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Modeling and Forecasting Trade Volume in Tehran Stock Exchange: An Application of ARCH Family Models

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Abstract

The main goal of this paper, is modeling the dynamic volatility pattern of monthly time series data of trade volume in Tehran Stock Exchange (TSE) based on flexible ARCH family models. Therefore, in addition to modeling the dynamic volatility pattern of TSE trade volume growth rate, prediction performance of ARCH family models will be compared based on RMSE criterion. The results show that, asymmetric TGARCH and EGARCH models have more forecast accuracy performance for modeling the behavior of dynamic volatility of trade volume than symmetric ARCH models. Interpretation of EGARCH coefficients show that, good news has more effects than bad news on volatility of trade volume growth rate in TSE. Thus, information flow in TSE is asymmetric. In the other hand, the results don't confirm significant leverage effects in trade volume growth rate in TSE. In the other words, decreasing the growth rate of trade volume doesn't lead to increasing of its volatility. These results, highlight the necessarily of operations to increasing the information transparency in order to increasing market efficiency and reducing the investment risk in TSE. These results provide valuable information for investors in TSE, especially for traders with asymmetric information flow with the lack of leverage effects.

Keywords: *trade volume, information flow, asymmetric GARCH models, volatility, Forecasting.*

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1. Introduction

Trade volume plays a major role in financial markets, such that facilities the discovery and forecasting process of prices and give to investors the ability of dividing investment risk. Trade volume as a key variable for companies, guarantees the possibility of financial resources increasing in order to increase investment in future (Sabiruzzaman and et.al, 2010). In the other hand, this variable has high ability to measure information flow in stock markets (Girard and Biswas, 2007).In fact, change in trade volume happens following entry the new information into market and it can be considered as an alternative measure of information flow in stock markets. Therefore, modeling and forecasting of trade volume, as a tool for analyzing investment decisions and risk management, has a particular importance.

In the theoretical literature, there are two alternative overall views to explain the behavior of trade volume variable. These two main theoretical views are traditional New Classical and behavioral finance. New Classical view believes that in order to reduce costs, investors must avoid from successive buying and selling their assets. In contrast, behavioral finance view tries to explain trading behavior of people within prospect theory, heterogeneity among investors or naïve investor hypothesis and overconfidence theory. The maintained behavioral finance theories contain multiple and ambiguous results about investor’s behaviors by considering concepts such as point of reference and information asymmetry in financial markets (Kahneman and Tversky, 1979, Wang, 1994).

Because of existence volatility, uncertainty and asymmetry properties of trade volume, it must be considered to elect a suitable and flexible model that embeds these factors. Dynamic Heteroscedasticity ARCH and GARCH models that proposed by Engle (1982) and Bollerslov (1986) and widely are used in order to modeling volatility of financial variables can consider the maintained properties of trade volume. In the empirical literature of trade volume modeling and prediction, Lamoure and Last rapes (1990) first time used from ARCH and GARCH models in order to modeling trade volume of stock markets of emerging and developed economies. Girard and Biswas (2007) claim that attitudes and expectations difference among investors are the most resources of trade volume volatility. They employed asymmetric TGARCH model in order to modeling trade volume volatility. Sabiruzzaman and et.al (2010) in order to modeling and prediction trade volume of Hong Kong stock market employed GARCH and TGARCH models. Their empirical results show that, TGARCH specification is superior to GARCH specification. Carrol and Kearney (2012) investigated trade volume increasing effects on stock returns in

Australia by using GARCH models. Their results show that, trade volume has positive and significant effects on stock returns of Australia stock markets.

In this paper, in order to modeling and forecasting trade volume as a measure for information flows in TSE, alternative specification of ARCH family models will be compared. Our results show that, asymmetric version of ARCH family models have more accuracy performance in modeling and prediction trade volume in TSE. So we conclude that information flow is asymmetric in TSE. In the other hand, obtained empirical results show that, there are not leverage effects in TSE. These results have very valuable guidance for traders and investors, especially angel traders in TSE.

The rest of paper organized as follow. Section 2 contains literature review. Section 3 presents the econometrics framework. Section 4 describes the data. Section 5 presents the empirical results. Finally conclusion remarks are offered in section 6.

2. Literature Review

In the theoretical literature of finance, traditional theories are seeking to explain behavior of financial variables based on assumptions such as, rational and risk-averse investors and market efficiency. However, there are some variables in financial markets that these theories cannot explain their behaviors. In real, trade volume is more than level that New Classical theory predicts. Based on New Classical theory, rational investors maintains their investment fixed for a long time and avoid from successive trading because increasing number of transactions lead to lower level of earning and higher level of transactions cost (raee and falahpour, 2004). However, in practice, trade volume is higher than that level that this theory predicts. Behavioral finance theory combines psychological and economics concepts to explain the behavior of investors which it is inconsistent with the traditional view. Behavioral finance view is looking for explain how investor's psychology effects on financial decisions and market behavior. One of the behavioral aspects in order to explain inconsistent behavior of investors is overconfidence hypothesis. Based on this hypothesis, people who have too much trust with overconfidence on available information do more transactions and so trade volume increase (raee and falahpour, 2004).

In the other hand, Kahneman and Tversky (1979) proposed prospect theory in order to explain behavior of investors. Prospect theory is based on nonlinear value function that it has a reference point. The points above reference point represent risk-averse investors and vice versa points that are below the reference point show risk lover investors (Johnson, et.al, 2002). Based on prospect theory, investors sell stocks when stock price is higher than reference point and vice versa they buy stock if stock price be lower than reference point. Also Daniel and et.al (1998) analyzed over reaction and lower reaction of investors based on psychological concepts.

In the other hand, transactions in financial markets occur in two informed and uninformed categories (chae, 2003). Accordingly, traders are divided in two informed and uninformed groups. Uninformed transactions are exogenous and so are not sensitive to price changes. These types of transactions increase in asymmetric information situation that it is subsequently lead to an increase in total trade volume level because informed traders are trying to use their private information in these situations (Kyle, 1985, chai, 2003). However, if uninformed traders have time authority in asymmetric information situation, it may be trade volume reduced (Admati and Pfleiderer, 1988, Foster and Viswanathan, 1990). If uninformed traders receive past information in order to assessment, they postpone transactions until information asymmetry completely eliminates. Therefore, it is possible to reduce trade volume before assessment and rise after it.

3. Methodology

Autoregressive Conditional Heteroscedasticity (ARCH) models are a class of time series models that first proposed by Engle (1982). These models widely have been used in empirical studies in order to dynamic modeling conditional variance of time series. In these models, it is assumed that the variance of residuals in period t is formulated as follows:

$$y_t = \alpha + \beta' x_t + \varepsilon_t \tag{1}$$

$$\sigma_t^2 = \alpha_0 + \alpha_1 \varepsilon_{t-1}^2 + \alpha_2 \varepsilon_{t-2}^2 + \ldots + \alpha_p \varepsilon_{t-p}^2 + \nu_t \tag{2}$$

In equation (1), y_t is an endogenous variable that is presented according to a set of exogenous variables $x_t = [x_{t-1}, \ldots, x_{t-p}]$ and $\beta = [\beta_1, \ldots, \beta_p]$ is vector of coefficients. Equation (2) represents ARCH (p) model. In this equation, σ_t^2 is variance of residuals in period t, ε_{t-p}^2 is p-lag of residuals square and ν_t are residuals of variance regression. Bollerslov (1986) proposed generalized specification of ARCH model that it is kwon as GARCH model. This model has a regression form as:

$$\sigma_t^2 = \alpha_0 + \alpha_1 \varepsilon_{t-1}^2 + \ldots + \alpha_p \varepsilon_{t-p}^2 + \beta_1 \sigma_{t-1}^2 + \ldots + \beta_q \sigma_{t-q}^2 + \nu_t \quad (3)$$

In GARCH models, σ_{t-q}^2 presents the q-lag of variance. GARCH model has an important restriction. The shocks that generate volatility divided into two positive shocks (good news) and negative shocks (bad news). The reactions of traders to these good and bad shocks are not same. Asymmetric GARCH models such as threshold GARCH (TGARCH) proposed by Glosten and et.al (1993) and Zakoian (1994) and exponential GARCH (EGARCH) that it is introduced by Nelson (1991) separate effects of various positive and negative shocks on dynamic volatility. A simple specification of TGARCH model has a following regression form:

$$\sigma_t^2 = \gamma_0 + \gamma \varepsilon_{t-1}^2 + \upsilon \varepsilon_{t-1}^2 d_{t-1} + \delta \sigma_{t-1}^2 + \nu_t \quad (4)$$

Where d_{t-1} is a dummy variable that it is equal to 1 where $\varepsilon_t \prec 0$ and it is equal to zero other case. The coefficient υ measure asymmetry effects of shocks. If υ be statistically significant and positive then bad news has larger impact than good news on volatility vice versa if υ be negative and statistically significant then good news has more effects than bad news on volatility. It is clear that if υ not statistically significant then effects of good news and bad news are same.

In the other hand, a simple specification of EGARCH model has a following form.

$$\log(\sigma_t^2) = \omega + \xi \left| \frac{\varepsilon_{t-1}}{\sqrt{\sigma_{t-1}^2}} \right| + \gamma \frac{\varepsilon_{t-1}}{\sqrt{\sigma_{t-1}^2}} + \beta \sigma_{t-1}^2 + \nu_t \quad (5)$$

The EGARCH model can test asymmetry effects of shocks as well as the TGARCH model. If $\gamma \prec 0$ and be statistically significant then the positive shocks have lower effect on volatility and vice versa if $\gamma \succ 0$ and also be statistically significant then negative shocks have lower effects on volatility of variable.

One of the main problems in financial econometrics is measuring the effects of volatility of a variable on its returns. Engle and et.al (1987) proposed GARCH-M models for this regard. In this model, conditional dynamic variance appears in mean equation in order to investigate the effects of volatility on returns. This model specified as:

$$y_t = \alpha + \beta' x_t + \theta \sqrt{\sigma_t^2} + \varepsilon_t \quad (6)$$

$$\sigma_t^2 = \alpha_0 + \alpha_1 \varepsilon_{t-1}^2 + ... + \alpha_p \varepsilon_{t-p}^2 + \beta_1 \sigma_{t-1}^2 + ... + \beta_q \sigma_{t-q}^2 + \nu_t \qquad (7)$$

Where equation (6) shows mean or returns regression and equation (7) specifies the behaviors of dynamic conditional variance.

Therefore, in this paper the forecasting performance of symmetric GARCH and GARCH-M models compare with asymmetric TGARCH and EGARCH models.

4. Data

In this study, we use monthly data of trade volume in TSE from March 2002 to December 2012. Data are taken from central bank of Iran. Table 1 represents descriptive statistics of Trade volume monthly data.

Mean	Std.Dev	Min	Max	Skewness	Kurtosis	Jarqe-Bera
10009.3	10299.4	642	89137	3.94	28.47	3820.6*

Table 1. Descriptive Statistics Of TSE Trade Volume

Source: research finding, * represents significance in 5 percent.

Based on descriptive statistics, in 10 years period the mean of trade volume in TSE is above 10000 BR2. Standard deviation is 10299 that it is large and show high level of volatility in TSE trade volume. In the figure (1), time trend of TSE trade volume is represented.

[2] Billion Rials

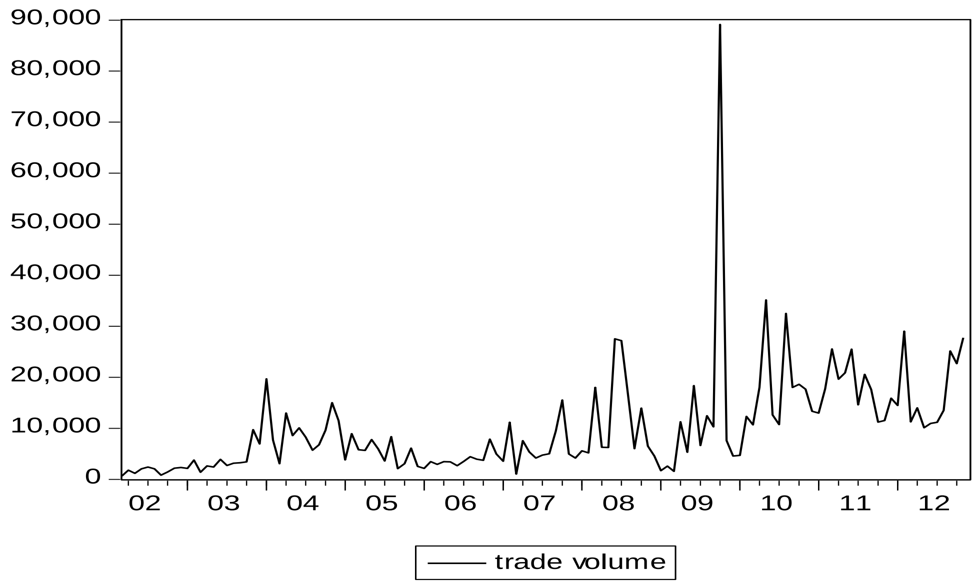

Figure 1. Time Series Plot Of TSE Trade Volume

Based on figure (1), from 2002 onwards due to increasing the number of companies in TSE and stock markets development, level of trade volume in TSE has been increased. In 2005 trade volume has been decreased as a result of presidential election. It can be seen a volatile trend in TSE trade volume particularly from 2008 to 2012. Political tensions and enforcement the law of subsidies in 2010 have to be considered as two main reasons that causes trade volume volatility in these periods.

5. Empirical Finding

In this section of paper, the dynamic variance of TSE trade volume is modeled based on alternative ARCH family models. First, the growth rate of trade volume is calculated based on the following formula (Asteriou, 2006).

$$rtv_t = 100\log(\frac{tv_t}{tv_{t-1}}) \tag{8}$$

In equation (8), tv_t presents trade volume in period t and rtv_t indicate the growth rate of trade volume in period t. In addition, first stationary of rtv_t time series is examined. Then the optimal autoregressive model of rtv_t variable is found and estimated based on autocorrelation functions and then diagnostic test such as ARCH-effect test and serial correlation LM test is examined on residuals of estimated autoregressive model of rtv_t .

variable	ADF unit root test	PP unit root test	Optimal AR model	Serial correlation LM test	ARCH effect test
rtv_t	-11.79*	-36.22*	AR(1)	1.31(0.52)	4.61(0.03)

Table 2. Estimation Results Of Autoregressive Model And Diagnostic Tests For Trade Volume Growth Rate

Source: research finding, * present significant in 5 percent. Numbers in parentheses indicate significant level.

The results of ADF and PP unit root test indicate stationary of rtv_t variable. rtv_t Variable has AR (1) pattern. The results of diagnostic tests show that residuals of AR (1) model are not serially correlated but have Heteroscedasticity. Therefore we use the ARCH family models in order to modeling conditional variance. Now we use various versions of ARCH family models in order to modeling and prediction TSE trade volume. We compare these models in out of sample forecasting of trade volume based on RMSE criterion that it has been reported in table 3.

Model	GARCH(1,1)	TGARCH(1,1)	EGARCH(1,1)	GARCH-M
RMSE	0.692	0.577	0.568	0.693

Table 3: Prediction Error Of Various Models

Source: research findings

Based on RMSE criterion, the asymmetric EGARCH model has minimum level of prediction error among other models; therefore in addition we report estimation results of this model in table 4.

	Parameter	Coefficient	Std.Dev	Z statistics	probability
Mean equation	α	5.81	3.76	1.55	0.12
	β_1	-0.46	0.08	-5.37	0.00
Variance equation	ω	0.59	0.59	1.01	0.31
	ξ	0.22	0.14	1.60	0.11
	γ	0.20	0.09	2.14	0.03
	β	0.91	0.07	12.07	0.00
	R^2	0.22	F statistics	6.92(0.00)	

Table 4: Estimation Results Of EGARCH (1, 1) Model

Source: research finding

We conclude that positive shocks (good news) have higher effects on trade volume volatility than negative shocks (bad new), because γ is positive and statistically significant in 5 percent. In the other word, TSE trade volume volatility has more responses to good news than bad news; therefore we conclude that information flow is asymmetric in TSE. Figure 2 presents time trend of TSE trade volume growth rate volatility.

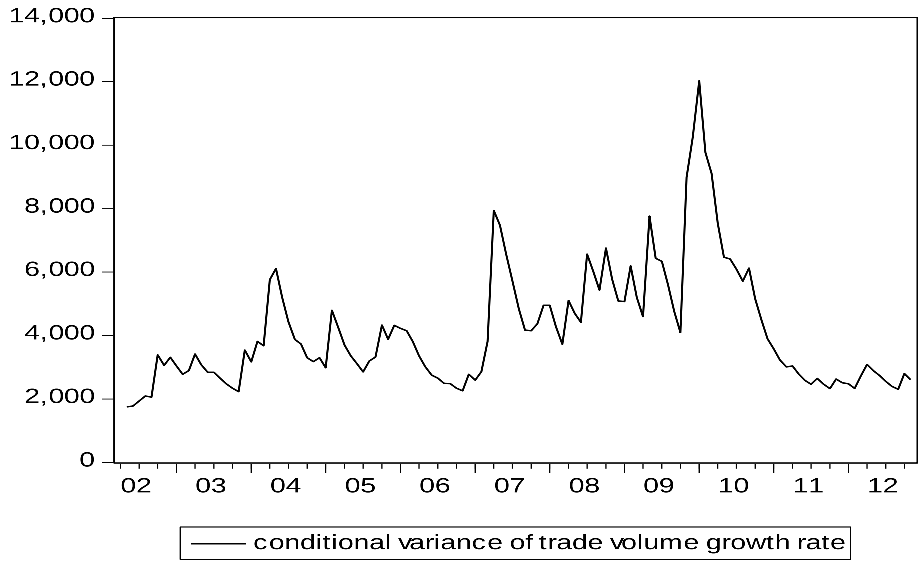

Figure 2. Conditional Variance Of TSE Trade Volume Growth Rate

As it can be seen in figure (2), TSE trade volume growth rate has high volatility especially during 2007 to 2010 period. Following from the Sabiruzzaman and et.al (2010), in order to investigate leverage effects the following regression model will be estimated.

$$\hat{s}_t^2 = \beta_0 + \beta_1 \hat{s}_{t-1} + e_t \tag{9}$$

Where $\hat{s}_t = \dfrac{\hat{\varepsilon}_t}{\hat{\sigma}_t}$, that $\hat{\varepsilon}_t$ is residuals of mean regression equation of trade volume growth rate and $\hat{\sigma}_t$ is conditional standard deviation that it is obtained from GARCH (1, 1) model. If Statistics of equation (9) will be statistically significant then we conclude significant leverage effects in TSE. Estimation results show that, F statistics equal to 0.45 with probability equal to 0.64 therefore leverage effects don't accept. Simply we cannot claim that trade volume growth rate increasing lead to high volatility of its variable.

6. Conclusion

In this paper, we model and forecast pattern of trade volume in TSE by using symmetric and asymmetric versions of ARCH family models based on theoretical background about asymmetry properties of information flow. Our results show that based on RMSE criterion, asymmetric class of ARCH family models has more accuracy performance for out of sample forecasting of TSE trade volume. In particular, EGARCH model has lowest level of out of sample prediction error. Based on the obtained results good news has more effects than band news on trade volume volatility. The results show that, there are no significant leverage effects in TSE trade volume growth rate.

We conclude that information flow is asymmetric in TSE; therefore it is necessarily to increasing information transparency via disclosure and publication accurate and rapid information in order to increasing market efficiency and redacting investment risk.

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