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Modeling the Daily Volatility of Oil, Gold, Dollar, Bitcoin and Iranian Stock Markets: An Empirical Application of a Nonlinear Space State Model

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ABSTRACT

Using the daily data of returns of 9 assets during the period from 04/29/2013 to 09/20/2021, the volatilities of different asset markets were modeled in this paper. The multivariate factor stochastic volatility model (MFSV) under the nonlinear space-state approach provides the basis for decomposing asset return volatility into two components, "volatility rooted in latent factors" and "idiosyncratic volatility", and for estimating the time-varying pairwise correlation of time series. The results show: First, there are three latent factors so that the volatility of returns of five Iranian stock markets is affected by the first and third hidden factors, while the volatility of the other four international markets is mainly affected by the second latent factor. Second, the idiosyncratic volatility of the different Iranian stock returns exhibits clustering behavior, and there is a relatively strong correlation among them. Third, the volatility of oil returns is explained by the hidden factors, and consequently their idiosyncratic volatility is almost smooth. Fourth, the correlations between the return volatility of bitcoin and the volatilities of other conventional assets are negligible. The results of this paper may be useful for future research on investment opportunities and risk-return characteristics of portfolios.

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1. Introduction

One of the indispensable components of financial time series modeling is the time-dependent variance-covariance structure. Already Markowitz (1952) focused on a method that accounts for variance heteroskedasticity better than rolling window estimation, and by 1982 two different basic approaches had been introduced to address this need. On the one hand, Engle (1982) introduced a group of time-varying volatility models known as generalized autoregressive conditional heteroskedasticity models (Bollerslev, 1986). The main feature of these models was the conditional deterministic change in variance. On the other hand, Taylor (1982) focused on similar work using nonlinear space-state models with hidden factors, which led to the stochastic volatility models (SV). Despite empirical evidence confirming the superiority of SV models over alternative GHARCH models, they have received less attention due to the lack of standard software (Boss, 2012). Recently, thanks to the efforts of Kastner (2016), Kastner et al. (2017), Kastner and Huber (2020), and Hosszenjini and Kastner (2020), it has become possible to use Bayesian estimates of MFSV model for a wide range of different financial economic topics.

Although MFSV is superior to GARCH models due to its consideration of latent stochastic processes in modeling the volatility of financial time series and its high flexibility in explaining the stylized facts, the use of MFSV has been neglected by Iranian researchers because their focus has been on using a family of univariate and multivariate GARCH models. Moreover, issues related to cryptocurrencies have attracted much attention in recent years and the market capitalization of cryptocurrencies is growing rapidly. Yet, there is no study on the relationship between the volatility of cryptocurrencies and traditional asset markets, especially the Iranian Stock market. Due to the increasing volatility in asset markets, especially Iranian stock market and cryptocurrency market, in this paper, we use MFSV for the first time to answer two questions: first, what is the contribution of latent factors and idiosyncratic volatility to the return volatility of each asset? And second, how have the correlations between asset return volatilities changed over time?

The remainder of this paper is organized as follows. Section 2 deals with the theoretical framework and literature review. An explanation of the research method with a focus on MFSV models is provided in Section 3. Statistical foundations and empirical results are presented in Section 4, and finally, Section 5 provides a summary and conclusion.

2. Theoretical Foundations and Literature Review

2.1 Theoretical Foundation

The theoretical basis of the relationship between financial markets and the cause of transmission of shocks is anchored in the volatility literature. According to the World Bank classification, three definitions of transmission can be introduced: “broad definition”, “narrow definition” and “very narrow definition”. According to the broad definition, shock transmission between markets or countries reflects the volatility contagion that occurs in both bad and good times. However, it mainly emphasizes the transmission phenomenon in times of crisis. In the narrow definition, contagion reflects the transmission of shocks between financial markets or countries, regardless of whether there are fundamental links between them, referring to the extreme common movements of markets that confirm the existence of herd behavior. In a very narrow definition, transmission occurs when financial market volatility correlations increase in a bear market relative to a bull market.

Transmission theories in the financial economics literature can be divided into two groups: mechanical contagion and psychological contagion. In the first group, financial and real interdependencies between markets or countries lead to volatility transmission (Calvo and Reinhart, 1996), and fundamental factors such as universal shocks, trade relationships, and financial linkages explain volatility contagion. The second group of theories assumes that contemporaneous volatilities across financial markets are due to investors’ behavior and investment decisions (Dornbusch et al., 2000). In fact, some aspects such as liquidity and incentives, asymmetric information, market coordination problems and investors' revaluation are the main causes of volatility transmission (Classeness and Forbes, 2004). Some economists also believe that new and unexpected information leads to fluctuation in expected asset returns and any revolution in financial market volatility is due to changes in national, regional or global economic conditions (Tsay, 2002).

Many researchers have focused on volatility modeling because it is important to know the nature of these volatilities. Although the focus of many studies has been on modeling the mean return on real or financial assets, researchers have recently turned their attention to modeling the volatility of asset returns.

Volatility is generally considered as the standard deviation of the sample and is modeled using three different types of models, including "time series", "option", and "nonparametric" models (Keshavarz Hadad and Samadi, 2009). According to Poon & Granger (2003), time series models are also divided into two groups: "historical standard deviation" and "conditional heteroskedasticity" models. The first group, which includes random walk models, mean square returns, simple moving averages, weighted exponential average models, etc., is based on two assumptions: "uniform distribution" and "non-correlation of error terms", which are inconsistent with stylized facts. Clustering of volatility, co-movement of volatility, serial correlation between disturbance terms and abnormal distribution are important features of asset volatility, which are discussed by Bollerslev et al. (1994).

The emphasis on proving existing volatility correlations and abnormal distributions formed the basis for the introduction of conditional heteroskedasticity models, which in turn are divided into ARCH /GARCH and stochastic volatility (SV) models. In the family of ARCH /GARCH models, changes in variance are assumed to have a "deterministic function", whereas in the SV models the equation describing the variance follows a stochastic process. Harvey et al. (1994) and Aguilar and West (2000) developed and applied SV models, which have recently been used by Philipov and Glickman (2006), Chib et al. (2006), Han (2006), Lopes and Carvalho (2007), Nakajima and West

(2013), and Zhou et al. (2014). Since parsimony of dimensions is one of the most important problems for researchers, Kastner (2019) overcame this problem using Bayesian approach to identify and eliminate unimportant components in the factor loading matrix.

2.2 Literature Review

Evaluating the co-movement of cryptocurrencies with conventional assets and modeling their volatility are the main categories of studies that have been considered in recent years. As mentioned above, time series models are generally used to model the volatility of financial markets, which can be classified into two groups: historical standard deviation and conditional heteroskedasticity models. The conditional heteroskedasticity models can be divided into ARCH /GARCH models and SV models.

The first group of studies focused on analyzing the co-movements between different cryptocurrencies and other assets. For example, Baumohl (2019) focused on analyzing the correlation between cryptocurrencies and the forex market, and observed a negligible correlation, which was unexpected. Al-Yahyaee et al. (2019) and Conard et al. (2018) observed significant co-movements between some cryptocurrencies and stock market indices. Kurka (2019) also studied the co-movements of some assets, including commodities, exchange rates, stock indices and other financial assets, with cryptocurrencies and found that there were very weak correlations between them. Rehman and Apergis (2019) analyzed the movement between several commodities and cryptocurrencies and concluded that there was significant causality between cryptocurrencies and commodity markets. The findings of Kim et al. (2020) confirmed the significant relationships between gold, bitcoin and the S&P index. Jaroenwlryakul and Tanomachat (2020) reported a volatile relationship between Litecoin and the stock indices of 5 Asian countries, such that the correlation between them is high from 2013 to 2015, but remains relatively stable until January 2020.

The focus of many studies in Iran has been on asset volatility analysis using a family of univariate and multivariate GARCH models, with the following papers falling into this group: Teimoori et al. (2021), Rezazadeh and Fallah (2020), Kashanitabar et al. (2020), Abounoori et al. (2020), Khodayari et al. (2020), Rastinfar and Hematfar (2020), Ghazi Fini and Panahian (2019), Karimi et al. (2019), Arbabi (2018), Shirazian et al. (2018), Botshekan and Mohseni (2018), Keshavarz Hadad and Moftakhar Daryaee (2018), Moghaddasi et al. (2018), Ranaei et al. (2018), Sefidbakht and Ranjbar (2017), Fattahi et al. (2016), Nabavi Chashami and Mokhtarinezhad (2016), Hosseinioun et al. (2016), Mamalipour et al. (2016), Keshavarz Haddad and Mohammadi (2016), Nademi et al. (2015), Jahangiri and Hekmati Farid (2014), Nazifi et al. (2012), Heidari et al. (2012), Keshavarz Haddad et al. (2011), Keshavarz Haddad and Heidari (2011), Keshavarz Haddad and Esmaeilzadeh (2010), Rasekhy and Khanalipour (2009), and Abounoori and Motameni (2007). The volatility correlations of cryptocurrencies and conventional assets and the use of SV models have been neglected in the above studies.

Modeling the volatility of different types of assets and financial markets is the focus of the second group of studies. The various families of GARCH models introduced by Bollerslev (1986) have been the basis for modeling volatility in many studies. The most important reason for the popularity of the GARCH model is the simplicity of estimating the parameters due to the deterministic dependence of the conditional variance on prior observations. Most studies that focused on volatility modeling used a variety of GARCH class models, such as Katsiampa (2017), Stavroyiannis and Babalos (2017), Chu et al. (2017), Catania and Grassi (2017), Liu et al. (2017), Bouri et al. (2017), Urquhart (2017), Charle and Darne-Lemna (2018), Catania et al. (2018), Rahim et al. (2018), which focus on modeling the volatility of Bitcoin. In addition, we can refer to the papers by Cheong et al. (2012), Naimy and Hayek (2018), Catania et al. (2018), and Peng et al. (2018) that focus on the potential ability of volatility predictions. Some studies have also focused on modeling the volatility of cryptocurrencies, including Charfeddine and Maouchi (2018), Peng et al. (2018), Caporale and Zekokh (2019), Charle and Darne-Lemna (2018), and Fakhfekh and Jeribi (2020). Moreover, some studies have modeled the volatility correlations between cryptocurrencies and other conventional assets, such as Corbet et al. (2018), Lee et al. (2018), Kim et al. (2020), and Jaroenwlryakul and Tanomchat (2020).

In contrast to the GARCH class models, the SV models developed by Taylor (1986) have recently been considered in modeling asset market volatility. The inclusion of latent stochastic processes in the modeling of volatility and the high flexibility of these models in describing the stylized facts of financial series are the main advantages of these models. In this context, we can refer to the works of Zhang and Zhuang (2017), Liu and YU (2019), Kastner (2019), Yamauchi and Omori (2020), Shi et al. (2020), Zaharieva et al. (2020), Kastner and Huber (2020), Zhang and Zhuang (2020), and Esposti (2021) refer.

In this paper, for the first time, the volatility correlations of 9 asset returns (including bitcoin with the highest share of cryptocurrency market capital, gold, oil, dollar and 5 Iranian stocks) are estimated using MFSV model.

3. Methodology

To achieve the objectives, the MFSV model was used, which not only satisfies the principle of parsimony but also takes into account the time-varying asset returns. Moreover, this model captures the potential characteristics of assets such as “clustering volatility” and “volatility co-movements”. At the same time, the model must be robust to idiosyncratic shocks to assets. On the one hand, the MFSV model is robust and consistent with the stylized facts of asset volatility returns, and on the other hand, this model uses orthogonal latent factors with fewer dimensions. These factors can capture time-varying volatility co-movements. Moreover, this approach accounts for clustering volatilities and is robust to idiosyncratic shocks related to the nature of stochastic volatility processes.

Briefly, this approach can be explained as follows. Assuming that each time point is denoted by $t = 1, \dots, T$, also $y_t = (y_{1t}, \dots, y_{mt})'$ is the vector with zero mean of m observed returns and $f_t = (f_{1t}, \dots, f_{rt})'$ is the vector of r latent factors. Compared to the static factor model, the observations are assumed to be affected by latent factors and idiosyncratic shocks. In stochastic factor volatility, both the idiosyncratic variance and the variances of the latent factors are time-varying and depend on m+r hidden volatilities, ie $h_t = (h_t^U, h_t^V)$ where $h_t^U = (h_{1t}, \dots, h_{mt})'$ and $h_t^V = (h_{m+1,t}, \dots, h_{m+r,t})'$. In short, we have:

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

where Λ stands for the $m \times r$ loading factors matrix, $U_t(h_t^U) = diag\,(\exp(h_{1t}), \dots, \exp(h_{mt})$ vindicate the $m \times m$ diagonal idiosyncratic variance matrix and $V_t(h_t^V) = diag\,(\exp\big(h_{m+1,t}\big), \dots, \exp\big(h_{m+r,t}\big)$ is the $r \times r$ diagonal variance matrix of latent factors. The variances, in turn, are modeled as hidden variables whose logarithm follows a first-order autoregressive process, i.e., for $i = 1, \dots, m + r$.

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

That the initial value of h_{i0} is unknown. It is assumed that all variances have 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 $\eta_t = (\eta_{1t}, \dots, \eta_{m+r,t})'$. This implies the following structure:

$$y_t = \Lambda f_t + \epsilon_t, \qquad f_t | h_t \sim \mathcal{N}_r(0, V_t(h_t^V)) \qquad (3)$$

That $\epsilon_t | h_t \sim \mathcal{N}_m(0, U_t(h_t)$. One of the most important reasons for using the MFSV model is the reliable estimates of the time-varying conditional covariance matrix that models the trough $cov(y_t | h_t) = \sum_t(h_t) = \Lambda V_t(h_t^V)\Lambda' + U_t(h_t^U)$. It should be noted that due to the diagonal of $U_t(h_t^U)$, all covariances of the time series are affected by the latent factors. Finally, for a given h_t, y_t will have a process with non-Gaussian distribution.

It is impossible to obtain a consistent estimate of the variances given the constraints on the parameters. Under such conditions, Bayesian inference for the posterior distribution can provide flexible estimates. Thus, the Markov Chain Monte Carlo (MCMC) estimation techniques can be used (Shi et al., 2020). Yet, this algorithm struggles with the problem of lack of convergence leading to biased parameter estimates. The estimation procedures developed by Kastner et al. (2017) offer several solutions to overcome these potential problems.

In short, we use the MFSV model of Kastner et al. (2017) for three reasons. First, this model can capture the key features of financial assets, in particular "volatility clustering" and "time-varying co-movement of volatility". Second, this model is robust to idiosyncratic shocks. Third, the use of Bayesian inference for the posterior distribution in this approach not only allows the estimates to be flexible, but also handles the "lack of convergence" problem well.

4. Statistical Foundations and Empirical Results

4.1 Statistical Foundations

To model MFSV, which is much more flexible than other models, the daily volatility correlations of 9 asset returns (including oil, gold, dollar, bitcoin, Iranian petrochemical and chemical, base metal, banking, food, and pharmaceutical stock returns) are estimated under a nonlinear state space approach. All data were collected from Rahavard Novin and Marketcap websites for the period from April 29, 2013 to September 20, 2021. Finally, due to the different trading days of these assets, we have 1150 observations to estimate the model. The revolutions of the different asset returns show that the volatilities are clustered between the asset returns except oil, especially the five Iranian stock indices and the dollar, which show a more similar behavior than other markets.

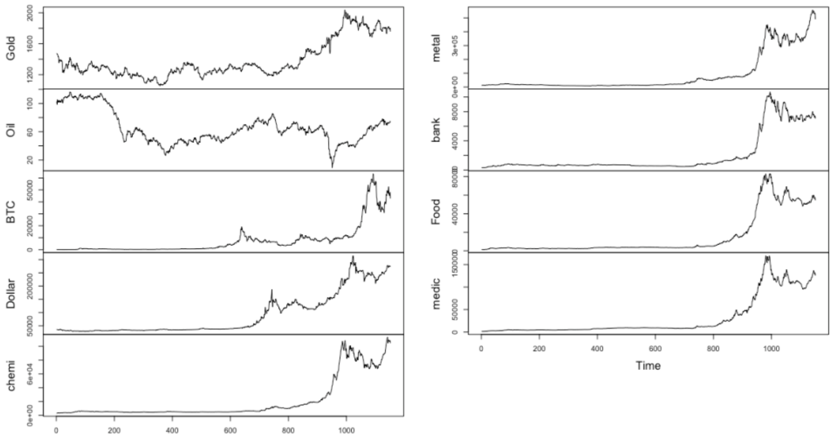

Figure 1. Asset Prices from 04/29/2013 to 09/20/2021
Source: Research finding.

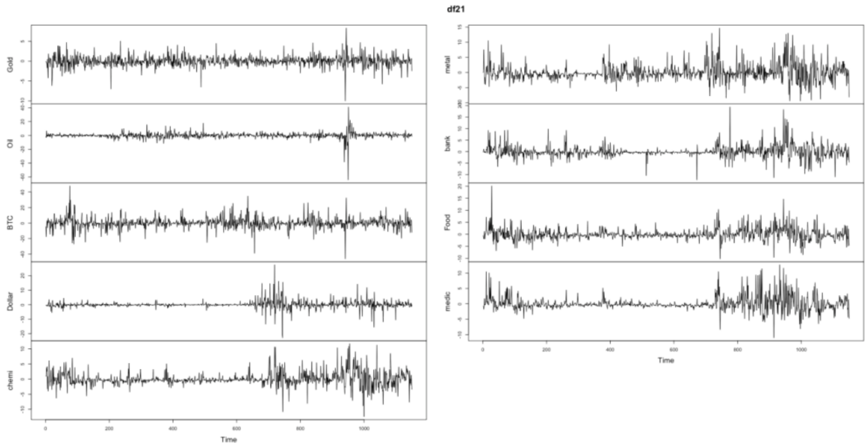

Figure 2. Logarithm of Asset Returns from 04/29/2013 to 09/20/2021
Source: Research finding.

According to the Figures 1 and 2, we can focus on some stylized facts: First- the volatility return processes is not constant with respect to time. For example, the Iranian stock returns in last 3 years are much more volatile than at the beginning and middle of the period. Time varying volatilities of other asset returns can be also detected in Figure 2. Second- The absolute returns are highly autocorrelated and returns are observed closely in time (volatility clustering). All returns especially Iranian stock returns, Dollar and Bitcoin have cluster volatilities which means that low fluctuations followed by small volatilities in subsequent periods and high fluctuations intensify volatilities of next periods. Third- Contemporaneous movements are not constant over time. Fourth- Extreme observations is one return series are often accompanied by extremes in the other return series. The co-movement with respect to the volatility between the five Iranian stock returns is similar and there is also a co-movement between the return volatility of Bitcoin and Gold.

4.2 Empirical Results

The main purpose of using MFSV model is to decompose the volatility of returns into two unobservable components: idiosyncratic volatility and the impact of latent factors. The decomposition of volatility and the estimation of MFSV model is possible using the space-state model and Bayesian methods in the R software package. Thus, the first step is to determine the number of latent factors that affect the returns of different assets. The most common method of identification is to derive the triangular relationship of the factor loading matrix and the eigenvalues of $\Lambda^{\prime}\Lambda$ can be used as a rough guide for choosing the number of latent factors[1]. According to Figure 3, three hidden factors can be identified that are significantly different from zero.

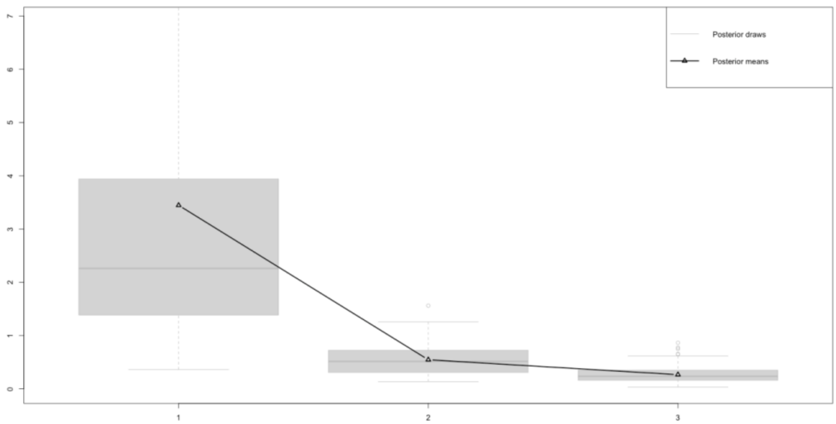

Figure 3. Values and Identifying the Number of Latent Factors
Source: Research finding.

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

The second step is to examine the posterior means of the latent factor volatilities plotted plus/minus two standard deviations. Some of the common volatilities of asset returns can be explained by the latent factor volatilities.

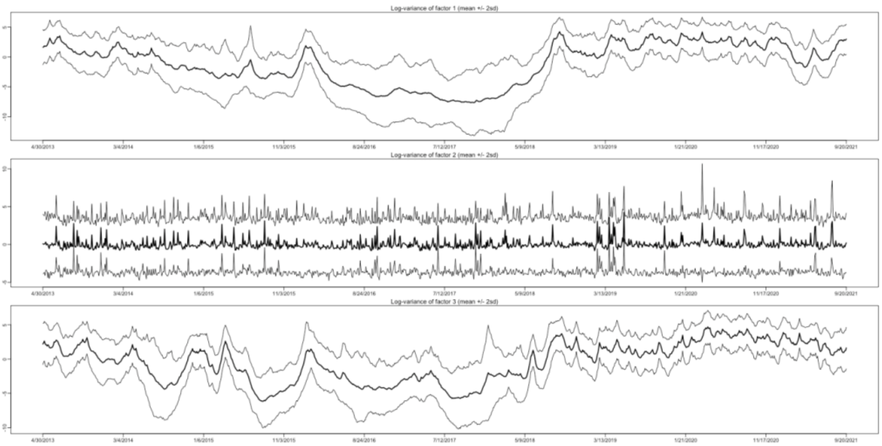

Figure 4. The Posterior Mean Volatility of Latent Factor during 04/29/2013 to 09/20/2021

Source: Research finding.

According to Figure 4, the volatilities of the first and third latent factors have a more fluctuating trend than the second hidden factor. The second latent factor, which has a significant effect on the volatility of oil, Bitcoin, Dollar and gold returns (see Figures 5 and 6), fluctuated around zero on average. It appears that the second factor captures all international political and economic events that affect the volatility of the four aforementioned international markets. The first and third latent factors, while having a particular effect on the volatility of five Iranian stock returns, have negligible effects on the returns of the international asset markets. It seems that these factors capture the domestic and international political and economic shocks related to Iran. As shown in Figure 4, these factors have experienced a more volatile trend after the withdrawal of the United States from the Joint Comprehensive Plan of Action in early 2018.

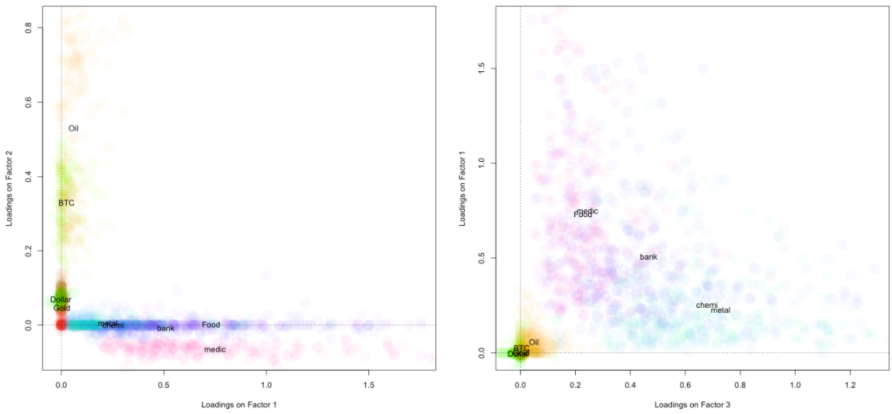

Figure 5. Posterior Loading Factor Distribution of Latent Factors
Source: Research finding.

The third step is to estimate the posterior distribution of the loading factors on the return volatility of each asset, which is shown in Figures 5 and 6. As mentioned earlier, the volatilities of five Iranian stock returns are significantly positively affected by the first and third latent factors, while they are not affected by the second factor. In contrast, the second latent factor positively affects the volatilities of oil, bitcoin, Dollar and gold returns, while the first and third hidden factors have negligible effects on their volatilities.

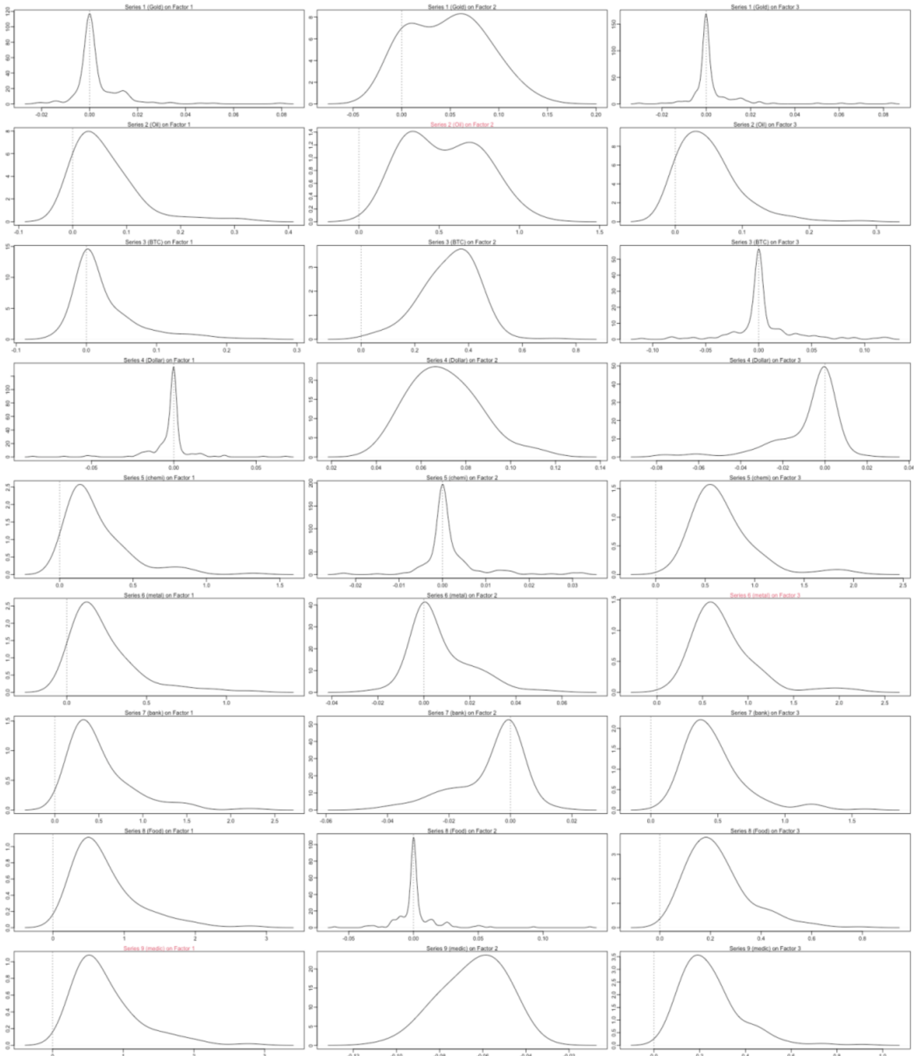

Figure 6. Posterior Loading Factor Distribution of Latent Factors for Each Asset
Source: Research finding.

The volatility of the return on any asset can be decomposed into two components: "hidden factor based volatilities" and "idiosyncratic volatility". After estimating the effects of each latent factor on the volatility of nine asset returns, the idiosyncratic volatility can be estimated in the fourth step. The idiosyncratic log variances plus/minus two standard deviations are shown in Figure 7, which illustrates the marginal posterior distribution of the diagonal elements of $U_t(h_t^U)$. As can be seen in this figure, the idiosyncratic volatility of oil returns exhibits a relatively smoother trend compared to other assets. Moreover, a clustering of volatility among the five stock returns can be observed.

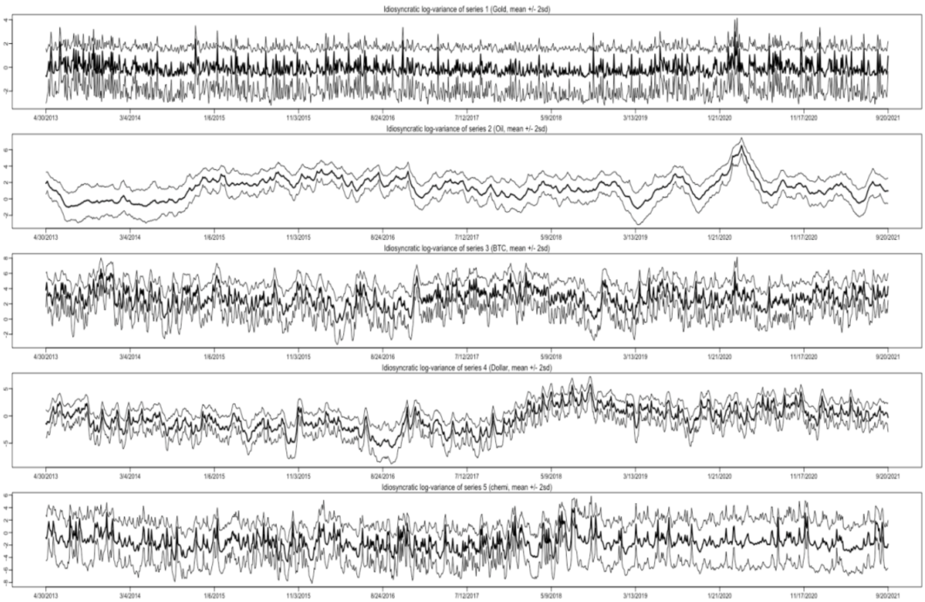

Figure 7. Idiosyncratic Volatility of Each Asset from 04/29/2013 to 09/20/2021
Source: Research finding.

Estimating time-varying posterior mean correlations is one of the main advantages of using MFSV model, which are shown in Table 1. The results show that, first, there are slightly positive correlations between the return volatilities of international assets, such that the highest correlation is observed between oil and gold and the lowest correlation is observed between bitcoin and dollar and gold. Second, the volatilities of the five Iranian stock returns have a significant positive correlation with each other, with the highest correlation between the food and medical sectors and base metals with the petrochemical and chemical industries. Third, the correlation of daily volatility between oil and five Iranian stock returns is relatively higher than the correlations of other international assets with Iranian stock markets. Fourth, the volatilities of Bitcoin (as the main cryptocurrencies with the highest market capitalization) and gold are not correlated with the volatilities of Iranian stock returns.

Table 1. The Mean Correlation Matrix of Daily Volatilities in Asset Returns

	Gold	**Oil**	**BTC**	**Dollar**	**Chemi**	**Metal**	**Bank**	**Food**	**Medic**
Gold	1	0.08	0.01	0.01	0.00	0.00	0.00	0.01	-0.01
Oil	0.08	1	0.05	0.05	0.08	0.06	0.06	0.08	0.03
BTC	0.01	0.05	1	0.01	0.00	0.00	0.00	0.00	-0.01
Dollar	0.01	0.05	0.01	1	-0.01	0.00	-0.01	-0.01	-0.02
Chemi	0.00	0.08	0.00	-0.01	1	0.42	0.39	0.34	0.47
Metal	0.00	0.06	0.00	0.00	0.42	1	0.26	0.22	0.30
Bank	0.00	0.06	0.00	-0.01	0.39	0.26	1	0.27	0.37
Food	0.01	0.08	0.00	-0.01	0.34	0.22	0.27	1	0.46
Medic	-0.01	0.03	-0.01	-0.02	0.47	0.30	0.37	0.46	1

Source: Research finding.

Table 1 shows the mean posterior correlations between the volatilities of different asset returns, where the magnitude of the correlations has varied at different points in time. The posterior correlation chart can also be plotted for different time periods, which is shown in Figure 8 for 9 time periods using colored circles. In this figure, the color blue represents a negative correlation and the color red represents a positive value. The results show the following:

- The volatility correlations between the five stock returns are positive, but the degree of correlation is time-varying. At the beginning of the period, there are significant positive correlations between Iranian stock price volatilities, which have decreased over time, reaching almost zero in the middle of the period, but have increased sharply in the last three years, reaching a peak in the third quarter of 2020 and then have slightly decreased again.
- Among the different international asset markets, the volatility of oil returns is positively correlated with five Iranian stock returns. However, there are almost no correlations between the volatilities of other international returns and the volatilities of various Iranian stock returns. These results are in the line with the findings of Fallahi et al. (2014), according to which, the correlations between

returns of stock market and dollar or gold is low. Also, our findings confirm the results of Botshekan and Mohseni (2018), Hosseini Nasab et al. (2011) and Karimi et al. (2020) who are discovered a positive correlations between Iranian stock return volatility and oil market.

- There is no correlation between the volatility of Bitcoin returns and other international assets and Iranian stock returns. This result is in line with the findings of Baumohl (2019) who found a weak correlation between cryptocurrencies and Forex market, Kurka (2019) who found a negligible correlation between the co-movement of some assets (including commodities, exchange rates, stocks and other financial assets) and cryptocurrencies, and Aslanidis et al. (2019) who discovered a negligible correlations between cryptocurrencies and traditional assets.

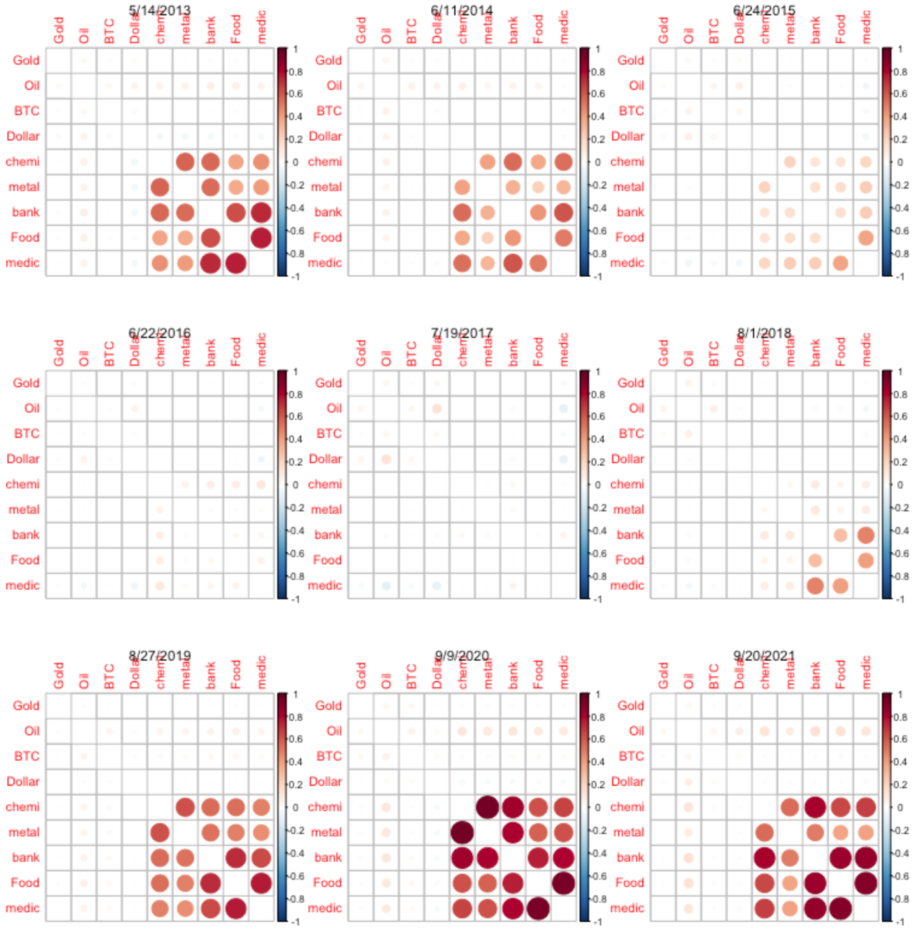

Figure 8. The Posterior Volatility Correlation Matrix of 9 Asset Returns in 9 Different Times

Source: Research finding.

5. Conclusion

This paper attempted to apply an efficient method based on the parsimony principle to estimate the time-varying correlation matrix using MFSV model. In this paper, the covariance structure of the nine asset returns is modeled using a Bayesian approach that conforms to the principle of parsimony by using latent factors and estimating their factor loading matrices. The results show:

- The volatilities of different asset returns exhibit clustering behavior, which has increased at times, especially in recent years. Part of these volatilities is due to idiosyncratic variances, while another part is influenced by the hidden factors.
- The identification of the factor loading matrix indicates the existence of three latent factors. The volatilities of the five Iranian stock returns are positively affected by the first and the third factors, but the effect of the second factor is almost negligible and negative. In contrast, the first and third latent factors have little effect on the volatility of international asset returns, while the second factor affects them positively.
- Decomposing the volatilities of asset returns into two components, “idiosyncratic variances” and “loading latent factors”, it is found that the idiosyncratic volatilities of Iranian stock returns exhibit clustering behavior. Moreover, the main volatility of oil returns is affected by the fluctuations of the second hidden factors, and the idiosyncratic variance of oil returns exhibits a rather smooth trend.
- The estimation of the dynamic correlations of the volatility of asset returns shows that the volatilities of Iranian stock returns are positively correlated with each other, with the most correlations observed between the food and medical industries, and the base metal industry and the petrochemical industry. Moreover, the correlation between the daily volatility of oil returns and the volatility of Iranian stock returns is relatively higher than the correlations between the volatilities of other international assets. The existence of positive correlations between Iranian stock return volatilities and oil market was confirmed Botshekan and Mohseni (2018), Hosseini Nasab et al. (2011) and Karimi et al. (2020).
- There is no significant correlation between bitcoin and other conventional assets, which confirms the results of Aslandis et al. (2019), Baumhol (2019) and Kurka (2019).

Since efficient portfolio diversification requires sufficient knowledge of the correlations between assets, the results of the present work can help to provide a clear insight into the analysis of the different return volatilities of assets and to choose an appropriate investment strategy. Moreover, Value-at-Risk (VaR) estimation, option pricing and portfolio optimization using MFSV model can be the subject of future research, which have been neglected in the literature.

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