# JURNAL ILMIAH EKONOMI BISNIS

# **JOURNAL OF ECONOMIC AND BUSINESS**

DAFTAR I ISI	
Ethic As A foundation Of Management - A Valuable Or Relic In The Times Of Crisis?  Joanna Hernik, Marcin Gębarowski	147
Consumer Trust And Country Of Origin (Chinese Product Case on Indonesian Market) Hotniar Siringoringo, E.S. Margianti, Anacostia Kowanda, Trini Saptariani	158
Theory, Reality And Perception Of CSR: Comparative Study Between India And The Slovak Republic Peter Bielik, Elena Horsk, Andrea Ubreziova	168
Capital Market Trading Behaviour Within Crisis Period  Bramantyo Djohanputro	179
Technical Analysis In Predicting Stock Prices Movement And Testing Eficient Market Hypothesis In Indonesian Stock Exchange Sri Murtiasih, Ferry Ferdian	190
Residences Satisfaction Towards Service Quality Provided By Bogor Local Government Adi Kuswanto, Teddy Oswari, Budi Setiawan	201
Management's Need For Web Based CSR Communication : Application Of Media Richness Theory Ati Harmoni	210

Diterbitkan oleh:

Lembaga Penelitian Universitas Gunadarma

#### CAPITAL MARKET TRADING BEHAVIOUR WITHIN CRISIS PERIOD

# Bramantyo Djohanputro

Corporate Finance, Risk, and Governance
PPM School of Management
Jl Menteng Raya 9 Jakarta 10340
brm@ppm-manajemen.ac.id; bram.finance@gmail.com

#### Abstract

This paper aims at exploring the investors' behavior on investment decisions, especially on how they express their daily behavior in considering trading volume, market returns, and market volatility in their trading or investment decisions within the crisis period as the impact of the subprime mortgage crisis in the United States of America. They are expected to employ current and past information contained in trading volume, returns, and volatility, in their decision making under market pressure because of crisis. To explore those relationships, regressions with Autoregressive Conditional Heteroskedasticity, or ARCH, are employed. More specifically, TARCH model is applied to explore the possibility of asymmetric response of negative and positive information. The study reveals that traders are more concerned with volatility than with return within the crisis period. Also, they tend to behave differently to different types of information, i.e. negative and positive information.

Keywords: return, volatility, volume, TARCH, asymmetry

#### INTRODUCTION

Indonesian capital market is expected to become more mature and efficient after experiencing the economic crisis that hit most Asian capital markets in 2009. Within that period, most market indices went down sharply, many investors retreated from the market, and most short term traders behaved carefully in very trading decision. The maturity and efficiency mean that traders tend to exploit various data to extract information and to make decision. Investors are quite confident to the information contained in the trading activities. They believe to be able to learn and extract some material information from those trading activities to make buy, hold, sell, and portfolio decisions.

Trading volume represents trading activities. Brown, Crocker, and Foester

(2009) argues that trading volume is important because it reflects some proxies, including liquidity, momentum, information. Rompotis (2009) suggests that trading volume is a determinant factor, but not the sole factor, to influence market movements. Some studies suggest that trading volume influences returns (Lamoureux, 1990; Chowdury, and Howe, Ji-Chai-Lin, 1993; Andersen, 1996; Easly, Kiefer, Maureen, and Joseph, 1996; Hrazdil, 2009; Kymaz and Girard, 2009; Yen and Chen, 2010). Other studies propose the influence of trading volume on both market returns and volatility (Gerety and Mulherin, 1992; Lee, Mark, and Paul, 1994; Sabri, 2004).

How does information influence market? Trading volume may indicate the flow of information, and the flow of information encourages price changes

and Mendelson, 1991: (Amihud Brailsford, 1994; Nawrocki, 1996). Note that the information is diverse in quality, depending on the ability of traders to treat the data. Traders distinguish private from public information. Private information only belongs to certain persons who have ability to evaluate data and certain access to the sources of information. Public information belongs to everybody. have different Sometimes traders confidence on those types of information (Lin, Rahman, and Yung, 2010). In addition, the magnitude of price change depends on the quality of information contained in the trading volume (Choi, Hovem, and Jung-Wook, 2009).

Trading activities may influence returns and volatility permanently or temporarily. It is permanent if traders are able to extract material information that influences the fundamental values of stock listed in the market. It is temporary is traders are only able to obtain news that creates a shock in the market. The returns or volatility movements under a shock survive in a short period and they will reverse as soon as traders realize their mistakes. Therefore, the sustainability of returns and volatility depends on whether the trading activities have fundamental information or merely reflect The existence of psychological shock. fundamental information in the trading activities will affect permanent volatility, while psychological shock in the trading activities will only influence volatility temporary. Girard and Omran (2009) use the words expected and unexpected components to express fundamental information and news.

Based on the arguments aforementioned, it is interesting to explore the investors' behavior on investment decisions, especially on how they express their daily behavior in considering trading volume, market returns, and market volatility in their trading or investment decisions. They are expected to employ current and past information contained in trading volume, returns, and volatility in their decision making under market pressure because of crisis.

This research, then, attempts to answer the following questions. Firstly, how and to what extent do investors use the trading volume and past returns as the sources of information on trading that affect returns? Secondly, to what extent do investors use trading volume and past volatility as the sources of information on trading that affect current volatility? Thirdly, how do investors behave on different types of information, i.e. positive and negative information?

To answer those questions, this research employs the data within a crisis period, i.e. the data from January to December 2009. This study employs the following variables: trading volume, market returns, market volatility, their lags, and dummy variables. Trading volume is represented by the natural logarithm of trading volume. The use of natural logarithm is to scale down their values. Besides, the use of the natural logarithm provides information regarding the elasticity of returns and volatility on the trading volume. Market daily returns derive as the difference in the logarithms of stock index levels. Volatility generated as the squared daily returns. Dummy variables represent days of the week effect.

This study indicates the return-volume relationship as expected, while volatility-volume relationship is not quite clear. Apart from that, one may expect that the market response is quick enough, and quicker than under normal trading period. By employing total, expected, and unexpected trading volume, this study gives a rich explanation on those relationships.

This paper is organized as follows. The first section is introduction. The following section describes the proposed models and hypotheses. The next section elaborates data employed in this study and their analysis. This paper is closed with the conclusion.

#### RESEARCH METHOD

The following models derive from two main bases: the linear relationship models of return - volume and volatility - volume, and the asymmetric response to different types of information. Assume that transactions are conducted by both informed and non-informed traders. An informed trader has some choices. He (she) may trade on one stock with large volume, or many stocks with low volume for each stock. He (she) may also transact index or a stock portfolio. Depending on the type of information, he (she) will trade on a certain side, either buy side or sell side. Even though his (her) transaction for each stock is not large, his (her) persistence in trading may cause the trading volume increases significantly.

As informed traders are able to predict the market movement, they know the expected trading volume. Non-informed traders, however, do not know exactly the volume they want to transact until the time come. For this reason, trading volume needs to be separated between informed-based against non-informed-based trading volume, as shown in the Equation 1.

 $[Total Volume]_{t} = \\ [Expected Trading Volume]_{t} \\ + \\ [Unexpected Trading Volume]_{t}$  (1)

Following Epps (1975), Copeland (1977), and Campbell, Sandford, Jiang (1993), Andersen (1996), Easly et al (1996), and Kim and Karanasos

(2006), trading volume becomes one of independent variables. The data of trading reflect underlying information structure according to the directions, either buying or sellingpressure conditions. Furthermore, joint dependence of return and volume applies on an underlying latent event or information variable. Traders may arrive at the market sequentially and in a random and anonymous fashion. This type of information arrivals induces a dynamic learning process of price discovery or information assimilation phase. When all agents agree on the price, the market goes to the equilibrium direction characterized by uniformed valuation and low buy-sell spread.

ARCH is put as the variance equation to accommodate the way traders respond to information arrivals. More specifically, Threshold Autoregressive Conditional Heteroskedasticity (TARCH) is applied to capture the possibility of asymmetric response to different types of information, i.e. negative and positive types of information.

# Return-Volume Relationships

Hypothesis 1: Past and current trading volume, together with past market returns, significantly influence the current market return, as shown in Equation 2 and Equation 3.

 $Return_t =$ 

$$a + \sum_{i=1}^{n} b_{i} \operatorname{Re} turn_{t-i} + \sum_{j=0}^{m} c_{j} Volume_{t-j} + \sum_{k=1}^{4} d_{k} D_{k} + e_{t}$$
 (2)

$$\sigma_t^2 = \omega + \sum_{j=1}^q \beta_j \sigma_{t-j}^2 + \sum_{i=1}^p \alpha_i \varepsilon_{t-i}^2 + \sum_{k=1}^r \gamma_k \varepsilon_{t-k}^2 I_{t-k} + \zeta_t$$
 (3)

With  $I_t = 1$  if  $C_t < 0$  and 0 otherwise. Return, is the daily market return. It is defined as the change in daily market index, as shown in Equation 4.

$$Return_{t} = \frac{Index_{t}}{Index_{t-1}}$$
 (4)

The closing daily indices are used in this study. The reason is that closing indices accommodate all flows information before and within the day. Therefore the closing indices reflect the fair market prices. The daily returns do not include dividend yield as the reasons are the fact that this model of calculation is common for daily returns and the distribution of dividend is very rare, i.e. normally only twice a year. Therefore, excluding dividend vield does significantly influence the time series of return.

The use of the lags of return, Return, is to extract the information contained in the previous trading days. Some investors, either informed or noise traders, may find certain information to follow from the way prices moves. The number of lag very much depends on the speed of those traders obtain information and their capability to bear risk in trading.

Volume as an independent variable represents how traders behave in the market. This model employs current trading volume (Volume<sub>t</sub>) as an independent variable. The reason is that transaction takes place before the last, or closing, price is formed. This means that Volume<sub>t</sub> may contain information useable to influence the closing price. The use of natural logarithm of trading volume is to scale down the figure and to find information on sensitivity.

Variables D<sub>k</sub> represent daily dummy variables. Because there are five trading days within a week, this study employs four daily dummy variables. These variables are to extract the difference in trading behavior and characteristics on daily basis.

In addition, Equation 2 employs TARCH model (Threshold Autoregressive Conditional Heteroskedasticity). This

follows previous implementation of ARCH and its variance process (Bollerslev, 1986; Bierens ,1993; Kim and Schmidt, 1993; Scwaiger, 1995, Kim and Karanasos, 2006, and Faff and McKenzie, 2007). The use of TARCH process is to improve the efficiency of the volatility in Equation 1. The use of conditional variance, h2, is to make the homoskedasticity variance. The use of TARCH is to catch the asymmetric effect of information on traders' behavior on negative and positive information. Such effect is captured by by  $\gamma_t$  on Equation 2.

Under a crisis period, in which selling pressure is stronger than buying pressure, trading volume is expected to influence market return negatively. The higher the trading volume, the lower the market price, hence the lower is the market return.

# Volatility-Volume Relationship

Hypothesis 2: Current and past trading volumes influence current market volatility. These hypothesis represent in Equation 5 dan 6.

 $Volatility_t =$ 

$$a + \sum_{i=1}^{n} b_{i} Volatility_{t-i} + \sum_{j=0}^{m} c_{j} Volume_{t-j} + \sum_{k=1}^{4} d_{k} D_{k} + e_{t}$$
 (5)

$$\sigma_{t}^{2} = \omega + \sum_{i=1}^{q} \beta_{j} \sigma_{t-j}^{2} + \sum_{i=1}^{p} \alpha_{i} \varepsilon_{t-i}^{2} + \sum_{k=1}^{r} \gamma_{k} \varepsilon_{t-k}^{2} I_{t-k} + \zeta_{t}$$
 (6)

This study employs the squared returns to represent the market volatility. The use of past volatility in Equation 5 is because traders may behave to previous price fluctuation before considering trading. In this case, one expects b<sub>i</sub>'s are significant. The length of the lags depends on how fast traders react to the volatility.

The explanation of the remained variables and the variance equation is similar to the explanation in the previous part.

Traders tend to watch the market

movement closely within a crisis period. When the market is in rush, traders jump to the market. The problem is that some traders have various types of information, while noise traders do not have information at all. This last type of traders makes market volatile because the way they trade depends on which informed traders are followed.

The above argument lead to the hypothesis that trading volume positively influence market volatility. In other words, the coefficients of trading volume are expectedly to be significantly positive.

## RESULT AND DISCUSSION

This study employs data from the beginning to the end of year 2009, the year after the subprime mortgage crisis in the US. The use of only one year period is because the economy of Indonesia started to rebound from the beginning of year 2010. Most companies were very optimistic that business was much better in year 2010.

The Jakarta Composite Index and trading volume data are taken from yahoo. com. The index is applicable because they are always adjusted to every corporate action (as comparison, see Pinfold and Qiu, 2007). However, the time series is scrutinized line by line because there are many missing data. As applied in many studies, the missing index is filled with index of its previous day. The missing data of trading volume, on the other hand, are replaced by zero.

# Return - Trading Volume

Table 1 shows the results of three main regressions. The difference among them is the use of volume<sub>t-i</sub> as an independent variable. The first regression, shown in column 2, employs total trading volume. The second regression, shown in column 3, employs expected trading volume.

The third regression, shown in column 4, employs unexpected trading volume. The results of TARCH models are shown at the bottom part of the table.

Based on experience of using data outside crisis period, those three regressions employ a quite long lags of return and volume as regressions. In some cases, the use of lags 5, 10, and 20 is quite normal to capture the weekly, bi-weekly, and monthly effects. Before coming to those final models, this study has tried to implement longer lags for both returns and volume. However, those final models are employed based on maximum likelihood, Akaike information criteria, and Schwarz criteria, besides the fulfillment of stationary and normality requirements.

Regressions using the data within the crisis period seem that the market responds much more quickly. As Table 1 indicates, only trading from the last two days influences the current market return. Table 1 column 2 shows that past return and trading volume does not influence the current market return at all. There is no single independent variable that has significant coefficient, even at 10% significance level.

The variance equation shown in column 2 indicates the behavior of asymmetric response to different types of information. In relation to TARCH model, the coefficient of  $\mathcal{E}_{t-1}{}^2I_{t-1}$  is positive and significantly different from zero at 10% significance level.

The regression of return on the expected trading volume, as shown in column 3, indicates different responses from those shown in column 2 and confirms the importance of trading volume. All coefficients of trading volume, i.e. Volume, Volume, and Volume, are significantly different from zero at 1% significant levels. This means that current and past trading volumes very

significantly influence the current market return.

The coefficients also tend to be as expected, i.e. they tend to have negative signs. They indicate the opposite relations between market trading and return. The increase in market trading activities within crisis period indicates the selling pressure. Therefore, the increase in market volume tends to push the price down or results in negative return. This is shown by the coefficients of Volume, and Volume, 2.

The positive coefficient of Volume, indicates that market prices tend to fluctuate within three days of trading. Suppose that today's trading volume is high. This pushes the price down, and results in the negative return today. However, the price tends to rebound or reverse the next day. This suggests that traders are not sure about the price movements as a result of yesterday's information contained in the trading volume. Traders want to remove the noise in the price. The third day, however, traders still attempt to revise the price on the basis of information contained in the trading volume.

The last column of Table 1 shows the result of regression using unexpected trading volume as independent variables. In terms of significance levels of all variables, the regression results of column 4 and column 2 are the same, in the sense that there is no single independent variable that has a significant coefficient, except the coefficient of variance equation shown at the bottom of the table. This result could indicate the dominance of noise trading over informed trading within the crisis period. Because of the small portion of informed trading compared to noise trading, the importance and the significance of informed trading do not significantly appear in the total effect.

The minority influence of informed

trading is supported by the regression results, especially in terms of R<sup>2</sup>. The low R<sup>2</sup> of all three regressions suggest that even though informed trading significantly influence the price movement, there are other factors that have significant influence on the price movements. If one could identify those factors and accommodate them into the models, the explanation power of the model will go up.

The fluctuation of returns significantly in relation to trading volume within three days indicates some important lessons learned. First, crisis period, similar to the bearish condition, tend to be dominated by selling pressure. Under this situation, the increase in trading volume means the increase in stock to be sold. This is perceived as negative information that brings the price down. Second, traders tend to evaluate the expectation of trading as the sources of information to be accommodated into price. Third, even though there is a diversity of interpretation and existence sequential trading activity, interpretation of information tends to be quick and informed traders tend to come up with the converged information within a short period, i.e. within two days. Fourth, traders are not affected by noise trading activities in evaluating the market price.

# Volatility-Trading Volume

Table 2 shows the results of three regressions. Each regression contains both main equation and variance equation. Similar to the return-volume regressions, the volatility-volume models also employ three types of trading volume, i.e. total trading volume, as shown in column 2, expected trading volume, shown in column 3, and unexpected trading volume, shown in column 4.

In terms of significance levels, columns 2 and 4 indicate some significant coefficients of independent variables.

Table 1
The Regression of Return on Its Lags and Trading Volume with TARCH Model for Variance Equation

Independent Variable	Coefficient (Volume)	ume <sub>t</sub> =	ne <sub>t</sub> = Coefficient (Volume <sub>t</sub> = Expected Volume) (3)		Coefficient (Volume <sub>t</sub> = Unexpected Volume) (4)			
(1)	(2)							
	(-)	Main	Equation		(1)			
C	0.002					0.003		
Return <sub>t-1</sub>	0.003		-0.037		0.025			
Return <sub>t-2</sub>	-0.038	-0.055 0.052						
Return <sub>t-3</sub>	0.000	0 -0.013 0.0						
Return <sub>t-4</sub>	-0.039	-0.044						
Return <sub>t-5</sub>	0.029		-0.014		-0.007			
DUM1	-0.003		-0.004		-0.003			
DUM2	-0.002		-0.002		-0.001			
DUM3	-0.001		-0.001		0.001			
DUM4	-0.001		-0.002		-0.000			
Volume <sub>t</sub>	0.000		-0.063	***	0.000			
Volume <sub>t-1</sub>	0.000		0.154	***	0.000			
Volume <sub>t-2</sub>	-0.000		-0.084	***	0.000			
		Varian	ce Equation					
C	0.000	*	0.000	**	0.000	***		
Resid <sub>t-1</sub> <sup>2</sup>	0.054	*	0.029	**	0.046	**		
$\operatorname{Resir}_{t-1}^{2} \times [\operatorname{Resid}_{t-1} < 0)]$	0.083	*	0.112	**	-0.108	***		
GARCH <sub>t-1</sub>	0.955	***	0.996	***	0.968	***		

Note:

However, column 3, mainly on the main regression, indicates no single significant coefficient. It is the opposite of the results shown in Table 1, in which some significant coefficients appear on column (3) while no single significant coefficient appears on columns (2) and (4).

Let focus on columns (2) and (4). The significant coefficients of the lags of volatility shown in column (2) are different from those shown in column (4). In column (2), the coefficient of yesterday's volatility, or lag 1, is significantly different from zero at 10% significant level. In column (4), the coefficients of lags 3 and 4 are significantly different from zero at 10% and 5% significant levels, consecutively.

In terms of significant levels, Dummy and Volume, variables have similar characteristics between column (2) and (4). The coefficient of DUM1, or dummy for Monday, is different from zero at 1% significant level. The positive figure for this coefficient indicates that the volatility of Monday tends to be higher than the volatility of Friday. The coefficient of DUM4, or dummy for Thursday, is different from zero at 5% significant level. The positive figure for this coefficient indicates that the volatility of Thursday tends to be higher than the volatility of Friday.

The coefficients of Volume, are quite interesting. The coefficient of Volume, or the current trading volume,

<sup>-</sup> All coefficients are rounded to three decimals; as a result, some coefficients which are very smalls are shown as 0.000, even though they are actually not zero.

<sup>-</sup> The sign of significance level: \*\*\* means significant at 1%; \*\* means significant at 5%; \* means significant at 10%.

tends to be negative even though it is not significantly different from zero. This indicates that there is a tendency that the increase in trading volume is followed by lower volatility and the decrease in trading volume is accompanied by the increase in market volatility. On the next day, however, the volatility significantly increases as an impact of yesterday's increase in trading volume. The result shown on column 4 indicates that the similar directions of trading volume and volatility still take place on the third day.

Another important lesson from columns 2 and 4 is the concern of the unexpected trading volume. The coefficients of trading volume which are significantly different from zero shown in

columns 2 and 4 are similar, i.e. Volume<sub>t-1</sub> and Volume, ... These may indicate that the fluctuations of total and unexpected trading volume are strongly in line. If it is true, the lesson is as follows. While informed traders transact in an ordered sequence, non informed traders transact randomly and this behavior makes the total trading move randomly. While informed traders focus on the expected trading volume and know the price movements, non informed traders do not know exactly the price movement and cannot distinguish the informed trading from non informed trading. As a result, non informed trading tends to encourage the higher volatility at the time of large trading volume.

Table 2
The Regression of Volatility on Its Lags and Trading Volume
with TARCH Model for Variance Equation

Independent Variable (1)	Coefficient (Volume <sub>t</sub> = Total Volume) (2)		Coefficient (Volume <sub>t</sub> = Expected Volume) (3)		Coefficient Volume <sub>t</sub> = Unexpected Volume) (4)	
(1)	(2)	Main	Equation			
C	0.002		-0.003		0.000	
Volatility <sub>t-1</sub>	0.166	*	0.115		0.147	
Volatility <sub>t-2</sub>	-0.066		0.016		-0.047	
Volatility <sub>t-3</sub>	0.072		0.050		0.083	*
Volatility <sub>t-4</sub>	0.076		0.042		0.088	**
Volatility <sub>t-5</sub>	-0.051		-0.017		-0.050	
DUM1	0.000	***	0.000		0.000	***
DUM2	0.000		0.000		0.000	
DUM3	0.000		0.000		0.000	
DUM4	0.000	**	0.000		0.000	**
Volume <sub>t</sub>	-0.000		0.001		-0.000	
Volume <sub>t-1</sub>	0.000	*	-0.001		0.000	**
Volume <sub>t-2</sub>	-0.000	**	-0.001		0.000	**
		Varianc	ee Equation			
C	0.000	***	0.000	**	0.000	***
Resid <sub>t-1</sub> <sup>2</sup>	0.113	**	0.150	**	0.106	**
$\operatorname{Resir}_{t-1}^{2} \times [\operatorname{Resid}_{t-1} < 0)]$	-0.524	***	0.050		-0.497	***
GARCH <sub>t-1</sub>	0.406	**	0.600	***	0.495	***

Note:

The sign of significance level: \*\*\* means significant at 1%; \*\* means significant at 5%; \* means significant at 10%.

<sup>-</sup> All coefficients are rounded to three decimals; as a result, some coefficients which are very smalls are shown as 0.000, even though they are actually not zero.

## **CONCLUSION AND SUGGESTION**

This study attempts to investigate the relationships of market return and volatility against trading volume within a crisis period. The analysis focuses on the Indonesian Stock Exchange for the period of January 2009 to December 2009. It is expected that a crisis period indicates specific characteristics in terms of return-volume and volatility-volume relationships.

The study of return-volume volatility-volume and employs ARCH-autoregressive conditional heteroskedasticity-and because is a possibility that variance influences the return and volatility behavior. Considering that traders may behave differently to positive and negative information, the study employs TARCHthresholds autoregressive conditional heteroskedasticity - to extract and to accommodate that asymmetric behavior on information. To assure the effect of variance on return and volatility, this study also uses conditional variance as a regressor on the models whenever statistically appropriate to be implemented.

It is important to note at the first place that return behavior is significantly affected by expected trading volume while volatility behavior is significantly affected by total and unexpected trading volume. This implies that the fluctuation of total trading volume is in line with the fluctuation of unexpected trading volume. In other words, the fluctuation of trading is mainly the result of non informed traders jumping into the market to transact.

Second important point to note is that market response to information contained in the trading is much faster than the market response in the normal trading period. While the response and the extraction of information exhaustively needs only two or three days within a crisis period, the response may take a month within a normal period. It seems that traders attempt to rush to the market as soon as they find new information. Traders still exploit information on the trading volume last week, last two weeks, and last month. In this sense, market sequential hypothesis does not really work in the crisis period but it works quite well in the normal period.

Third important lesson is that the return-volume relationship within the crisis period under study is as expected. The increase in market trading activities within crisis period indicates the selling pressure. Therefore, the increase in market volume tends to push the price down or results in negative return. The volatility-volume relationship, on the other hand, is not as one expects, at least there is a confusing relationship. It is shown by the relationship within the first three days in which the relationship fluctuates, not in one direction, but in mixed positive or negative relationships. This is understandable because of the dominance of unexpected traders that influence the market trading fluctuation.

The last point is the fact that the low powers of explanation of return-volume as well as volatility-volume indicate the importance of other variables that influence the return and volatility movement. The market behavior, shown by the significances of variance equations of TARCH, is one factor, in which market tends to behave differently to positive and negative information. Other factors are not identified in these models and quite interesting to be explored.

#### REFERRENCES

- Amihud, Y and Mendelson, H. 1991 "The volatility, efficiency, and trading: Evidence from the Japanese Stock Market" *The Journal of Finance* XLVI(5) 1765–1789.
- Andersen, T.G. 1996 "Return volatility and trading volume: An information flow interpretation of stocastic volatility" *The Journal of Finance* LI(1) 169–204.
- Bierens, H.J. 1993 "Higer-order sample autocrrelation and unit root hypothesis" *Journal of Econometrics* 57: 137–160.
- Bollerslev, T. 1986 "Generalised autoregressive conditional heteroskedasticity" *Journal of Econometrics* 307–327.
- Brailsford, T. J. 1994 "The Empirical relationship between trading volume, returns, and volatility" *Research Paper* accessed on December 11th 2010 <a href="http://www.google.co.id/#hl=id&source=hp&biw=1024&bih=384&q=market+trading+volume+return+journal&btnG=Penelusuran+Google&aq=f&aqi=&aql=&oq=market+trading+volume+return+journal&gs\_rfai=&fp=f66d875781a0bed0>
- Brown, J.H., Crocker, D.K, and Foester, S.R. 2009 "Trading volume and stock investments" *Financial Analysts Journal* 65(2) 67-85.
- Campbell, J.Y., Sandford J. G, and Jiang W. 1993 "Trading volume and serial correlation in stock returns" *The Quarterly Journal of Economics* November 905–939.
- Choi, W, Hoyem K, and Jung-Wook K. 2009 "Analyst forecast dispersion, trading volume, and stock return" *Seoul Journal of Economics* 22(2) 263–287.

- Chowdury, M., Howe, J.S., Ji-Chai-Lin. 1993 "The relation between aggregate insider transaction and stock market return" *Journal* of Financial and Quantitative Analysis 28(3) 431–437.
- Copeland, T.E. 1977 "A Probability model of asset trading" *Journal of Financial and Quantitative Analysis* November: 563–578.
- Easley, D., Kiefer, N.M., Maureen, O., and Joseph B.P. 1996 "Liquidity, information, and infrequently trade stocks" *The Journal of Finance* LI(4) 1405–1436.
- Epps, T.W. 1975 "Secutiry price changes and transaction volume: Theory and evidence" *American Economic Review* 586–597.
- Faff, R.W., and Mc.Kenzie, M.D. 2007
  "The relationship between implied volatility and autocorrelation"

  International Journal of Managerial Finance 3(2) 191–196.
- Gerety, M.S., and Mulherin J.H., 1992 "Trading halts and market activity: An Analysis of volume at the open and the close" *The Journal of Finance* XLVII(5) 1765–1784.
- Girard, E. and Omran, M. 2009 "On the relationship between trading volume and stock price volatility in CASE" *International Journal of Managerial Finance* 5(1) 110–134.
- Hrazdil, K. 2009 "The Price, Liquidity, and information asymmetry changes associated with New S&P 500 additions" *Managerial Finance* 35(7) 579-605.
- Kim, J, A. K., and Karanasos, M 2006 "The volume–volatility relationship and the opening of the Korean mtock market to foreign investors after the financial turmoil in 1997" Springer Science and Business Media B.V 245-271.

- Kim, K and Schmidt, P. 1993 "Unit root test with conditional heteroskedasticity" *Journal of Econometrics* 59:287–300.
- Kiymaz, H., and Girard, E. 2009 "Stock market volatility and trading volume: An emerging market experience" *IUP Journal of Applied Finance* June 15(6) 5-32.
- Lamoureux, C.G., and William D. L. 1990 "Heteroskedasticity in stock return data: volume versus GARCH effects" *The Journal of Financial Economics* 45: 221–229.
- Lee, C.M.C., Mark J. R., and Paul G. S. 1994 "Volume, volatility, and New York Stock Exchange trading halts" *The Journal of Finance* XLIX(1) 183–213.
- Lin, C.Y., Rahman, H., and Yung, K. 2010 "Investor overconfidence in REIT stock trading" *Journal of Real Estate Portfolio Management* Jan April 16(1) 39-57.
- Narowcki, D. N. 1996 "Market dependence and economic events"

- The Financial Review 31(2) 287–312.
- Sabri, N. R. 2004 "Stock Return Volatility and market crisis in emerging economies" *Review of Accounting and Finance* 3(3) 59–83.
- Pinfold, J., and Mei Q. 2007 "Price and trading volume reactions to index constitution changes: Australian evidence" *Managerial Finance* 34(1) 53–69.
- Rompotis, G.G. 2009 "Performance and trading characteristics of iShares: An evaluation" *IUP Journal of Applied Finance* July 15(7) 24-39.
- Schwaiger, W.S.A. 1995 "A note of EGARCH predictable variances and stock market efficiency" *Journal of Banking and Finance* 19: 949–953.
- Yen, S.M., and Chen, M. 2010 "Open interest, volume, and volatility: evidence from Taiwan Futures Markets" *Journal of Economics and Finance* April 34(2) 113–141.