Original Article

Bayesian estimation of the relationship between return volatility and the trading volume of pharmaceutical index in Tehran stock exchange using dynamic conditional correlation model

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ABSTRACT

The study was conducted to develop Bayesian model of stock behavior of the pharmaceutical companies in Tehran Stock Exchange. Accordingly, the return volatility of the pharmaceutical group index in Tehran Stock Exchange and its trading volume were examined on daily, weekly, and monthly bases from April 21, 2015 to February 27, 2019. The results show that the correlation between variables is negative dynamic conditional correlation. Moreover, it is observed that investors are reluctant to sell their stocks as they expect prices to increase more with the increase in returns and thus reduce the trading volumes in the market by not selling them and vice versa. On the other hand, the results show that considering the skewed student-t distribution for the residuals with a wider tail than the normal distribution and applying skewness bring about better performance compared to other distributions.

Keywords: stock return volatility, trading volume, Bayesian approach, GARCH-DCC

JEL Classification: C11, C15, C32, D14

Introduction

One of the most significant areas in financial studies is the maximum use of the information hidden within the data. In the financial markets, the variables raw data is prepared according to the financial-reporting standards and predefined rules to increase transparency, including total index and trading volume.

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Performing transformations like calculating the returns on this type of data is necessary to avoid the receiving misleading results and to obtain stable outputs. Return is used instead of prices in the financial literature for two major reasons. Firstly, return provides the investors with an average on complete, unmetered information. Secondly, return is much easier to analyze than price given its specific statistical properties [1]. In other words, the return of a variable reveals a better description of the incidents.

Another aspect focused on in the financial analyses is the trading volume in the market. Trading volume can be considered as the representative of the market information flow in the process of generating stock returns where the successive data entry leads to the changes in stock returns.

Trading volume contains valuable information on the capital market participants' behavior that along other variables, can be widely used by capital market audiences. Among the most significant management uses of volume trading analysis, the following can be cited:

- Simultaneous observation of changes in trading volume and in trading codes shows the entry or exit of capital market investors.
- The widespread change in trading volume, selling or purchasing some trading codes, shows the flow of information in the market.
- Changes in trading volume offer a true image of the emotional behavior of positive and negative news.
- Trading volume shows the depth of a market and its effects on other economic sectors of the country.

In all the stated cases, the analysis of price and return volatility, even in multivariate modes, reflects only some of the realities of the market and adding trading volume seems to increase the accuracy of interpretations. Hence, one of the objectives of the study was to examine the relationship between return and volume of trading.

With the expansion of the financial markets in the world, modeling volatility for risk reduction and gaining profitability has experienced significant growth over the past few decades, and a wide range of approaches, especially the ones from Multivariate GARCH family are used nowadays. The present study used Bayesian estimation Dynamic Conditional Correlation GARCH as innovation to examine the dynamics of the relationship between returns volatility and trading volume. According to the abovementioned points, the main focus of the study is on the following two main axes.

- Explaining the relationship between the volatility of returns and the trading volume
- Bayesian modeling of dynamic conditional correlation between volatility of returns and trading volume

The paper has been divided into six main sections in this regard. After the introduction in Section 2, the external and internal literature is examined. Section 3 introduces the research hypotheses and Section 4 describes the research model. Section 5 presents the results of the research and finally Section 6 presents the suggestions conclusion.

Literature review

Among the first attempts to model volatility and to solve the variance heteroscedasticity problem, the model presented by Engle (1982) can be cited where the conditional variance Autoregressive Conditional Heteroskedasticity (ARCH) is symmetrically modeled [2]. ARCH model states that large changes lead to large changes and small changes to small ones. In other words, the current level of variability has a positive relationship with its past values. Bollerslev (1986) introduced Generalized Autoregressive Conditional Heteroskedasticity (GARCH) by generalizing Engle's model and adding lagged variance statement, which became the cornerstones of today's conditional variance modeling [3].

Lamoureux and Lastrapes (1990) examined the effect of ARCH on the daily stock returns of 20 companies from Standard and Poor's (S&P) index [4]. Moreover, by fitting the two models, one containing trading volume and the other lacking it, they indicated that the volatility in the daily stock returns shows the information entered to the market and daily trading volume can be used as representative of this information.

Blume et al. (1994) examined the role of information in stock trading volume and showed that price dynamics and trading volume are correlated [5]. Moreover, daily trading volumes contain information price alone cannot reflect with a role well beyond a descriptive variable, using which can improve the traders' performance in financial markets.

By examining 9 international stock markets from 1973 to 2000, Chen et al. (1995) found a positive correlation between trading volume and the absolute magnitude of stock changes [6]. Moreover, the results of Granger causality test show that in some of the countries studied there is a significant bilateral relationship between trading volume and return. Given the dynamic relationship between the two variables, the results show that stock returns can predict trading volumes and can be used in both rising and diminishing markets.

Bollerslev et al. (2018) examined the effect of announcing public news on trading volatility and volume [7]. Their results for the S & P500 Index show that the news announced is very effective in the volatility and volume of trading within a day.

From another view, Bayesian inference approach has attracted the attention of researchers in the last two decades. Hence, it is seen that in recent years, many of the conventional methods of financial econometrics have been developed within Bayesian inference framework. In their study entitled "On Bayesian Inference in GARCH Models Using Gibbs Sampling," Bauwen and Lubrano (1996) explain the use of Gibbs sampling and compare it with the Metropolis Hastings and Importance Sampling methods [8]. Importance Sampling was performed in GARCH modeling and then modeled the Brussels Stock Exchange index.

Nakatsuma (1999) extended Bayesian analysis of ARMA-GARCH models to Monte Carlo simulation of Markov Chains using Metropolis-Hasting algorithm and showed that this method can be used to model the GARCH family [9].

Cappuccio et al. (2004) compared Bayesian and skewed distributions for exchange rates in the US using Bayesian stochastic modeling [10]. Their results show an asymmetry in the exchange rate data and skewed Generalized Error Distribution showed the best performance among the examined distributions.

Asai (2006) has dealt with comparing Bayesian modeling with various Markov Chain Monte Carlo simulation methods for GARCH family using the acceptance and rejection algorithm [11]. His results show that the best approach is the Metropolis-Hasting algorithm with Taylor's approach.

Ardia and Hoogerheide (2009) estimated the Bayesian exchange rate efficiency in England using Importance Sampling algorithm for GARCH family models using residual with t-student distribution and showed that the best model for the returns logarithm in the studied period is GARCH (1, 1) [12].

Abanto-Valle et al. (2014) dealt with Bayesian modeling of stock returns of 4 firms from the New York Stock Exchange using random oscillation models [13]. Their results showed a significant relationship between the volatility and the volume of stock trading and among the statistical distributions studied skewed t-student test had the best performance.

Iqbal and Triantafyllopoulos (2019) examined Bayesian inference about multivariate GARCH models with skewed residuals [14]. Their results showed that the skewed t-student distribution performs better than other distributions.

According to what presented in the literature section, it is observed that so far, no comprehensive studies have been done to explain the relationships governing return volatility and trading volume in Tehran Stock Exchange using Bayesian methods. Thus, the present study was conducted to do so.

Research hypotheses

- There is a significant relationship between stock return volatility and trading volume.
- Bayesian estimation can model the dynamic conditional correlation (DDC) between the volatility of returns and the trading volume and to show the correlation changes over time.

Methodology

Multivariate conditional variance heteroscedasticity modeling

Engle (1982) introduced ARCH model and Bollerslev (1986) introduced GARCH model [2, 3]. The general form of GARCH model can be shown as follows.

$$\sigma_t^2 = \alpha_0 + \alpha_1 u_{t-1}^2 + \beta\sigma_{t-1}^2 \qquad (1)$$

Since then, different approaches have been proposed to generalize the modeling of conditional variance homogeneity from univariate to multivariate. Among the earliest attempts, the study by Engle et al. (1993) and introducing Baba–Engle–Kraft–Kroner (BEKK) model can be cited. However, due to some reasons like the difficulty of computing and the lack of easy interpretation of the parameters, this approach was not so welcomed. Bollerslev (1990) introduced Constant Conditional Correlation (CCC) model to consider the effect of dynamic correlation between variables [15]. This model is defined as follows for the multivariate time series $y_t = (y_{1t}. \dots . y_{kt})$.

$$H_t = D_t R D_t \qquad (2)$$

$$D_t = \mathrm{diag}\left(h_{11,t}^{1/2}, \dots, h_{kk,t}^{1/2}\right) \qquad (3)$$

Where R is a definite symmetric positive matrix and its components are conditional correlations $\rho_{i,j}$ and have constant values.

$$\begin{cases} \rho_{i,j} & i.j = 1. \dots . k \\ \rho_{i,j} = 1 & i = j \end{cases} \qquad (4)$$

Equation 4 is easily obtained by sorting the conditional correlation formula for the conditional covariance.

$$h_{ij,t} = \rho_{i,j}\sqrt{h_{ii,t}\, h_{jj,t}} \qquad (5)$$

Moreover, each of the conditional variances in their D_t is defined as a univariate GARCH (1,1) model.

$$\begin{cases} h_{ii,t} = \omega_i + \alpha_i y_{i,t-1}^2 \beta_i h_{ii,t-1} & i = 1. \dots ,k, \\ \omega_i \geq 0 ,\beta_i \geq 0 \;\; \alpha_i + \beta_i < 1 & i = 1. \dots ,k, \end{cases} \qquad (6)$$

As is seen, defining H_t matrix is of great significance as the difference in volatility modeling comes from the difference in the definition of this matrix. Furthermore, H_t matrix will be positive if and only if we have

$$\begin{cases} h_{ii,t} > 0 & i = 1. \dots ,k \\ R_t & \text{Positive and finite} \end{cases} \qquad (7)$$

Among the major complaints against CCC model is the assumption of a consistency between variables over time that is not necessarily established by empirical observations and is often violated in financial markets. Engle (2002) and Tsui and Tse (2002) have independently introduced dynamic constant correlation (DCC) model assuming the stability of the correlation between variables over time. Both methods lead to the same results and are only slightly different in normalizing the data. The present study is based on the model presented by Engle. In this approach, which can be considered as generalized CCC model, the correlation matrix R_t can be changed over time and H_t is defined as follows.

$$H_t = D_t R_t D_t \qquad (8)$$

To calculate Rt, we have

$$R_t = \mathrm{diag}(Q_t)^{-1/2}\, Q_t\, \mathrm{diag}(Q_t)^{-1/2} \qquad (9)$$

Where Q_t is the positive definite matrix $k \times k$ and u_t is the standardized returns, with the help of which H_t can be calculated.

$$\begin{cases} Q_t = (1-\alpha-\beta)R + \alpha u_{t-1}u_{t-1}' + \beta Q_{t-1} \\ u_t = D_t^{-1} y_t \quad \alpha > 0 \quad \beta > 0 \quad \alpha + \beta < 1 \end{cases} \qquad (10)$$

Now, the conditional likelihood function for estimating $y = (y_1, \dots ,y_2, \dots ,y_n)$ series model in model (1) can be defined as follows.

$$L(\theta) = \prod_{t=1}^{n} |H_t|^{-\frac{1}{2}}\, p_\epsilon\left(H_t^{-1/2} y_t\right) = \prod_{T=1}^{N}\left[\prod_{i=1}^{K} H_{ii,t}^{-1/2}\right] |R_T|^{-1/2} p_\epsilon\left((D_T R_T D_T)^{-1/2} Y_T\right) \qquad (11)$$

Where p_{ϵ} is the joint density function for ϵ_t. The choice of ϵ_t distribution has a crucial role in modeling. Although the normal distribution is one of the first suggestions in this regard, empirical studies by Tsay (2014) show that it can be possible to use more Fat-Tail distributions than the normal distribution such as the t-student distribution and the generalized error distribution if necessary in the financial markets due to the volatile nature of the data [16]. Moreover, Fernandez and Steel (1998) presented a general model framework for converting symmetric single-particle continuous distribution to continuous skew distribution, and using Bayesian approach showed that skewed student distribution t performs better in Fat Tail and skewed modeling and distributions [17].

Lambert (2018) explains the main difference between the Bayesian and classical approaches with the help of difference in the nature of the mathematical definition of θ. In the classical framework a real and constant value is assumed for the parameter θ. However, in Bayesian approach, it is assumes that θ is a random variable and is explained by the prior density P (θ). One can calculate the posterior distribution of P (θ | Data) by using the Bayes formula and multiplying the prior distribution by P (Data | θ) function and calculating the fractional denominator.

$$P(\theta|\text{Data}) = \frac{P(\text{Data}|\theta)\times P(\theta)}{P(\text{Data})} \qquad (12)$$

As in many applied problems, it is impossible to calculate the posterior distribution directly, various simulation and sampling methods are used to obtain the posterior distribution according to the nature of the problem. The advantage of the Bayesian approach compared to the classical approach is in applying prior information in the model known as prior informative distribution. Moreover, this approach can be used in the absence of prior knowledge by considering uninformative distributions in the prior distribution. Bayesian economics scholars have used this approach to estimate the conventional models using Bayesian analyses, especially in the last three decades. One of the most difficult parts of Bayesian estimation is determining the prior distribution. Although the significance of initial values decreases with increase in the steps, initial values are needed to improve estimates and to achieve faster convergence. In the present study, according to Ardia's (2006) proposed initial values for DCC-GARCH model (1, 1), the initial values are calibrated according to Table 1 to calibrate the initial values [18].

Table 1: The explanation of the proposed constraints for hyperparameters of the model Source: Ardia (2006)

Row	Parameter
1	$\omega_i \sim N(\mu_{\omega i}.\sigma^2_{\omega i})I_{(\omega_i>0)}$
2	$\alpha_i \sim N(\mu_{\alpha i}.\sigma^2_{\alpha i})I_{(0<\alpha_i<1)}$
3	$\beta_i \sim N(\mu_{\beta i}.\beta^2_{\alpha i})I_{(0<\beta_i<1)}$
4	$V \sim N(\mu_V.\sigma^2_V)I_{(V>2)}$
5	$\delta \sim N(\mu_\delta.\sigma^2_\delta)I_{(\delta>0)}$
6	$\beta \sim N(\mu_\beta.\beta^2_\alpha)I_{(0<\beta<1)}$
7	$\alpha \sim N(\mu_\alpha.\sigma^2_\alpha)_{I_{(0<\alpha<1)}}$
8	$b = [\Gamma(a+1/2)/\Gamma(a)]^2$

Data and statistical information

The data used in the study was collected from libraries of Tehran Stock Exchange with daily, weekly and monthly series with the examination period from April 21, 2015 to February 27, 2019. Calculating the total index return is based on $100 \times \log\left(\frac{I_t}{I_{t-1}}\right)$ formula and the estimations are done in Eviews10 and R software.

Results and model estimation

This section first examines the graphical analysis of returns behavior of total index and total trading volume of Tehran Stock Exchange index in daily, weekly and monthly series. As the graphs show, for the daily returns of total index and trading volume, both variables have variance heteroscedasticity, and the variance of the variables examined varies over time. Hence, the assumption of Independent and Identically Distributed of time series is violated. This shows that financial markets are sensitive to the news and react to it.

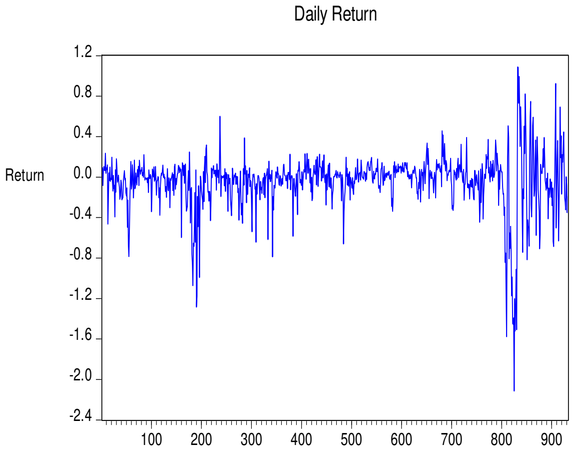

Figure 1.1: Daily return of Total Index

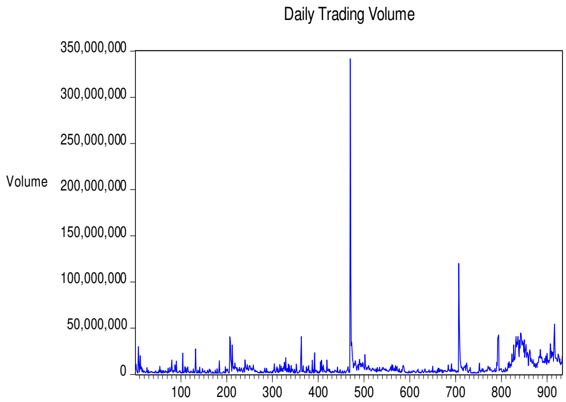

Figure 1.2: Daily trading volume of total index

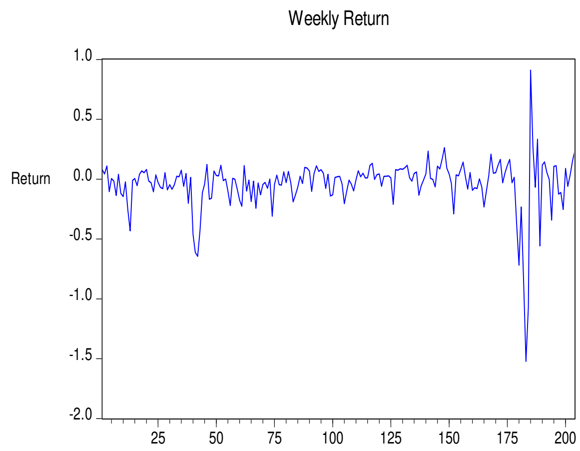

Figure 1.3: Weekly return of total index

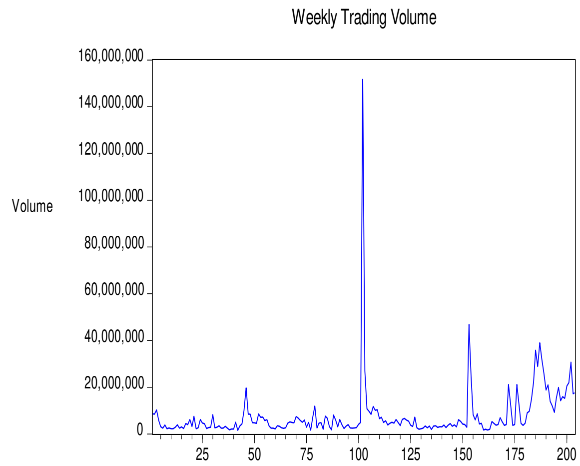

Figure 1.4: Weekly trading volume of the total index

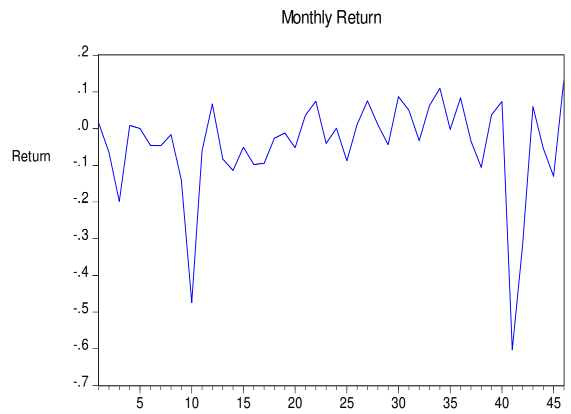

Chart 1.5: Monthly return on total index

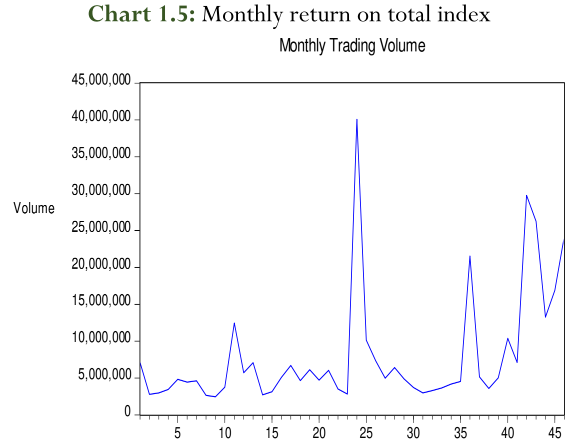

Chart 1.6: Monthly trading volume

For more detailed explanation of the behavior of the variables examined, descriptive statistics of total index return and trading volume in daily, weekly, and monthly series are presented in Table 2. It is observed that the average returns on daily, weekly, and monthly series for total stock index during the period examined are -0.04, -0.03 and -0.04%, respectively. Hence, one can conclude that the average return of the whole market has been partially negative during the period under review. The median of the data was analyzed to interpret the concentration index to reduce the negative effect of outliers. The median for daily, weekly and monthly series is -0.01, -0.02 and -0.02 percent, respectively. Thus, the return on investment in the stock market has been negative during the examined period. In other words, although individuals could make positive returns in this market, investors have seen negative and near-to-zero returns in the macro market. Moreover, examining the mean and median of daily, weekly, and monthly trading volumes shows that the trading volume increases with moving towards weekly and monthly volumes. Thus, one can conclude that most users are trading in Tehran Stock Exchange in long term. The Kurtosis obtained for both variables shows a large value, which is much greater for trading volume than the daily returns of the total index. Jarque–Bera test, affected by the Kurtosis and skewness of the variables, shows a large test statistic rejecting the assumption that the distribution of the variables is normal.

Table 2: Descriptive statistics of Tehran total index return and trading volume (Source: Research Findings)

Statistics	Total index return			Trading volume		
	Daily	Weekly	Monthly	Daily	Weekly	Monthly
Mean	-0.04	-0.03	-0.04	753469	7810239	8024853
Median	-0.01	-0.02	-0.02	3986754	4558024	4930212
Max.	1.08	0.91	0.13	341662568	151691674.7	40102780
Min.	-2.11	-1.52	-0.60	552569	1522059	2441090
SD	0.27	0.21	0.13	14380327	12414577	8061137
Skewness	-1.89	-2.47	-2.24	14.79	8.14	2.35
Kurtosis	13.35	18.48	9.20	320.99	90.43	8.14
Jarque–Bera test	4728.18	2245.88	112.45	396505	67236	93.16
Sig,	0.00	0.00	0.00	0.00	0.00	0.00

Note: Significance level 0.05 is shown with *
Source: Research calculations

Two nonparametric tests of variance ratio are used in this section to measure the efficiency of the capital market to examine the efficiency of the capital market to implement Bayesian DCC-GARCH model (1,1). Wright (2000) introduced two nonparametric tests of rank and sign of variance ratio to measure the capital efficiency. Wright's nonparametric tests have two main benefits. Firstly, they do not require asymptotic approximations in performing them, and secondly, these tests are stronger and more reliable than other tests if the data are highly abnormal. Thus, in this section, Wright's tests of rank and ratio of variance are used and the results of the tests are summarized in Table 3. As is seen in the table, moving to weekly and monthly series increases the efficiency of the capital market. In other words, the release of capital market information in monthly sequence is such that the market functions efficiently and the time series of returns can be considered as white noise.

Table 3: Summary of Wright's rank and sign tests results and variance ratio (Source: research findings)

Variable	Sequence		R_1 statistic	R_2 statistic	S statistic	Status
Return	**Daily**	K=2	9.92*	10.74*	7.46*	**Significant**
		K=5	11.63*	12.28*	9.74*	
		K=10	11.68*	11.79*	11.42*	
	Weekly	K=2	4.11*	2.93*	4.61*	**Significant**
		K=5	3.48*	2.47*	3.98*	
		K=10	2.91*	2.53*	2.68*	
	Monthly	K=2	0.92	0.84	0.48	**Insignificant**
		K=5	-0.38	-0.43	-0.17	
		K=10	-0.84	-0.89	0.06	

Note: Significance level 0.05 is shown with *
Source: Research findings

According to the Bayesian framework of the study and considering that the posterior distribution of the parameters examined is uncertain, Random Walk Metropolis Hastings algorithm with an acceptance rate range from 20% to 50% was used to simulate DCC-GARCH model parameters (1, 1). The initial Burn-in was set at 30,000 to avoid adhesion of Markov chain and the total iterations to reach a stable output were 200,000 iterations. According to EAIC, EBIC, and DIC modeling criteria in Table 4, the skewed t-student distribution has the best performance due to the minimization of the criteria stated.

Table 4: Comparison of Bayesian modeling indices

Distribution	EAIC	EBIC	DIC
Normal	34274.57	34322.59	34247.60
t student	31457.60	31510.42	31439.72
Generalized error distribution	32960.25	33013.07	32943.17
Normal skew	34176.84	34224.86	34158.57
Skewed t student	30589.86	30642.68	30577.40
Generalized skewed error distribution	32053.07	32105.90	32038.55

Source: Research calculations

Table 5 shows the estimation coefficients of DCC-GARCH model parameters (1,1) with skewed t-student residual distribution using Bayesian averaging method. Based on the results, the negative relationship between the volatility of total index returns and the volume of monthly trading is confirmed. The results show that the values of parameters A and B are non-negative that meets the condition A + B <0. This condition stated that the occurrence of shocks in the time series of returns lead to the increase in the conditional correlation for the next period. Parameter B in DCC model indicates the effect of prior period conditional correlation on current period conditional correlation. The larger the value of this parameter is and the closer to 1, the conditional correlation of the current period is expected to be closer to the conditional correlation of the previous one. Moreover, the null hypothesis A = B = 0 for CCC between variables is rejected that shows the correlation between returns and trading volumes varies over time. One has to note that the value obtained for constant correlation between variables is -0.26. Hence, the conditional correlation between the variables examined is dynamic (DCC), and according to Engle (2002), Tsui and Tse (2002), it is suggested to use DCC model for data modeling.

Additionally, the results indicated that the trading volume representing the information flow in the market affects the overall return volatilities and the coefficients obtained for the values of parameters A and B show that due to the mutual relationship, return volatilities act as news and intensify trading volatility as well.

Moreover, given the values obtained for the skewness parameters γ_1 and γ_2, one can conclude that both monthly return variables of total index and trading volume have skewness towards right but the skew intensity is higher for returns. Skewness to the right for the returns means more positive returns than the negative returns of the market, and the skewness of the volumes shows the strong market influence on the news.

Table 5: Estimating DCC-GARCH (1,1) model with skewed t-student residual distribution (Source: Research calculations)

Title	Parameter	Mean	Quantile 2.5%	Quantile 97.5%
Main Index	ω_1	19.53823	6.265559	31.3665
	α_1	0.35535	0.353535	0.3566
	β_1	0.40107	0.394480	0.4060
	γ_1	0.14243	0.124740	0.1599
Pharmaceutical Index	ω_2	7.88086	1.172012	22.5394
	α_2	0.32800	0.327156	0.3288
	β_2	0.46196	0.457548	0.4659
	γ_2	1.20943	1.172012	1.2555
Total	A	0.70401	0.586932	0.8435
	B	0.06113	0.003465	0.1501
	V	2.04611	2.045865	2.0464

Examining DCC diagram between return and trading volume shows that in the monthly sequence, there is a reverse relationship between the return and trading volume. The reason for such phenomenon can be traced back to the investor behavior. The negative relationship between DCC shows that when returns increase, individuals are reluctant to sell their shares in the market and optimistically keep their stocks, which reduced the trading volume. Nonetheless, when the returns decrease, people tend to sell their stocks and are willing to sell their stocks to avoid further losses. Thus, with the decrease in returns, the tendency to sell stocks increases so the trading volume increases. As Figure 2 shows, DCC between the variables examined is some variable that changes over time and with the increase in volatility in the end period, this value becomes strongly negative and moves towards negative one.

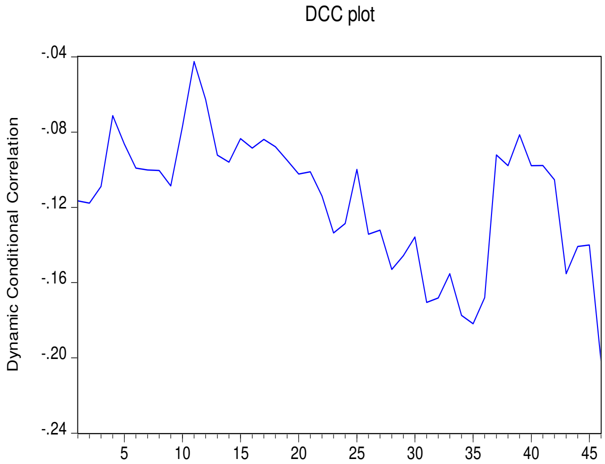

Figure 2: DCC between returns and total index trading volume (Source: Research findings)

Discussion and Conclusion

Being aware of the behavior of financial variables seems necessary because of the expansion of the role of the capital market in Iran over the two decades. The purpose of the study was to explain the relationship between the daily return volatility of the total index and the daily trading volume. The results showed a causal mutual relationship between the variables. Hence, one can conclude that the increase in volatility in trading volume, which is because of the news in the market, leads to the increased volatility in returns and increased returns acts as news and increases volatility in the trading done in the market.

Moreover, a dynamic conditional correlation between the daily return volatility of the total index and the daily trading volume of DCC model is observed that varies over time. This means that the correlation between the two variables examined will not be a constant value over time and will change as conditions change and one cannot consider a constant coefficient for the effect of these two variables. Therefore, the assumption that the two financial variables always have a constant conditional correlation as CCC model is rejected.

Another aspect dealt with is using more fat tail and skewed distributions than the normal distribution for residuals. The results showed that the skewed t-student distribution is better than the other distributions. It is seen that applying asymmetry in the reactions to positive and negative shocks by t-student distribution increased the precision of the final model compared to other models.

Suggestions

Given the expanded use of Bayesian approach in financial econometric modeling, it is seen that using these methods properly enhances the modeling precision. According to the results, it is suggested that the scholars consider trading volume as an effective variable in their studies. Moreover, given the existing research gaps, it is suggested that the relationship between returns and trading volume be examined for effective capital market shares and the relationship between other variables. It is suggested that the relationship between the volatility of the returns in macroeconomic variables at the international level be examined on the macroeconomic variables of the Iranian economy to measure the effect of these volatilities on the Iranian economy using the methodology applied in this study. As the present study used only Random Walk Metropolis Hastings algorithm because of the complexities of coding Bayesian modeling, it is suggested other algorithms be compared to extend the discussion.

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