extreme value, all coins fluctuate negatively. Investors are recommended to consider “bad news” and “movement patterns” to make a quick selection on three sorts of investments. Antonakakis et al., 2019 explored that the total dynamic connectivity of different cryptocurrencies has a considerable dynamic variability ranging from 25% to 75%. Times of high (low) market uncertainty, in particular, coincide with periods of excellent (weak) connectivity. Their results were indicative of using a basic program that focuses on bivariate portfolios. Findings of Omane-Adjepong & Alagidede, 2019 showed that investors and risk managers should be cautious about integrating such market dynamics into any trading strategy for these asset markets. Therefore, their results had many implications for diversifying portfolios and managing risk. The results of Nekhili & Sultan, 2020 highlighted that the stochastic process that considers volatility and returns surges is the most acceptable execution model for the bitcoin market. On the other hand, Katsiampa, 2019 identified the interdependency behavior among various cryptocurrencies. The findings of Ji et al., 2019 demonstrated that Bitcoin and Litecoin are the most important cryptocurrencies. Their correlations are higher in negative returns, which was confirmed by the results of Lahajnar & Rožanec, 2020, who showed that the findings are not affected by data frequency. Moreover, they concluded that strong correlations in the bearish markets could obstruct pursuing the portfolio diversification strategy.

The second strand is dedicated to investigating the co-movements between different cryptocurrencies and other assets. For instance, Baumöhl 2019 analyzed the correlation between six cryptocurrencies and six forexes. His empirical findings demonstrated some significant negative connections between investigated assets in the short and long term. Furthermore, the linkage between cryptocurrencies is not as robust as many people envisage. The findings of Al-Yahyaee et al., 2019, and Conrad et al., 2018 verified significant co-movements between some cryptocurrencies and stock market indices. Kurka, 2019 examined the co-movements between some assets, such as commodities, exchange rates, stock indices, and other financial assets with cryptocurrencies. His results confirmed very weak correlations between them. The results of Rehman & Apergis, 2019 showed that in terms of volatility and mean, in the majority of quantiles, considerable causality flows from cryptocurrencies to commodity. Kim et al., 2020, explored the interlinkages between the S&P 500, Bitcoin, and Gold as the most significant financial assets. According to their findings regarding volatility and long-return, the S&P 500 and the price of gold are statistically significant to Bitcoin. Jaroenwiriyakul & Tanomchat, 2020 deliberated the relationship between four leading cryptocurrencies and stock market indices for 5 ASEAN countries. Their outcomes showed a high correlation between studied assets from 2013 to 2015 but continued relatively steady until January 2020.

Modeling the volatility of different types of assets and financial markets is the central theme of the third strand of studies. The most studied have used the GARCH model introduced by Bollerslev (1986) and its various version as the basis for modeling volatility. For instance, Katsiampa, 2017; Stavroyiannis & Babalos, 2017; Chu et al., 2017; Bouri, et al., 2017; Charles & Darné, 2019; who emphasized modeling the volatility of Bitcoin. On the other hand, some studies have focused on the potential capability of volatility predictions, such as Naimy & Hayek, 2018 and Peng et al., 2018. Modeling the volatility of cryptocurrencies is the central focus of studies like Baur & Dimpfl, 2018; Peng et al., 2018; Charfeddine & Maouchi, 2019; Charles &

[DOI: 10.61186/jme.18.2.263]

Darné, 2019; Caporale & Zekokh, 2019; Borri, 2019 and Fakhfekh & Jeribi, 2020.

Contrary to the GARCH class models, the stochastic variation (SV) models developed by Taylor (1986) have recently been considered in modeling financial time series volatility such as cryptocurrencies. The main advantages of these models could be listed as including latent stochastic processes in modeling volatility and the high flexibility in describing the stylized facts of financial series. In this regard, modeling the return volatility of Bitcoin and Litcoin by using different GARCH and SV models Shi et al. (2020) confirmed the superiority of the SV over the GARCH models. Moreover, comparing several SV models for modeling the volatility of four cryptocurrencies (Bitcoin, Litecoin, Ripple, and Ethereum), Zahid, M, & Iqbal (2020) showed that heavy-tailed SV models are superior performance than the others.

3 Methodology

The MFSV model is used to model the volatilities of 20 different cryptocurrencies. This model is based on the principle of parsimony and considers the time-varying cryptocurrency returns. However, it incorporates the possible characteristics of cryptocurrencies, such as "clustering volatility" and "volatility co-movements." At the same time, it must be resistant to idiosyncratic shocks of that asset. The MFSV model is robust and consistent with the stylized facts of asset volatility returns since it uses orthogonal latent factors with fewer dimensions. These factors can include all time-varying volatility co-movements. Moreover, this approach envisages clustering volatilities, which makes it resilient to idiosyncratic shocks related to the nature of stochastic volatility processes (Bollerslev, 1986; Kastner et al., 2017; Yamauchi & Omori, 2020).

To get a better understanding of this approach, assume that each time point is denoted by $t = 1, \dots, T$, $y_t = (y_{1t}, \dots, y_{mt})'$ shows the vector of m observed returns with zero means and $f_t = (f_{1t}, \dots, f_{rt})'$ indicates the vector of r latent factors. Unlike the static factor model, the observations are assumed to be affected by latent factors and idiosyncratic shocks. In stochastic factor volatility, the idiosyncratic variance and the variances of the latent factors are time-varying and depend on m+r hidden volatilities, i.e. $h_t = (h_t^U, h_t^V)$ where $h_t^U = (h_{1t}, \dots, h_{mt})'$ and $h_t^V = (h_{m+1,t}, \dots, h_{m+r,t})'$. Briefly, we have (Eq. (1)):

[DOI: 10.61186/jme.18.2.263]

$$y_t = \Lambda f_t + U_t(h_t^U)^{1/2}\,\varepsilon_t\,,\ f_t = V_t(h_t^V)^{1/2}\xi_t \tag{1}$$

Where:

- Λ stands for the $m \times r$ factor loading matrix,
- $U_t(h_t^U) = diag\,(\exp(h_{1t})\,, \dots, \exp(h_{mt})$ justify the $m \times m$ diagonal idiosyncratic variance matrix,
- $V_t(h_t^V) = diag\,(\exp\big(h_{m+1,t}\big)\,, \dots, \exp\big(h_{m+r,t}\big)$ is the $r \times r$ diagonal variance matrix of latent factors.

The variances, in turn, are modeled as hidden variables, which their logarithm follows a first-order autoregressive process, i.e., for $i = 1, \dots, m + r$ (see Eq. (2))

$$h_{it} = \mu_i + \phi(h_{it-1} - \mu_i) + \sigma_i\eta_{it} \tag{2}$$

That the initial value of h_{i0} is unknown. It is assumed that all variances follow an independent normal distribution, i.e. $\varepsilon_t \sim \mathcal{N}_m(0, I_m)$, $\xi_t \sim \mathcal{N}_r(0, I_r)$ and $\eta_t \sim \mathcal{N}_{m+r}(0, I_{m+r})$. Where $\eta_t = (\eta_{1t}, \dots, \eta_{m+r,t})'$, implying the structure has been shown in Eq. (3):

$$y_t = \Lambda f_t + \epsilon_t, \quad f_t|h_t \sim \mathcal{N}_r\left(0, V_t(h_t^V)\right), \epsilon_t|h_t \sim \mathcal{N}_m(0, U_t(h_t) \tag{3}$$

One of the most significant advantages of the MFSV model is the reliable estimation of the time-varying conditional covariance matrix that models through $cov(y_t|h_t) = \sum_t(h_t) = \Lambda V_t(h_t^V)\Lambda' + U_t(h_t^U)$. It is noteworthy to be mentioned that all covariances of the time series are affected by the latent factors since $U_t(h_t^U)$ is diagonal. Finally, considering the characteristics of h_t, y_t follows a process with the non-Gaussian distribution.

It is impossible to obtain a consistent estimation of the variances given the constraints on the parameters. Under such conditions, Bayesian inference for the posterior distribution can provide a flexible estimation. Thus, the Markov Chain Monte Carlo (MCMC) estimation techniques can be used (Shi et al., 2020). Nevertheless, this algorithm mainly lacks convergence, which could lead to biased parameter estimation. Kastner et al. (2017) developed the estimation procedures to overcome these possible problems. Briefly, the MFSV model of Kastner et al. (2017) is employed in this study for three reasons. First, this model can capture the key features of financial assets, particularly "volatility clustering" and "time-varying co-movement of volatility." Second, this model is robust to idiosyncratic shocks. Third, using

[DOI: 10.61186/jme.18.2.263]

Bayesian inference for the posterior distribution in this approach allows the estimates to be flexible and handles the "lack of convergence" problem well.

4 Data and Empirical Findings

4.1 Descriptive Statistics

To model MFSV, the diurnal volatility correlations of 20 cryptocurrencies are estimated under a nonlinear state space approach from August 3, 2018, to September 20, 2022 (1509 daily observations). The market value of these cryptocurrencies varies from $0.5 billion for DASH to $372 billion for Bitcoin (Coinmarket Cap, 2022). Figure 1 depicts the prices of cryptocurrencies.

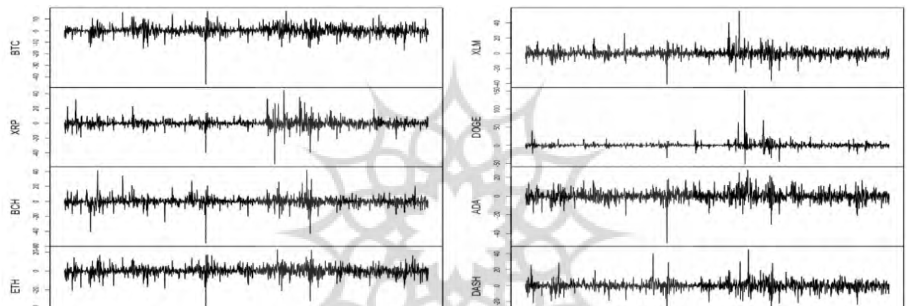


Figure 1. The volatilities of cryptocurrency return from 08/03/2018 to 09/20/2022
Source: Research findings

[DOI: 10.61186/jme.18.2.263]

Figure 1 shows the clustered volatilities of the other cryptocurrency returns, implying that small volatilities cause minor fluctuations in subsequent periods, and high volatilities intensify future fluctuations. Since Bitcoin accounts for more than a third of the global market capitalization of cryptocurrencies, the period can be divided into four sub-periods to clarify the findings as follows:

The first period- bull market, lasting from August 3, 2018, to April 13, 2021.

The second period- bear market, lasting from April 14, 2013, to July 19, 2021.

The third period- bull market, lasting from July 20, 2021, to November, 8, 2021.

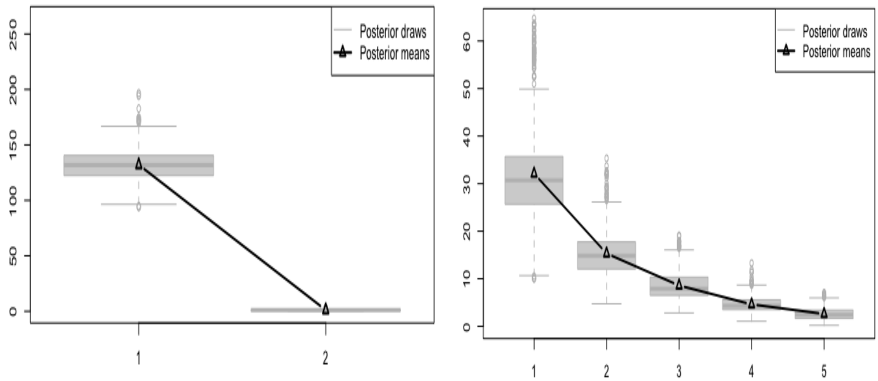
The fourth period- bear market, lasting from November 9, 2021, to September 20, 2022.

4.2 Empirical Findings

1) The primary purpose of employing the MFSV model is to decompose the volatility of returns into idiosyncratic volatility and the effect of latent factors, both of which are unobservable. Following that, time-varying pairwise correlations between the cryptocurrency volatilities in four sub-periods can be estimated. It needs to use the space-state model and Bayesian methods in the R software package. The empirical findings could be summarized as follows: *Determine the number of influential latent factors on the returns of different cryptocurrencies in each of 4 sub-periods*. The lower triangular matrix of the factor load is the most common method of pattern recognition in stochastic volatility models[1], in which the eigenvalues of $\Lambda'\Lambda$ is an accurate guide to identify and select the number of latent factors. Figure 2 illustrates the eigenvalues and identifying number of the latent factors in each of four sub-periods.

Panel A: from 08/03/2018 to 13/04/2021 Panel B: 14/04/2021 to 07/19/2021

[1] For more information, see Zhou et al. (2014)



Panel C: from 07/20/2021 to 11/08/2021   Panel D: from 11/09/2021 to 09/20/2022

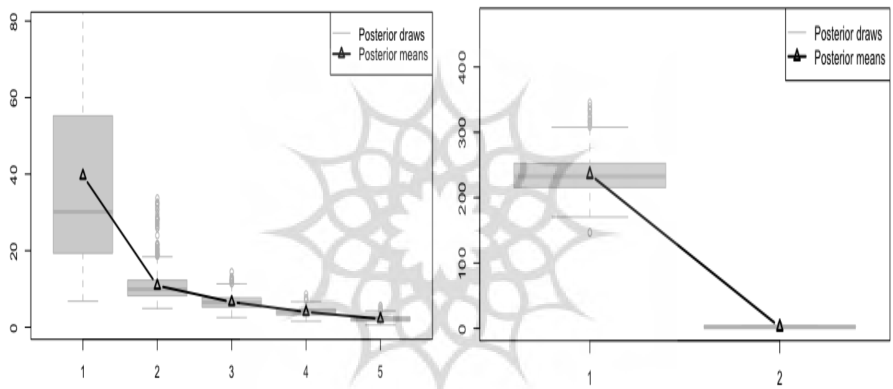
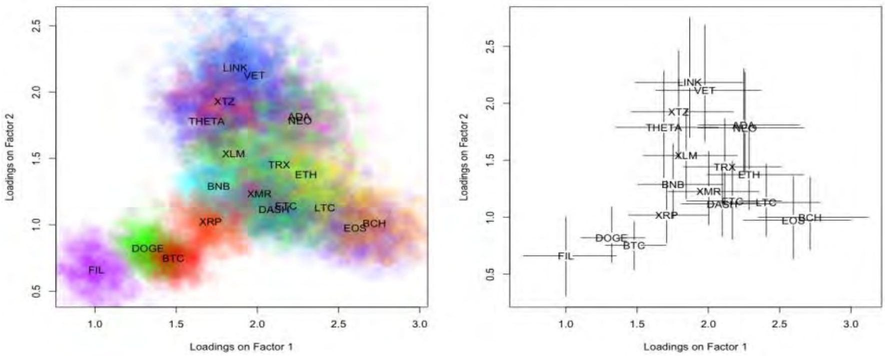


Figure 2. Eigenvalues and identifying the number of latent factors
Source: Research findings

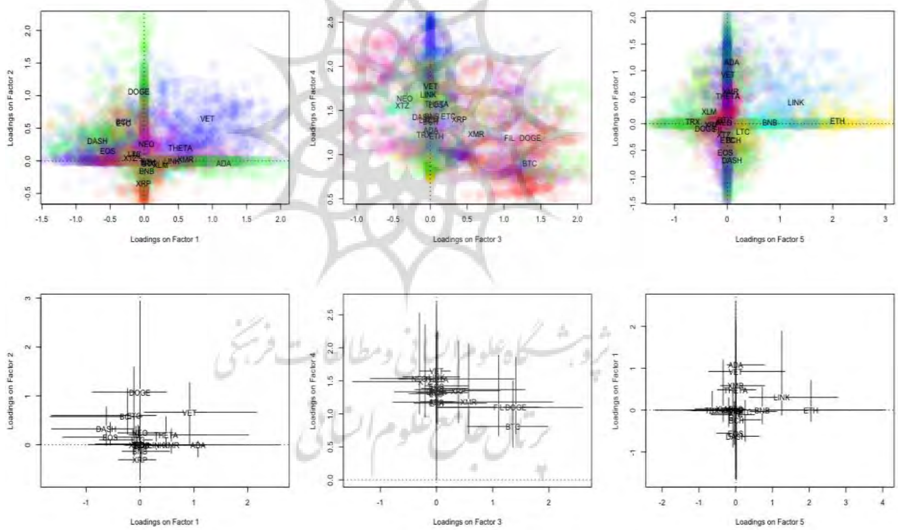
Figure 2 shows that, while there are two hidden factors that are significantly different from zero in the first and fourth periods, there are five and four latent factors in the second and third periods, respectively. Some of the common cryptocurrency volatilities could be explained by the latent factor volatilities.

2) Estimate the posterior distribution of the loading factors on the return volatility of each cryptocurrency in each sub-period (Figures 3).

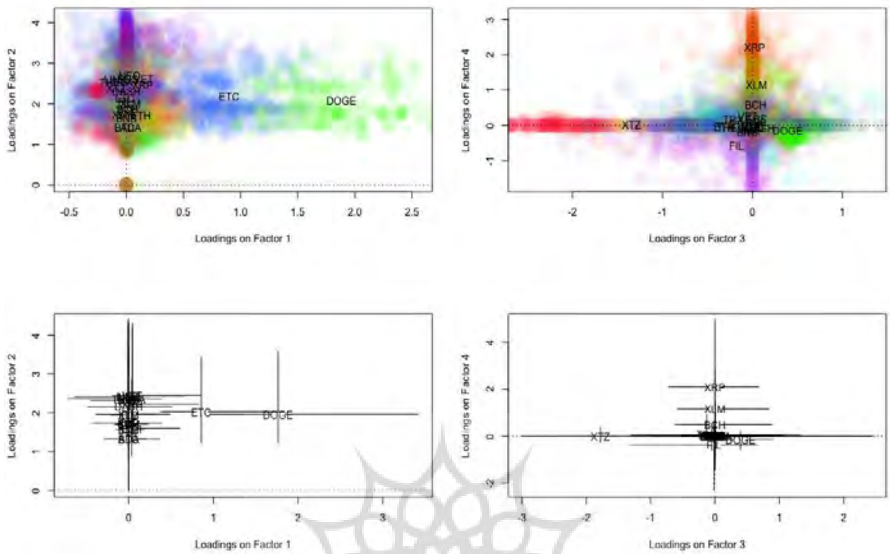
Panel A: from 08/03/2018 to 13/04/2021



Panel B: 14/04/2021 to 07/19/2021



Panel C: from 07/20/2021 to 11/08/2021



Panel D: from 11/09/2021 to 09/20/2022

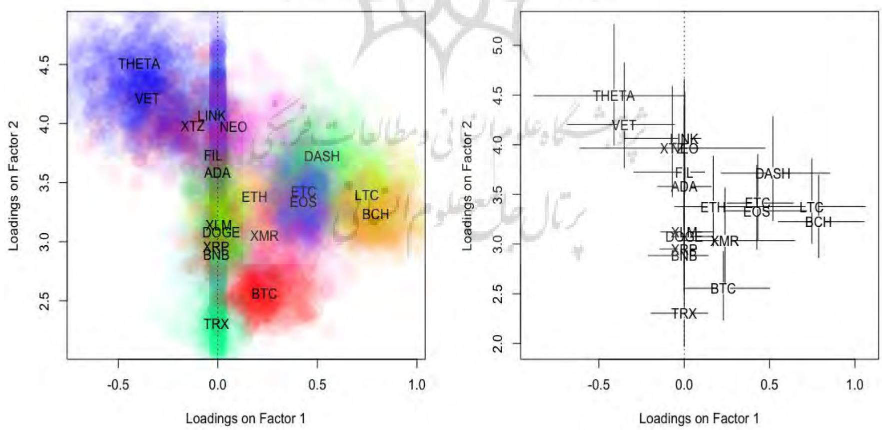


Figure 3. Posterior loading factor distribution of latent factors
Source: Research findings

[DOI: 10.61186/jme.18.2.263]

Based on Panel “A” in Figure 3, the first latent factor has impacted all cryptocurrencies positively, such that Filecoin (the lowest impact) and Bitcoin Cash (the highest impact) are opposite ends of the spectrum. Correspondingly, the second loading factor has affected cryptocurrencies positively. In this case, Filecoin and Chainlink have the least and the most impact, respectively.

Panel “B” shows that, with the exception of the fourth factor, which affects the volatilities of all cryptocurrencies in a positive way, the effects of other hidden factors vary by cryptocurrency, with some being affected in a positive way while others are impacted in a negative way.

Only the second hidden factor positively impacts the cryptocurrency volatility according to Panel “C”, which demonstrates the factor loadings of cryptocurrency volatility from the latent factors in third period. Other latent factors affect cryptocurrencies both positively and negatively, which are explained in the second period.

Panel “D” claims two latent factors in the fourth period. Some cryptocurrencies’ volatility goes up because of the first latent factor, while other cryptocurrencies’ volatility goes down because of it. However, all cryptocurrencies’ volatility goes up because of the second latent factor

Estimating time-varying posterior mean correlations is one of the main advantages of the MFSV model (see Tables 1 to 4).

Table 1

The mean correlation matrix of daily volatilities in cryptocurrency returns from 08/03/2018 to 13/04/2021

Cryptocurrency name	Abbreviation	BTC	XRP	BCH	ETH	LTC	XLM	DOGE	ADA	DASH	TRX	BNB	LINK	ETC	VET	THETA	EOS	FIL	NEO	XMR	XTZ
Bitcoin	BTC	1	0.45	0.60	0.66	0.65	0.49	0.19	0.60	0.63	0.48	0.35	0.41	0.65	0.41	0.45	0.63	0.29	0.61	0.52	0.51
XRP	XRP	0.45	1	0.47	0.53	0.51	0.41	0.15	0.50	0.50	0.39	0.29	0.35	0.51	0.35	0.38	0.50	0.23	0.50	0.42	0.43
Bitcoin Cash	BCH	0.60	0.47	1	0.69	0.69	0.50	0.19	0.62	0.66	0.49	0.36	0.41	0.68	0.42	0.46	0.67	0.30	0.62	0.54	0.52
Ethereum	ETH	0.66	0.53	0.69	1	0.77	0.59	0.21	0.73	0.74	0.56	0.42	0.49	0.76	0.50	0.55	0.74	0.33	0.73	0.61	0.62
Litecoin	LTC	0.65	0.51	0.69	0.77	1	0.56	0.21	0.69	0.72	0.54	0.40	0.46	0.75	0.47	0.51	0.73	0.32	0.70	0.60	0.59
Stellar	XLM	0.49	0.41	0.50	0.59	0.56	1	0.17	0.58	0.55	0.44	0.33	0.41	0.57	0.42	0.45	0.54	0.26	0.58	0.47	0.52
Dogecoin	DOGE	0.19	0.15	0.19	0.21	0.21	0.17	1	0.20	0.20	0.16	0.12	0.14	0.21	0.14	0.16	0.20	0.10	0.20	0.17	0.17
Cardano	ADA	0.60	0.50	0.62	0.73	0.69	0.58	0.20	1	0.68	0.53	0.40	0.50	0.70	0.51	0.55	0.67	0.31	0.71	0.57	0.63
DASH	DASH	0.63	0.50	0.66	0.74	0.72	0.55	0.20	0.68	1	0.53	0.39	0.46	0.72	0.47	0.51	0.70	0.31	0.68	0.58	0.58
TRON	TRX	0.48	0.39	0.49	0.56	0.54	0.44	0.16	0.53	0.53	1	0.31	0.37	0.54	0.38	0.41	0.52	0.24	0.53	0.44	0.47
Binance Coin	BNB	0.35	0.29	0.36	0.42	0.40	0.33	0.12	0.40	0.39	0.31	1	0.28	0.40	0.29	0.31	0.39	0.19	0.40	0.33	0.35
Chainlink	LINK	0.41	0.35	0.41	0.49	0.46	0.41	0.14	0.50	0.46	0.37	0.28	1	0.47	0.37	0.39	0.45	0.22	0.49	0.39	0.44
Etherum Classic	ETC	0.65	0.51	0.68	0.76	0.75	0.57	0.21	0.70	0.72	0.54	0.40	0.47	1	0.48	0.52	0.72	0.32	0.70	0.59	0.59
VeChain	VET	0.41	0.35	0.42	0.50	0.47	0.42	0.14	0.51	0.47	0.38	0.29	0.37	0.48	1	0.40	0.45	0.22	0.50	0.40	0.46
THETA	THETA	0.45	0.38	0.46	0.55	0.51	0.45	0.16	0.55	0.51	0.41	0.31	0.39	0.52	0.40	1	0.50	0.24	0.54	0.43	0.49
EOS	EOS	0.63	0.50	0.67	0.74	0.73	0.54	0.20	0.67	0.70	0.52	0.39	0.45	0.72	0.45	0.50	1	0.31	0.67	0.58	0.56
Filecoin	FIL	0.29	0.23	0.30	0.33	0.32	0.26	0.10	0.31	0.31	0.24	0.19	0.22	0.32	0.22	0.24	0.31	1	0.31	0.27	0.27
Neo	NEO	0.61	0.50	0.62	0.73	0.70	0.58	0.20	0.71	0.68	0.53	0.40	0.49	0.70	0.50	0.54	0.67	0.31	1	0.57	0.62
Monero	XMR	0.52	0.42	0.54	0.61	0.60	0.47	0.17	0.57	0.58	0.44	0.33	0.39	0.59	0.40	0.43	0.58	0.27	0.57	1	0.49
Tezos	XTZ	0.51	0.43	0.52	0.62	0.59	0.52	0.17	0.63	0.58	0.47	0.35	0.44	0.59	0.46	0.49	0.56	0.27	0.62	0.49	1

Source: Research findings

[DOI: 10.61186/jme.18.2.263]

Table 2

The mean correlation matrix of daily volatilities in cryptocurrency returns from 14/04/2021 to 07/19/2021

Cryptocurrency name	Abbreviation	BTC	XRP	BCH	ETH	LTC	XLM	DOGE	ADA	DASH	TRX	BNB	LINK	ETC	VET	THETA	EOS	FIL	NEO	XMR	XTZ
Bitcoin	BTC	1	0.81	0.80	0.72	0.81	0.74	0.63	0.79	0.72	0.78	0.79	0.79	0.75	0.79	0.69	0.77	0.68	0.77	0.76	0.79
XRP	XRP	0.81	1	0.86	0.77	0.88	0.80	0.67	0.84	0.78	0.84	0.85	0.86	0.80	0.85	0.70	0.85	0.73	0.84	0.82	0.85
Bitcoin Cash	BCH	0.80	0.86	1	0.78	0.93	0.79	0.66	0.84	0.83	0.86	0.84	0.86	0.83	0.84	0.74	0.88	0.72	0.86	0.81	0.88
Ethereum	ETH	0.72	0.77	0.78	1	0.80	0.71	0.59	0.78	0.70	0.74	0.78	0.83	0.73	0.77	0.68	0.74	0.64	0.75	0.74	0.76
Litecoin	LTC	0.81	0.88	0.93	0.80	1	0.81	0.67	0.86	0.83	0.87	0.87	0.89	0.84	0.87	0.75	0.89	0.73	0.88	0.83	0.89
Stellar	XLM	0.74	0.80	0.79	0.71	0.81	1	0.61	0.78	0.71	0.77	0.78	0.79	0.74	0.78	0.67	0.77	0.67	0.76	0.75	0.78
Dogecoin	DOGE	0.63	0.67	0.66	0.59	0.67	0.61	1	0.65	0.60	0.65	0.63	0.65	0.69	0.66	0.58	0.66	0.58	0.65	0.63	0.65
Cardano	ADA	0.79	0.84	0.84	0.78	0.86	0.78	0.65	1	0.76	0.82	0.84	0.86	0.79	0.84	0.75	0.80	0.71	0.81	0.81	0.83
DASH	DASH	0.72	0.78	0.83	0.70	0.83	0.71	0.60	0.76	1	0.78	0.77	0.77	0.74	0.76	0.67	0.78	0.65	0.78	0.73	0.79
TRON	TRX	0.78	0.84	0.86	0.74	0.87	0.77	0.65	0.82	0.78	1	0.82	0.82	0.79	0.83	0.73	0.83	0.71	0.83	0.79	0.84
Binance Coin	BNB	0.79	0.85	0.84	0.78	0.87	0.78	0.63	0.84	0.77	0.82	1	0.85	0.77	0.84	0.74	0.80	0.71	0.82	0.81	0.83
Chainlink	LINK	0.79	0.86	0.86	0.83	0.89	0.79	0.65	0.86	0.77	0.82	0.85	1	0.81	0.85	0.74	0.83	0.70	0.83	0.82	0.84
Etherum Classic	ETC	0.75	0.80	0.83	0.73	0.84	0.74	0.69	0.79	0.74	0.79	0.77	0.81	1	0.79	0.69	0.80	0.68	0.79	0.76	0.80
VeChain	VET	0.79	0.85	0.84	0.77	0.87	0.78	0.66	0.84	0.76	0.83	0.84	0.85	0.79	1	0.74	0.82	0.72	0.82	0.81	0.84
THETA	THETA	0.69	0.70	0.74	0.68	0.75	0.67	0.58	0.75	0.67	0.73	0.74	0.74	0.69	0.74	1	0.68	0.63	0.72	0.71	0.73
EOS	EOS	0.77	0.85	0.88	0.74	0.89	0.77	0.66	0.80	0.78	0.83	0.80	0.83	0.80	0.82	0.68	1	0.70	0.83	0.78	0.85
Filecoin	FIL	0.68	0.73	0.72	0.64	0.73	0.67	0.58	0.71	0.65	0.71	0.71	0.70	0.68	0.72	0.63	0.70	1	0.70	0.69	0.71
Neo	NEO	0.77	0.84	0.86	0.75	0.88	0.76	0.65	0.81	0.78	0.83	0.82	0.83	0.79	0.82	0.72	0.83	0.70	1	0.79	0.84
Monero	XMR	0.76	0.82	0.81	0.74	0.83	0.75	0.63	0.81	0.73	0.79	0.81	0.82	0.76	0.81	0.71	0.78	0.69	0.79	1	0.80
Tezos	XTZ	0.79	0.85	0.88	0.76	0.89	0.78	0.65	0.83	0.79	0.84	0.83	0.84	0.80	0.84	0.73	0.85	0.71	0.84	0.80	1

Source: Research findings

Table 3

The mean correlation matrix of daily volatilities in cryptocurrency returns from 07/20/2021 to 11/08/2021

Cryptocurrency name	Abbreviation	BTC	XRP	BCH	ETH	LTC	XLM	DOGE	ADA	DASH	TRX	BNB	LINK	ETC	VET	THETA	EOS	FIL	NEO	XMR	XTZ
Bitcoin	BTC	1	0.75	0.81	0.79	0.82	0.71	0.81	0.73	0.81	0.82	0.80	0.79	0.82	0.82	0.72	0.85	0.70	0.83	0.74	0.78
XRP	XRP	0.75	1	0.85	0.74	0.77	0.78	0.76	0.70	0.76	0.80	0.71	0.75	0.79	0.81	0.67	0.83	0.60	0.78	0.67	0.74
Bitcoin Cash	BCH	0.81	0.85	1	0.79	0.82	0.77	0.81	0.74	0.82	0.84	0.78	0.80	0.83	0.85	0.72	0.88	0.67	0.84	0.73	0.79
Ethereum	ETH	0.79	0.74	0.79	1	0.81	0.70	0.81	0.72	0.80	0.83	0.79	0.77	0.83	0.82	0.71	0.84	0.69	0.82	0.73	0.78
Litecoin	LTC	0.82	0.77	0.82	0.81	1	0.73	0.84	0.75	0.83	0.84	0.82	0.80	0.84	0.85	0.73	0.88	0.72	0.86	0.76	0.80
Stellar	XLM	0.71	0.78	0.77	0.70	0.73	1	0.72	0.66	0.72	0.74	0.69	0.72	0.74	0.75	0.64	0.77	0.59	0.74	0.64	0.70
Dogecoin	DOGE	0.81	0.76	0.81	0.81	0.84	0.72	1	0.74	0.83	0.83	0.82	0.79	0.92	0.85	0.72	0.87	0.71	0.85	0.75	0.78
Cardano	ADA	0.73	0.70	0.74	0.72	0.75	0.66	0.74	1	0.74	0.75	0.72	0.71	0.75	0.75	0.65	0.78	0.63	0.76	0.67	0.71
DASH	DASH	0.81	0.76	0.82	0.80	0.83	0.72	0.83	0.74	1	0.83	0.81	0.80	0.83	0.84	0.73	0.87	0.71	0.84	0.75	0.79
TRON	TRX	0.82	0.80	0.84	0.83	0.84	0.74	0.83	0.75	0.83	1	0.82	0.81	0.85	0.86	0.74	0.88	0.71	0.86	0.76	0.82
Binance Coin	BNB	0.80	0.71	0.78	0.79	0.82	0.69	0.82	0.72	0.81	0.82	1	0.78	0.82	0.82	0.72	0.85	0.72	0.83	0.75	0.79
Chainlink	LINK	0.79	0.75	0.80	0.77	0.80	0.72	0.79	0.71	0.80	0.81	0.78	1	0.81	0.81	0.70	0.84	0.68	0.82	0.72	0.77
Etherum Classic	ETC	0.82	0.79	0.83	0.83	0.84	0.74	0.92	0.75	0.83	0.85	0.82	0.81	1	0.86	0.73	0.88	0.71	0.86	0.76	0.82
VeChain	VET	0.82	0.81	0.85	0.82	0.85	0.75	0.85	0.75	0.84	0.86	0.82	0.81	0.86	1	0.74	0.89	0.71	0.86	0.76	0.81
THETA	THETA	0.72	0.67	0.72	0.71	0.73	0.64	0.72	0.65	0.73	0.74	0.72	0.70	0.73	0.74	1	0.76	0.63	0.74	0.66	0.71
EOS	EOS	0.85	0.83	0.88	0.84	0.88	0.77	0.87	0.78	0.87	0.88	0.85	0.84	0.88	0.89	0.76	1	0.73	0.89	0.79	0.84
Filecoin	FIL	0.70	0.60	0.67	0.69	0.72	0.59	0.71	0.63	0.71	0.71	0.72	0.68	0.71	0.71	0.63	0.73	1	0.73	0.65	0.69
Neo	NEO	0.83	0.78	0.84	0.82	0.86	0.74	0.85	0.76	0.84	0.86	0.83	0.82	0.86	0.86	0.74	0.89	0.73	1	0.77	0.81
Monero	XMR	0.74	0.67	0.73	0.73	0.76	0.64	0.75	0.67	0.75	0.76	0.75	0.72	0.76	0.76	0.66	0.79	0.65	0.77	1	0.73
Tezos	XTZ	0.78	0.74	0.79	0.78	0.80	0.70	0.78	0.71	0.79	0.82	0.79	0.77	0.82	0.81	0.71	0.84	0.69	0.81	0.73	1

Source: Research findings

[DOI: 10.61186/jme.18.2.263]

Table 4
The mean correlation matrix of daily volatilities in cryptocurrency returns from 11/09/2021 to 20/09/2022

Cryptocurrency name	Abbreviation	BTC	XRP	BCH	ETH	LTC	XLM	DOGE	ADA	DASH	TRX	BNB	LINK	ETC	VET	THETA	EOS	FIL	NEO	XMR	XTZ
Bitcoin	BTC	1	0.55	0.71	0.64	0.72	0.57	0.71	0.69	0.73	0.61	0.68	0.59	0.57	0.74	0.70	0.58	0.62	0.73	0.59	0.69
XRP	XRP	0.55	1	0.60	0.56	0.60	0.50	0.62	0.61	0.63	0.54	0.60	0.52	0.49	0.66	0.63	0.50	0.54	0.64	0.51	0.61
Bitcoin Cash	BCH	0.71	0.60	1	0.71	0.83	0.62	0.78	0.76	0.83	0.66	0.74	0.64	0.64	0.79	0.75	0.65	0.67	0.80	0.66	0.74
Ethereum	ETH	0.64	0.56	0.71	1	0.71	0.58	0.72	0.70	0.73	0.62	0.69	0.59	0.57	0.75	0.72	0.58	0.62	0.73	0.60	0.70
Litecoin	LTC	0.72	0.60	0.83	0.71	1	0.62	0.78	0.76	0.83	0.67	0.74	0.64	0.64	0.79	0.75	0.65	0.67	0.80	0.66	0.75
Stellar	XLM	0.57	0.50	0.62	0.58	0.62	1	0.64	0.63	0.65	0.56	0.61	0.53	0.51	0.68	0.64	0.51	0.56	0.66	0.53	0.63
Dogecoin	DOGE	0.71	0.62	0.78	0.72	0.78	0.64	1	0.78	0.81	0.69	0.76	0.66	0.63	0.85	0.81	0.64	0.69	0.82	0.66	0.78
Cardano	ADA	0.69	0.61	0.76	0.70	0.76	0.63	0.78	1	0.79	0.67	0.75	0.65	0.61	0.83	0.79	0.62	0.68	0.80	0.64	0.76
DASH	DASH	0.73	0.63	0.83	0.73	0.83	0.65	0.81	0.79	1	0.69	0.77	0.66	0.65	0.83	0.79	0.66	0.70	0.83	0.68	0.78
TRON	TRX	0.61	0.54	0.66	0.62	0.67	0.56	0.69	0.67	0.69	1	0.66	0.57	0.54	0.73	0.69	0.55	0.60	0.70	0.57	0.67
Binance Coin	BNB	0.68	0.60	0.74	0.69	0.74	0.61	0.76	0.75	0.77	0.66	1	0.63	0.60	0.81	0.77	0.61	0.66	0.78	0.63	0.75
Chainlink	LINK	0.59	0.52	0.64	0.59	0.64	0.53	0.66	0.65	0.66	0.57	0.63	1	0.52	0.70	0.66	0.53	0.57	0.67	0.54	0.64
Etherum Classic	ETC	0.57	0.49	0.64	0.57	0.64	0.51	0.63	0.61	0.65	0.54	0.60	0.52	1	0.65	0.62	0.52	0.54	0.65	0.53	0.61
VeChain	VET	0.74	0.66	0.79	0.75	0.79	0.68	0.85	0.83	0.83	0.73	0.81	0.70	0.65	1	0.87	0.66	0.74	0.87	0.69	0.83
THETA	THETA	0.70	0.63	0.75	0.72	0.75	0.64	0.81	0.79	0.79	0.69	0.77	0.66	0.62	0.87	1	0.63	0.70	0.82	0.65	0.79
EOS	EOS	0.58	0.50	0.65	0.58	0.65	0.51	0.64	0.62	0.66	0.55	0.61	0.53	0.52	0.66	0.63	1	0.55	0.65	0.54	0.62
Filecoin	FIL	0.62	0.54	0.67	0.62	0.67	0.56	0.69	0.68	0.70	0.60	0.66	0.57	0.54	0.74	0.70	0.55	1	0.71	0.57	0.68
Neo	NEO	0.73	0.64	0.80	0.73	0.80	0.66	0.82	0.80	0.83	0.70	0.78	0.67	0.65	0.87	0.82	0.65	0.71	1	0.68	0.80
Monero	XMR	0.59	0.51	0.66	0.60	0.66	0.53	0.66	0.64	0.68	0.57	0.63	0.54	0.53	0.69	0.65	0.54	0.57	0.68	1	0.64
Tezos	XTZ	0.69	0.61	0.74	0.70	0.75	0.63	0.78	0.76	0.78	0.67	0.75	0.64	0.61	0.83	0.79	0.62	0.68	0.80	0.64	1

Source: Research findings

The magnitudes of the correlations in Tables 1 through 4, have varied at different points in time. Figures 6- 9 shows the posterior correlation for the 24 time periods.

[DOI: 10.61186/jme.18.2.263]

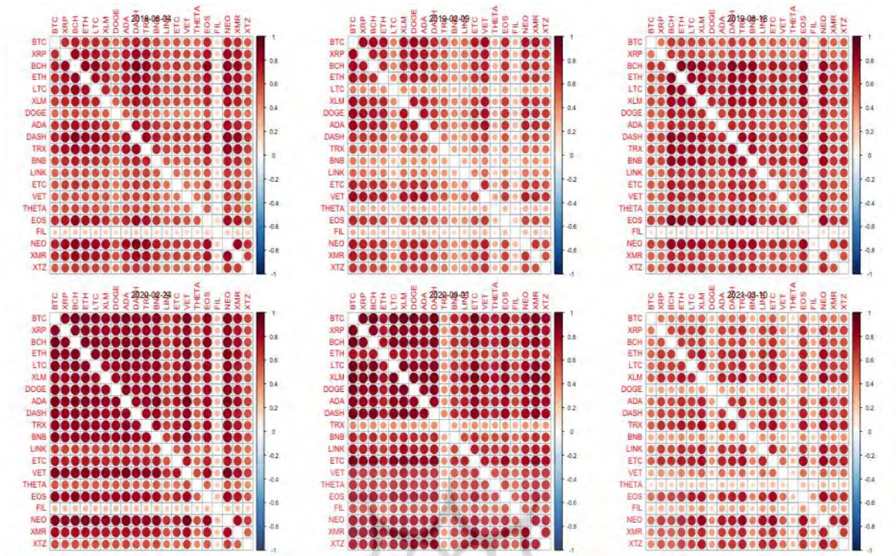


Figure 4. The posterior volatility correlation matrix of 20 cryptocurrency returns in 6 different times from 04/08/2018 to 13/04/2021
Source: Research findings

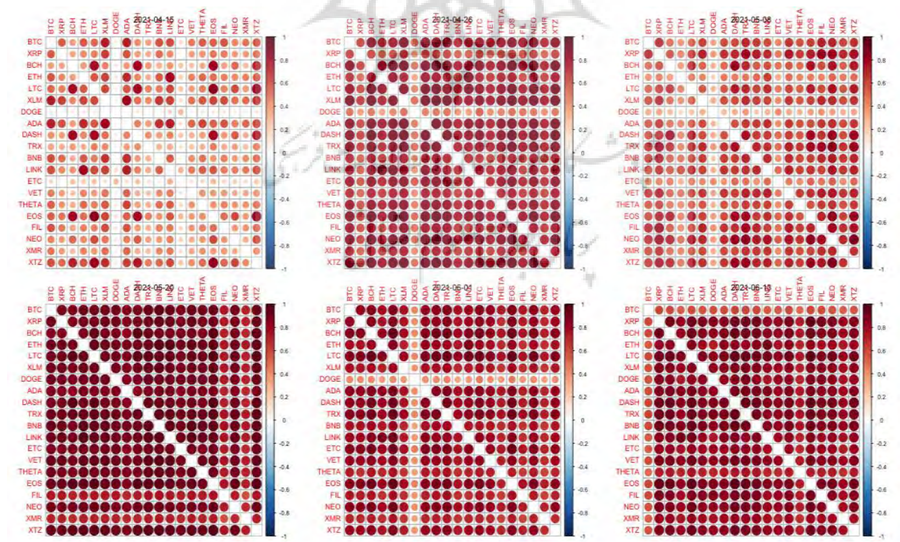


Figure 5. The posterior volatility correlation matrix of 20 cryptocurrency returns in 6 different times from 14/04/2021 to 07/19/2021

[DOI: 10.61186/jme.18.2.263]

Source: Research findings

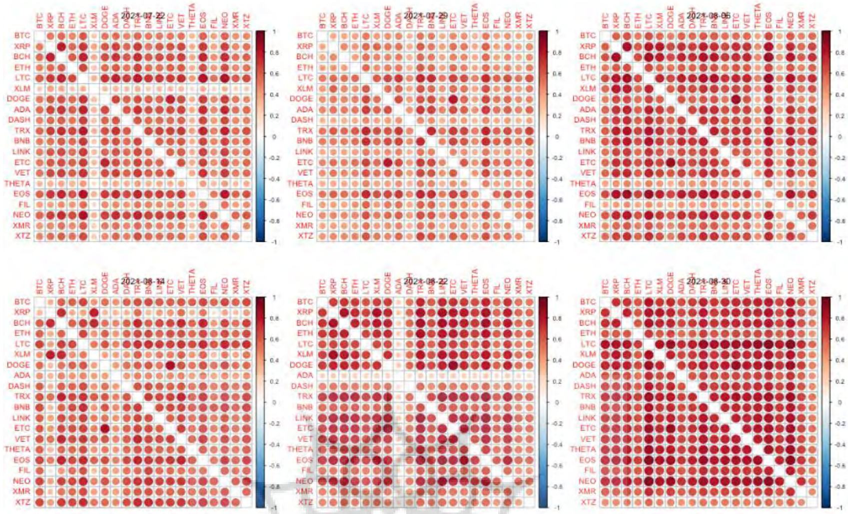


Figure 6. The posterior volatility correlation matrix of 20 cryptocurrency returns in 6 different times from 07/20/2021 to 11/08/2021
Source: Research findings

[DOI: 10.61186/jme.18.2.263]

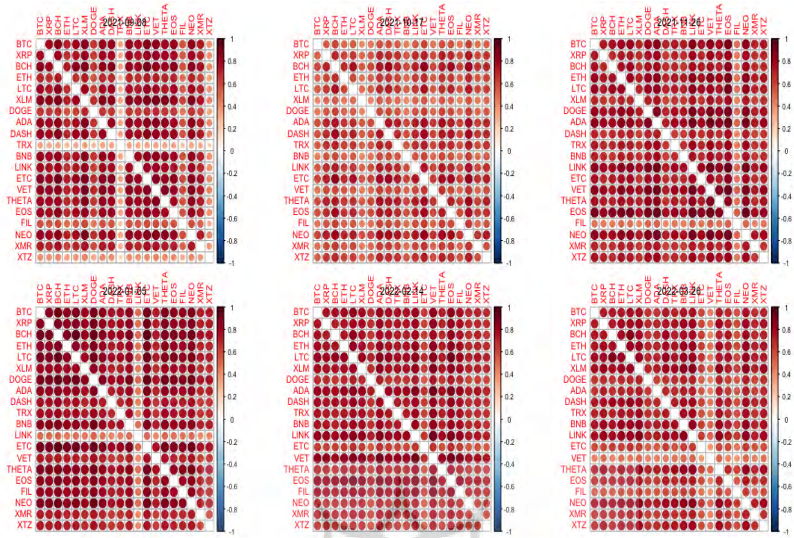


Figure 7. The posterior volatility correlation matrix of 20 cryptocurrency returns in 6 different times 11/09/2021 to 20/09/2022The darker the color of the circles, the stronger the positive correlation between cryptocurrency volatility.
Source: Research findings

The main findings from Tables 1 to 4 and Figures 4 to 7 are summarized as follows:

- Although the volatility correlations between all cryptocurrencies returns are positive, its degree is time-varying. This finding is in line with the study of Harjunpää (2017), Ji et al., (2019), and Lahajnar & Rožanec (2020).
- In the first period, when the market was bullish, the average of the mean pairwise correlation of cryptocurrency volatilities was 0.49, but after the market fell in the second period, the average of mean correlation increased to 0.78. Notwithstanding the market's change aligned with the third period and subsequent rise, the average mean correlation has no changed significantly. The degree of mean pairwise correlation was reduced to 0.69 at the start of the fourth period, when the market is bearish again.
- The highest mean correlation is attributed to various cryptocurrencies in different sub-periods, resulting in Ethereum, Litcoin, EOS, and Vet experiencing the strongest mean correlations of cryptocurrency volatilities in each of four sub-periods, respectively. In the second period, the mean

[DOI: 10.61186/jme.18.2.263]

pairwise correlation between Litcoin and Bitcoin Cash was 0.93, was the highest.

- DOGE, DOGE, Filcoin, and XRP have the lowest mean pairwise correlation in four different sub-periods, respectively. DOGE and Filecoin have the lowest pairwise correlation between them of all the sub-periods and cryptocurrencies. In the first sub-period, their volatilities were 0.10 times more similar than any other pair.
- Over time and in conjunction with the strengthening of the correlation of cryptocurrency volatilities, the advantages of diversifying cryptocurrency portfolio have diminished, particularly in the descending periods when relatively higher pairwise correlations are demonstrated. In fact, in bear markets, diversifying becomes significantly challenging.

5 Conclusion and Policy Implications

The time-varying correlation matrices were estimated in this research employing the MFSV model as an efficient method based on the parsimony principle. The covariance structure of the twenty cryptocurrency returns was modeled using the Bayesian approach, and considering the latent factors and their factor loading matrices were estimated. The findings could be listed as follows:

- The volatilities of different cryptocurrency returns showed the *clustering behavior* that intensifies at different points in time. These volatilities could be attributed to the idiosyncratic variances and the hidden factors.
- The factor loading matrix result revealed different latent factors in each sub-period. More specifically, two hidden factors can be identified in the first sub-period, both of which positively affect cryptocurrency volatility. There are five latent factors influencing in the second sub-period. The impact of other latent factors, excluding the fourth hidden factor, is determined by the type of cryptocurrency. In addition, four hidden factors can be discovered in the third sub-period, with only one of the hidden factors positively affecting all cryptocurrencies fluctuations. In the fourth sub-period, there are two latent factors. One of these factors makes all cryptocurrencies less volatile.
- The dynamic correlations of cryptocurrency return volatility affirmed their positive correlation. Indeed, Ethereum, Litcoin, EOS, and VET had the strongest correlations. DOGE, DOGE, Filecoin, and XRP, on the other hand, had relatively weak correlations in each of the four sub-periods.

[DOI: 10.61186/jme.18.2.263]

– Despite the positive correlation between the volatilities of cryptocurrency returns, the correlations differ in different periods to increase in bear market.

This finding has an important implication on the efficiency of portfolio diversification: (1). positive correlations between cryptocurrencies, which are strengthened in declining prices, indicate the failure of a *portfolio diversification strategy*, particularly in bearish markets. (2). Cryptocurrencies with the weakest correlation could be applicable to manage the portfolio risk. (3). Although Ethereum, Litcoin, EOS and VET have the strongest correlations in each sub-period, acquiring them simultaneously is not in line with portfolio diversification strategy.

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