# MARKET RETURN, VOLATILITY AND TRADING VOLUME DYNAMICS AFTER ECONOMIC CRISIS [1]

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## *ABSTRACT*

*This paper attempts to explore the relationships of return – trading volume and volatility – trading volume. Trading volume may represent a proxy of information, liquidity, and momentum. The up and down of trading volume, therefore, contain certain information that can be extracted by traders to make investment decision. Regressions of market return on its lags, volume, and conditional variance and regressions of volatility on its lags, volume, and conditional variance are employed. Traders may respond positive information differently from negative information. To accommodate such behaviour, threshold autoregressive conditional heteroskedasticity or TARCH is employed. Using market data of Indonesia Stock Exchange between economic crisis and before sub-prime mortgage crisis (from year 2000 to 2007) indicate the existence of return – volume relationships as well as volatility – return relationships albeit not very strong. There is also an indication that traders respond positive information differently from negative information concerning return movements but there is no indication concerning volatility movements.*

*Keywords: return, volatility, volume, TARCH*

## INTRODUCTION

After experiencing the economic crisis in 1997 – 1998 in Asia, and especially in Indonesia, the Indonesian Stock Exchange is expected to be more mature and efficient. There are some factors that support such an expectation. Firstly, the number of companies going public increased significantly, from less than 300 companies before the crisis to more than 400 companies. The increase is more than thirty percent and it is considered to be high. Secondly, the regulator has evolved to become more integrated in managing the capital market. Bapepam (*Badan Pengawas Pasar Modal*) or Capital Market Advisory Board extends its scope of authority to become Bapepam LK (*Badan Pengawas Pasar Modal dan Lembaga Keuangan*) or Capital Market and Financial Institution Advisory Board. This change is expected to cover more integrated information and monitoring to assure the capital market work efficiently and effectively.

Thirdly, and one of the most important factors, the maturity of market participants has improved considerably. They may have strong willingness to educate themselves in using information and exploiting investment opportunities in Indonesia capital market. By doing so, the ability of using the whole information can move the capital market forward to being more efficient. In terms of returns and trading activities, investors would not just ride the market. Instead, they carefully discern the information to obtain factors that may push

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[1] The data available in this paper may be used and distributed to anyone needed.

fundamental factors to move and, then, react to the expected movement accordingly.

Investors use trading activities to make investment decisions because they are confident that the trading activities contain material information. The possibility that trading activities contain information is supported by some previous studies. Brown *et al*. (2009) suggest that trading volume may contain several factors valuable including liquidity, momentum, and information. By scrutinizing trading volume, investors may extract some knowledge to make decisions such as buy, hold, sell, and portfolio allocation.

Apart from the possibility that trading activities represented by trading volume may influence market returns, the activities also potentially affects market volatility. However, the sustainability of volatility depends on whether the trading activities have fundamental information or merely reflect psychological shock. The existence of fundamental information in the trading activities will affect permanent volatility, while psychological shock in the trading activities will only influence volatility temporary. This is in accordance with Girard and Omran findings (Girard and Omran, 2009), suggesting that the impact of trading activities on market volatility depends on whether the trading activities derive from expected or unexpected components.

Based on those arguments, the paper aims at exploring the investors' behaviour on investment decisions, especially on how they behave daily by considering trading volume and its impact on share prices and fluctuation. In other words, this paper focuses the study on the relationships between market returns, market volatility and aggregate trading volume. It is expected to find information on how investors use the trading volume or volume change or the price movements and the volatility of the market.

This research, then, attempts to answer the following questions. Firstly, how and to what extent do investors use the trading volume as the sources of information on trading that affect returns? Secondly, to what extent are trading volume and volatility important to influence price movements? Thirdly, to what extent does trading volume influence the market volatility?

To answer those questions, this research employs the following variables. Market daily returns derive as the difference in the logarithms of stock index levels. Volatility is generated as the squared daily returns. Trading volume, on the other hand, is represented by several operating variables. Firstly, trading volume is defined as the nominal values of trading. Secondly, trading volume is also represented as the logarithm of trading volume. The use of logarithm is to downsize the figures and, at the same time, to reveal the exponential behaviour of trading volume. Thirdly, trading volume variable is represented as the change in the trading volume.

It is important to note that the relationship between return, volatility and volume is well known already (for example, Sabri, 2004). It is recognized too that the market reaction to volatility is different according to the direction of the volatility. Volatility represents risk, and market risk is considered as one of speculative risks. By definition, speculative risk means that the market movement may affect investors positively if the movement is in favour to the interest of investors, or negatively if the movement is against the interest of investors. In some cases, investors react differently to the different risk sides.

For that reason, this research employs TARCH (thresholds autoregressive conditional heteroskedasticity) model. This is in accordance with previous studies in order to allow changes in volatility and to reveal their asymmetric effects on market returns (Bierens, 1993; Kim and Schmidt, 1993; Schwaiger, 1995; Faff and McKenzie, 2007).

Based on the aforementioned arguments, the basic questions to be answered are as follows: firstly, is there any relationship between market return and trading activity after the economic crisis 1998? Secondly, is there any relationship between market volatility and trading activity after the economic crisis 1998? Thirdly, how do traders use conditional volatility on the trading activities?

This study indicates that the increase (decrease) in trading volume or activities encourages the increase (decrease) in return. An active market tends to attract traders into the market to trade causing the price to increase, while lower market activity tends to encourage market price to decrease. In relation to volatility – volume, this study indicates that trading volume still considerably has value on explaining the behaviour of volatility. The magnitude of explanation, however, is quite low. Traders prefer more to employ past volatility and behave accordingly than to employ trading volume.

This paper is organized as follows. The first section is introduction. The following section describes previous studies related to return – volume and volatility-volume relationship. This is then followed by the proposed models and hypotheses. The next section elaborates data employed in this study and their analysis. This paper is closed with the conclusion.

## PREVIOUS STUDIES

Some studies suggest that market returns and trading volume indicate various factors (Lamoureux and Lastrapes, 1990; Chowdury *et al*. 1993; Hrazdil, 2009). They focus the study on the relationship between returns and trading volume at market level. Some researchers also attempt to explore various trading volume against market return, such as foreign trading against market return and block or large trading volume against market return. The purpose is, basically, to extract the information contained in such a trading type

that may influence investor of a market as a whole. The behaviour of investors, as a result, encourages price or index movements or returns.

The argument saying that trading volume matters has been supported by several studies. Some studies focus solely on the volume as a determinant factor of price movement (Kymaz and Girard, 2009; Andersen, 1996; Easley *et al*. 1996). Trading data reflect the underlying information structure. On days when good news dominates the market, more buys are expected. This eventually encourages higher demand and, hence, price increase. On days with dominant bad news, on the other hand, more sells are expected. This, in turn, encourages the price to move down. Some others employ volume among other factors that influence the price movements. Rompotis (2009), for example, finds that volume together with expenses and risks have relationship with price premium and trading activity.

Market trading volume also reflects some proxy, including liquidity, momentum, and information (Brown, 2009). Liquid market, expressed by low trading volume as well as frequency, encourages investors to demand high premium. In other words, they ask for low price, with the expectation that they may be able to sell at high price, to obtain high return. In that sense, the relationship between market return and trading volume is negative.

In terms of information, traders may distinguish private and public information. Sometimes they have different confidence on those types of information (Lin *et al*. 2010). Without distinguishing the types of information sources, some studies clearly identify that trading volume may indicate the flow of information, and the flow of information encourages price changes (Copeland, 1977; Amihud and Mendelson, 1991; Brailsford, 1994; Nawrocki, 1996). Note that the information extracted by traders may diverse, depending on the ability of traders to treat the

data (Choi *et al*. 2009). The magnitude of price change depends on the quality of information content in the trading volume.

Some researchers propose the adverse selection model of trading (Glosten and Milgrom, 1985; Easly and O'Hara, 1987, 1992). They propose that certain traders bring new information and reveal certain characteristics of transaction. Those informed traders tend to trade on one side. At times when they have good news, they conduct to buy while at times when they have bad news they conduct to sell stocks. They also tend to trade in a large volume to exploit the opportunity or to avoid loss. They do this because they bear costs in processing public information into private information. Other traders, i.e. non-informed or free riders, tend to trade in small volume of transaction, and trade randomly. They just follow what large traders do.

Some informed traders, however, avoid transacting large trades because they want to keep their private information from free riders (for example, Admati and Pjeiderer, 1988, 1989; Foster and Vismanathan, 1994). In fact, at least there are two ways of hiding private information, i.e. through timing and trading size. Under a timing strategy, informed traders may choose to transact under a low total transaction volume. Under a size strategy, informed traders may transact on several consecutive days for every single stock. As an alternative, they may buy or sell portfolio, assuming that each portfolio contains small faction of each stock. At the end of the day, the total trading conducted by informed traders is large.

Informed traders continue to trade until all information is reflected in the price, or when the price reaches its equilibrium. However, they may not come to the consensus due to the different interpretation of information. Under this case, price equilibrium may be slow to reach. The wider the interpretation of information, the wider is the diversity of trading be-

haviour. This will result in another factor, i.e. the width of spread (Copeland, 1977).

The pricing and its forecast may improve gradually depending on the information arrival to the market. The smooth, fast, flow of information helps market participants to review their knowledge and forecast on every stock. The revision of the stock price will certainly move the market as a whole. Gemmil (1994) suggests the gradual improvement in forecast based on the speed of publication. The earlier information becomes public, the quicker traders learn and adjust the forecast.

Others believe that the relationship takes place between trading volume change against price change. However, this relationship may be complicated because the change in trading volume depends on whether the market movement is under selling pressure or buying pressure. Selling pressure of trading normally takes place under bearish condition, while buying pressure takes place under bullish condition. If trading volume increases due to the large investors willing to sell stocks, the price tends to decrease. This represents the increase of stock supply at the constant or even declining demand. On the other hand, if the trading volume increases because many investors want to buy stocks, the price tends to increase. This represents the significant increase in stock demand while the stock supply is constant.

To avoid problem of identifying the relationship between trading volume and price movement on either buying or selling pressure, one solution is to identify the existence of the relationship between the absolute of price change against trading volume. The purpose is to find whether trading volume encourages price movements whatever the direction of the price movement.

However, the behaviour is different for liquid stocks or market. Liquidity is related to ability to trade stocks easily with low cost and without significant impact on the market as a

whole. This is also known as asset liquidity. Asset liquidity is represented by trading speed, trading cost or spread, price impact, and trading volume (Amihud and Mendelson, 1991; Brown *et al.* 2009).

As the two relationships, i.e. return - trading volume and volatility – trading volume, are affected by momentum or timing, it is also known that those relationships may change as the time goes by. There are many factors that influence the dynamics of those relationships, such as the change in regulation, government regime, competition, technology applied to the stock market, etc. This is one reason why some studies employ certain period of time, of conduct a stability test before conducting research with a long period data.

## RESEARCH METHOD

Assume that a trader is an informed trader. S/he has some choices suitable for him/her. S/he may trade on one stock with large volume, or many stocks with low volume for each stock. S/he also can transact index, stock portfolio. Depending on the type of information, s/he will trade on a certain side, either buy side or sell side. No matter the trade size, his/her, his/her persistence in trading causes the trading volume increases significantly. This model follows the argument that total trading volume matters because the total volume may reflect the information contained in each transaction (see Andersen, 1996; Easly *et al.* 1996).

Following Andersen (1996), a joint dependence of return and volume applies on an underlying latent event or information variable. In a price discovery process, traders arrive to the market sequentially and in a random, 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 uniform valuation and low buy-sell spread. In other words, price

discovery phase is followed by an equilibrium phase. Volume and volatility of stock price are driven by similar mechanism.

Under the aforementioned argument, the proposed hypotheses are based on: market anticipation hypothesis and sequential informed trading hypothesis. Under the market anticipation hypothesis, it is argued that the ability of traders to predict future events can be applied to specific firm with market-wide scope. Traders are assumed to acquire ability to collect information that may influence market movement. As markets become more globalized, the traders need to collect domestic as well as foreign data of market factors.

There are two possibilities the way traders interpret information: optimistic and pessimistic. The interpretations depend on the quality of data and the ability to process the data. The market anticipation hypothesis does not explain how traders extract information from data. Instead, the hypothesis focuses on the argument that the trend of market price is the net impact of the optimistic and pessimistic forecast of all traders. As long as the traders tend to agree their interpretation on data to become information, the market movement tends to be less volatile and, in effect, the price reaches the equilibrium more quickly.

The sequential informed trading hypothesis assumes that the ability of traders to extract information from data diverse. This implies that some traders may extract information in advance and move to the market more quickly, while other traders work on the interpretation and forecast. In this case, traders enter the market in different point in time. In addition, every time a trader enters the market, other traders employ this movement as an additional data to be processed to extract private information.

The other traders, i.e. less on non-informed traders monitor the movement of informed traders. They may be market makers, liquidity traders, or free riders. They enter the

market in different point in time depending on their attitude toward risk and their own timing. However, there is no chance for them to enter the market prior to the best informed traders. In other words, it is possible for market makers, liquidity traders, and free riders to enter the market at same time with the second best informed traders, the third best informed traders, and so on. It is also conclusive to say that the last traders must be one of uninformed traders.

Under those basic hypotheses, the following are the hypothesis building for this research.

**Return–Volume Relationships**

Kim *et al*. (2006) develop a return–volume model from a simple model based on the direct relationship between return and volume (Epps, 1975; Copeland, 1977; Campbell *et al*. 1993). However, the relationship may be in two possibilities: negative or positive relationships between the two variables. Those studies add the quadratic form of trading volume as an independent variable and this gives a positive relationship with market return. However, this relationship does not give significant information to explain such a relationship.

Other studies attempt to exploit the magnitude of trading volume against price movement. They find that the increase in volume is higher when it is accompanied by the increase in price than by the decrease in price (for example, Epps, 1975; Lakonishok and Smidt, 1986). Other studies attempt to distinguish buying-pressure trading from selling-pressure trading. As expected, price decrease is accompanied by selling-pressure while price increase is accompanied by buying-pressure (Chan and Lakonishok, 1993; Gemmill, 1994; Keim and Madhavan, 1996)

Based on those arguments, it is important to extract the importance of information contained in the past and current trading volume

as well as past returns in relation to price movements.

Hypothesis 1: Past and current market volume are significantly related to current share price.

The equation becomes as follows:

$$\text{Re turn}_t = a + \sum_{i=1}^{n} b_i \, \text{Re turn}_{t-i} +$$

$$\sum_{j=0}^{m} c_j \text{Volume}_{t-j} + \sum_{k=1}^{4} d_k D_k +$$

$$\sum_{l=0}^{o} f_l \sigma_{i-l} + e_t \tag{1}$$

$$\sigma_t^2 = \omega + \sum_{j=1}^{q} \beta_j \sigma_{t-j}^2 + \sum_{i=1}^{p} \alpha_i \varepsilon_{t-i}^2 +$$

$$\sum_{k=1}^{r} \gamma_k \varepsilon_{t-k}^2 I_{t-k} + \zeta_t \tag{2}$$

With $I_t = 1$ if $\varepsilon_t < 0$ and 0 otherwise.

The variables of the above equations are as follows. Return is the daily market return. It is defined as the change in daily market index, i.e.

$$\text{Re turn}_t = \frac{\text{Index}_t}{\text{Index}_{t-1}} \tag{3}$$

The use of the lag variables, $\text{Return}_{t-i}$, is to extract the information contained in the previous trading days. Some investors, either informed traders 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. Basically there are two ways of representing volume variable, i.e. nominal value of trading volume and as the natural logarithm of the value. The main purpose of applying natural

logarithm, in this study, is merely to scale down the figure.

Variables $D_k$ represent daily dummy variables. Because there are five trading days within a week, this study employ four daily dummy variables. These variables are to extract the difference in trading behaviour and characteristics on daily basis.

The last independent variable, i.e. $\sigma_t$ or daily volatility, attempts to extract the impact of daily volatility to return. Together with the equation (2), the volatility may become a source of information explored by traders. They may behave differently in terms of trading decisions in high versus low volatility times.

In addition, equation (2) employ TARCH (Threshold Autoregressive Conditional Heteroskedasticity) model. This follows previous implementation of ARCH and its variance process (Bierens, 1993; Kim and Schmidt, 1993; Schwaiger, 1995; Kim *et al.* 2006). The use of TARCH process is to improve the efficiency of the volatility in equation (1). The use of conditional variance, $h^2$, is because conditional variance changes through times and it violates the homeoskedasticity assumption. The use of TARCH is to catch the asymmetric effect of information on traders' behaviour, i.e. to negative and positive information. Such differences will be captured by coefficients on equation (2), especially by $\gamma_t$.

Note that the implementation of equation (2) depends on the ability of traders to extract information from variance. As long as they believe the quality of information in the variance, equation (2) will be employed accordingly. Furthermore, equation may employ other regressor such as the trading volume. It is because sometimes traders do not only concern with the variance based on its past variance but also the trading activity. In this case, an independent variable needs to be added in equation (2).

In relation to the volume–return relationships, it is expected that volume positively effects return.

**Volatility–Volume Relationship**

Some studies support the existence of the volatility-volume relationship (among others: Epps, 1975; Smirlock and Starks, 1988, Amihud and Mendelson, 1991; Blume *et al.* 1994). Following previous studies, Yen and Chen (2010) attempts to evaluate the relationship between volatility and total trading volume. They add open interest as a factor under scrutiny. They tend to agree that trading volume contains noise that increases the volatility of prices. Furthermore, the use of volatility ignores the types of trading pressures, i.e. selling and buying-pressures. In either case, the increase in trading volume encourages in the high movement in price or volatility.

Based on the above argument, the second hypothesis is as follows:

Hypothesis 2: Current and past trading volume influence current market volatility

The equations to represent this hypothesis are as follows:

$$\text{Volatility}_t = a + \sum_{i=1}^{n} b_i \text{Volatility}_{t-i} +$$

$$\sum_{j=0}^{m} c_j \text{Volume}_{t-j} + \sum_{k=1}^{4} d_k D_k +$$

$$\sum_{l=0}^{o} f_l \sigma_{i-l} + e_t \qquad (4)$$

$$\sigma_t^2 = \omega + \sum_{j=1}^{q} \beta_j \sigma_{t-j}^2 + \sum_{i=1}^{p} \alpha_i \varepsilon_{t-i}^2 +$$

$$\sum_{k=1}^{r} \gamma_k \varepsilon_{t-k}^2 I_{t-k} + \zeta_t \qquad (5)$$

There are two ways of expressing volatility of daily returns. The first is in terms of absolute value returns. The second is in terms of the squared returns.

The use of past volatility in equation (4) is because traders may behave to previous price fluctuation before considering other variables, such as volume. In this case, one expects $b_i$'s are significant. The length of the lags depends on how fast traders react to the volatility. One also expects that volume positively influences market volatility.

## DATA AND ANALYSIS

As explained in the beginning, this study focuses on the period outside crisis. It is well known that economic crisis hit Indonesia and other countries severely in year 1997. The effect of crisis remained devastating until year 1999. Therefore, it is safe to start the analysis from January 1st 2000. It is also well known that economic crisis hit Indonesia again as the contagion effect of sub-prime mortgage crisis in the United States of America. The crisis started in mid-2008 and strongly influenced most industries and also capital market in Indonesia. For this reason, this study employs December 31st 2007 as the end period. The total data from January 1st 2000 to December 31st 2007 are more than 1,500.

The Jakarta Composite Index and trading volume data are taken from yahoo.com. The Jakarta Composite Index consists of all stocks traded in Indonesia Stock Exchange (previously Jakarta Stock Exchange). The index accommodates the change in stocks registered in those indices (Pinfold and Qiu, 2007). One should be careful in using yahoo.com. It is because the data source only records data with trading activity. For that reason, there are many missing working dates within the period employed. Therefore, the time series is scrutinized line by line and fill in the missing dates with the data. As a common practice, any missing data are filled with the data from previous day for indices and with zero for trading volume.

This study employs the closing index. It is based on an assumption that all information coming to the market are reflected immediately into the price on the same day. The closing price, therefore, reflected all information available. Any event taking place overnight is accommodated into next day's price.

### Return – Trading Volume

Table 1 shows the results of two main regressions processed with Eviews program with maximum 500 iterations. The first regression results, as shown in columns (2) and (3), applies to the return as the dependent variable and conditional variance, lags of return, and the value of trading volume as regressors. The second regression results, as indicated in columns (4) and (5), applies to the return as the dependent variable and conditional variance, lags of return, and the natural logarithm of value of trading volume as regressors. Both regressions use TARCH (1,1) as their variance equations. In relation to the treatment of time series data, this study applies the stationary test to the residuals. Heteroskedasticity and colinearity also apply to the residuals of regressions. Some measures used include Durbin-Watson Statistic.

Both regressions employ a quite long lags of return and volume. The use of 20 lags is to capture responds to monthly fluctuation on returns. The use of 5 lags, or one week lags, is to capture the days of the week effect. 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.

**Table 1.** The regression of Return on conditional variance, lags, and trading volume with TARCH model for variance equation

Dependent Variable: Return

| Main Equation | | | | |
|---|---|---|---|---|
| Independent Variable | Note: [Volume] is represented by [Trading Value] | | Note: [Volume] is represented by Ln[Trading Value] | |
| $\sigma^2$ | -0.056 | | 0.023 | |
| C | 0.003 | | -0.001 | |
| $Return_{t-1}$ | 0.132 | *** | 0.148 | *** |
| $Return_{t-2}$ | -0.019 | | -0.017 | |
| $Return_{t-3}$ | 0.022 | | 0.027 | |
| $Return_{t-4}$ | 0.028 | | 0.018 | |
| $Return_{t-5}$ | -0.016 | | -0.021 | |
| $Return_{t-10}$ | -0.020 | | -0.020 | |
| $Return_{t-15}$ | -0.028 | | -0.035 | ** |
| $Return_{t-20}$ | 0.019 | | 0.030 | |
| $Dum_1$ | -0.004 | *** | -0.004 | *** |
| $Dum_2$ | -0.002 | * | -0.002 | ** |
| $Dum_3$ | -0.002 | ** | -0.002 | ** |
| $Dum_4$ | -0.002 | ** | -0.002 | ** |
| $Volume_t$ | 1.13E-12 | | 0.0002 | ** |
| $Volume_{t-1}$ | -1.48E-12 | | -0.0002 | ** |
| $Volume_{t-2}$ | 2.97E-12 | ** | -4.76E-05 | |
| $Volume_{t-3}$ | -4.67E-14 | | 8.31E-05 | |
| $Volume_{t-4}$ | -9.47E-13 | | 1.81E-05 | |
| $Volume_{t-5}$ | 9.91E-13 | | 0.0002 | |
| Variance equation | | | | |
| C | 3.11E-05 | *** | 3.51E-05 | *** |
| $\varepsilon_{t-1}^2$ | 0.014 | | 0.019 | |
| $\varepsilon_{t-1}^2$ x $\varepsilon(-1)<0$ | 0.240 | *** | 0.283 | *** |
| $\sigma_{t-1}^2$ | 0.677 | *** | 0.620 | *** |

Notes: Significance: *** at 1%, ** at 5%, and * at 10%

Both main regressions indicate that conditional variances do not really influence the market returns. This is indicated by the coefficients of $\sigma^2$ that are not significantly different from zero. This conclusion is supported by the fact that the coefficient of the first regression tends to be negative while the coefficient of the second regression tends to be positive. This inconsistence leads to the inconclusive relationship between return and conditional variance.

The first lag of return, or $Return_{t-1}$, consistently and significantly influences the current return. The coefficient is significantly different from zero at 1% significance level. The positive coefficient, which is consistent in both main regressions, indicate that yester-

day's return is perceived as having certain information that is valuable to be carried to the next day. The positive coefficients indicate that yesterday's return encourage the movement of current return to the same direction. The higher yesterday's return, the higher is current return.

This kind of amplification must have a limit. Otherwise, there is an error correction or price reversal. It is assumed that price trend reverses after certain period because of noise or mispricing. In other words, price redemption exists to avoid excessive bubble. This is the reason for this study to employ longer lags, i.e. to identify the length of which the return reversal or redemption takes place.

The main regressions shown in Table 1 indicate that price reversal tends to take place at the next two trading days. This is indicated by negative coefficients of $Return_{t-2}$ even though the coefficients are not significantly different from zero. Furthermore, current return also has negative relationship with $Return_{t-5}$, $Return_{t-10}$, and $Return_{t-15}$. Those negative coefficients at least an indication that traders tend to correct price on the basis of prices from the same days of previous week, previous two weeks, and previous three weeks. The main regression that employs $Ln[Volume_{t-i}]$ as an independent variable gives a stronger message on the traders' behaviour concerning the price reversal issue. The significant coefficient (at 5% significant level) is an indication that traders really reverse the price based on the last three weeks price trend.

Both main regressions indicate similar information on how traders behave in trading activities. Hypothesis 1 says that "Past and current market volume are significantly related to current share price". Column (2) of Table 1 shows that only coefficient of $Volume_{t-2}$ is positive and significantly different from zero at 5% significance level. Based on column (4), $Volume_t$ has positive coefficient and $Volume_{t-1}$ has negative coefficient, and both are significantly different from zero at 5% significant

level. Before those models are chosen, several models with longer lags of volume have been tested. The longest lag is $Volume_{t-20}$. However, lags more than a week do not improve statistical indicators, such as maximum likelihood, Akaike information criteria, and Schwarz criteria. Instead, longer lags of volume seem to indicate autocorrelation that affect the coefficient of determinant.

The signs of coefficients of $Volume_t$ and $Volume_{t-1}$ are consistent for both main models. The coefficients of $Volume_t$ are positive, while the coefficients of $Volume_{t-1}$ are negative. Note that $Volume_t$ is the trading volume within a trading day, i.e. from opening until closing transaction. As returns are calculated based on closing price, this means that $Volume_t$ takes place prior to closing price.

Positive and significant coefficient of $Volume_t$ quite strongly indicate that the increase (decrease) in trading volume or activities encourage the increase (decrease) in return. Under an active market, in which trading volume within a day increases, traders may think that the market is getting more attractive and, as a response, more traders come into the market to transact. This increases buying pressure. As a result, prices are pushed to go up and, as a consequence, return increases.

On the other hand, at times when trading activities decrease, traders may think that the market is not attractive any longer. Some traders start to retreat from the market. As a result, buying pressure decreases, prices move more slowly, and the return becomes lower. On one extreme, prices decrease at times when trading activities or trading volume decrease.

The negative coefficients of $Volume_{t-1}$ suggest that the impact of trading shock today on price is immediately corrected in the next day. Traders may realize that trading volume contains noise. As a result, price reverses in the next day. Traders attempt to eliminate random price movement once they realize that the information content in the trading volume is

overvalued. However, the fact that the coefficient of the first main regression is not significant may indicate that traders do not always revise their pricing as an effect of trading activities.

The significance level at 5% of the coefficients of Volume$_t$ and Volume$_{t-1}$ leads to cautious interpretation of the return – volume relationships. As mentioned before, the price movements may be different between buying and selling-pressures. In general, the increase in trading volume under buying pressure tends to increase the price while the increase in trading volume under selling pressure tends to push the price down. The period of year 2000 to 2007 is dominated by buying period. It is due to the recovery period of Indonesia economy. For this reason, it is not surprising that trading volume gives positive impact on price movements. In certain period, selling pressures may take place. However, these events are less dominant within the period under study than buying pressure events.

It is important to briefly put some note on the variance regression. Both models show that the threshold components of TARCH are positive and different from zero at 1% significant level. These strong significance levels suggest the existence of different response made by traders on positive from negative information. Traders respond more strongly on negative information than on positive information for the equal level of information content.

**Volatility–Trading Volume**

Tables 2 and 3 show the results of regressions of volatility on trading volume. In Table 2, the volatility is represented by absolute value of return or Abs[Return]$_t$. In Table 3, the volatility is represented by the squared return, or [Return$_t$]$^2$. In both models, the two types of volume, i.e. the Value of trading volume, or Volume$_t$, and the natural logarithm of trading value, or Ln[Volume$_t$], are employed.

Note that there is a very significant difference between models shown in Table 2 and models shown in Table 3. Models in Table 2 employ TARCH model as the variance equation. These models are the best on the basis of several statistical criteria, such as homoeskedasticity, error stationary, Durbin Watson, maximum likelihood, Akaike information criteria, and Schwarz criteria compared to other models that have been tested before choosing these models.

The models also apply Mean-ARCH, by inserting conditional variance as an independent. This is to extract information contained in the error component to the volatility of the market return. Similar to the application to return-volume as explained above, the variance is conditional because this variable may change as the time goes by. This is in relation to the implementation of the variance equation.

This study also evaluates the use of volume variable as a variance regressor. However, the use of such variable does not improve the power of the models. Instead, some statistical indicators are worse than those without variance regressor. As a consequence, TARCH model is implemented without any variance regressor.

Models shown in Table 3, however, do not fit with variance equation model. It is based on several statistical indicators, such as $R^2$ and Durbin Watson statistics. For that reason, conditional variance as an independent variable in the main equation and the variance equation are dropped from the model. Other variables, however, are still applicable to the models.

All models presented in Tables 2 and 3 indicate the existence of autocorrelation. This is why the use of lags on those four models is properly applicable. Those models show that the coefficients of lags one to three are significantly positive at 1% and 5% significant levels. These strongly suggest the influence of past volatility behaviour on current behaviour.

They indicate that past volatilities are positively related to current volatility. If the volatility increases (decreases) in the last three days, the current volatility most probably increases (decreases) too.

The coefficients of Volatility$_{t-5}$ and Volatility$_{t-10}$ also give an indication on how traders respond to the past volatility with longer pe-

riod. As shown in Table 2, the significance of the coefficient of Volatility$_{t-10}$ shown in column (2) and (3) are different. In column (2), the coefficient is positive and different from zero at 5% significance level. In column (3), on the other hand, the coefficient is positive but not significantly different from zero.

**Table 2.** The regression result of volatility–volume relationships with Abs[Return$_t$] as dependent variable

| Main Equation | | | | |
|---|---|---|---|---|
| Independent Variable | Note: [Volume] is represented by [Trading Value] | | Note: [Volume] is represented by Ln[Trading Value] | |
| $\sigma^2$ | 0.612 | *** | 0.216 | |
| C | -0.0003 | | 0.004 | |
| Abs[Return$_{t-1}$] | 0.060 | ** | 0.089 | *** |
| Abs[Return$_{t-2}$] | 0.089 | *** | 0.069 | ** |
| Abs[Return$_{t-3}$] | 0.074 | *** | 0.053 | ** |
| Abs[Return$_{t-4}$] | 0.038 | | 0.011 | |
| Abs[Return$_{t-5}$] | 0.028 | | 0.028 | |
| Abs[Return$_{t-10}$] | 0.044 | ** | 0.021 | |
| Abs[Return$_{t-15}$] | 0.003 | | 0.034 | |
| Abs[Return$_{t-20}$] | -0.0105 | | 0.006 | |
| Dum$_1$ | 0.002 | *** | 0.002 | *** |
| Dum$_2$ | 0.0002 | | 0.0004 | |
| Dum$_3$ | 0.001 | ** | 0.001 | ** |
| Dum$_4$ | 0.0008 | | 0.001 | |
| Volume$_t$ | 1.02E-12 | | 0.0001 | |
| Volume$_{t-1}$ | -1.30E-12 | | -7.46E-05 | |
| Volume$_{t-2}$ | 1.87E-12 | * | -1.03E-05 | |
| Volume$_{t-3}$ | -4.76E-13 | | -6.02E-05 | |
| Volume$_{t-4}$ | -4.21E-13 | | -4.80E-05 | |
| Volume$_{t-5}$ | 2.44E-13 | | 2.31E-05 | |
| Variance equation | | | | |
| C | 2.04E-05 | *** | 9.21E-06 | *** |
| $\epsilon_{t-1}^2$ | 0.150 | *** | 0.141 | *** |
| $\epsilon_{t-1}^2 \times \epsilon(-1)<0$ | 0.050 | | -0.024 | |
| $\sigma_{t-1}^2$ | 0.600 | *** | 0.763 | *** |

Notes: Significance: *** at 1%, ** at 5%, and * at 10%

**Table 3:** The regression result of volatility–volume relationships with $[\text{Return}_t]^2$ as dependent variable

| Independent Variable | Main Equation | | | |
|---|---|---|---|---|
| | Note: [Volume] is represented by [Trading Value] | | Note: [Volume] is represented by Ln[Trading Value] | |
| C | 7.84E-05 | *** | 0.0001 | |
| $[\text{Return}^2]_{t-1}$ | 0.068 | *** | 0.059 | ** |
| $[\text{Return}^2]_{t-2}$ | 0.149 | *** | 0.178 | *** |
| $[\text{Return}^2]_{t-3}$ | 0.088 | *** | 0.095 | *** |
| $[\text{Return}^2]_{t-4}$ | -0.004 | | -0.019 | |
| $[\text{Return}^2]_{t-5}$ | 0.052 | ** | 0.064 | *** |
| $[\text{Return}^2]_{t-10}$ | 0.039 | * | 0.026 | |
| $[\text{Return}^2]_{t-15}$ | -0.006 | | 0.004 | |
| $[\text{Return}^2]_{t-20}$ | -0.031 | | -0.030 | |
| $\text{Dum}_1$ | 0.0001 | *** | 9.97E-05 | *** |
| $\text{Dum}_2$ | 6.43E-06 | | -2.69E-06 | |
| $\text{Dum}_3$ | 4.16E-05 | | 3.51E-05 | |
| $\text{Dum}_4$ | 1.99E-05 | | 1.00E-05 | |
| $\text{Volume}_t$ | 3.54E-14 | | 2.63E-06 | |
| $\text{Volume}_{t-1}$ | -2.78E-14 | | -1.41E-06 | |
| $\text{Volume}_{t-2}$ | 4.65E-14 | | 5.82E-07 | |
| $\text{Volume}_{t-3}$ | -1.70E-14 | | 2.29E-07 | |
| $\text{Volume}_{t-4}$ | -2.59E-14 | | -2.64E-06 | |
| $\text{Volume}_{t-5}$ | -9.96E-15 | | -7.61E-07 | |

Notes: Significance: *** at 1%, ** at 5%, and * at 10%

The coefficients of Volatility$_{t-5}$ and Volatility$_{t-10}$ shown in Table (3) are different. The coefficients of Volatility$_{t-5}$ are positive and significantly different from zero at 5% significant level for the first model and at 1% significant level. The coefficients of Volatility$_{t-10}$ are positive for both models and significantly different from zero at 10% significant level for the first model but not significantly different from zero for the second model.

Those results at least indicate the following information. Firstly, traders at least consider daily volatilities within a week, until 5 lags, to make the decision on transaction. The volatilities within a week positively influence traders on the pricing. The higher (lower) the daily volatilities within a week, the higher (lower) are the spread of interpretation on price because the price interpretation by traders is more (less) diverse.

Secondly, traders still consider the volatilities the same days within the last two weeks, as indicated by the coefficients of Volatility$_{t-5}$ and Volatility$_{t-10}$. Positive coefficients suggest that traders tend to follow the volatilities within the last two weeks. In practical terms, under the condition that market prices are very volatile, traders have very diverse interpretation on the volatility. As a result, price movement keeps volatile and this takes place until at least two weeks.

As one reason of volatility is the diverse information interpreted by traders, traders

cannot find other information to reduce the diversity within two weeks. This encourages the trading becomes more volatile. On the other hand, if the volatility is low, the interpretation of information among traders tends to converge. This becomes an important source of information utilized by traders to convince themselves that the market prices are at nearly true values. Therefore, their pricing tends to be similar from one to another.

## CONCLUSIONS

This study attempts to investigate the relationships of market return and volatility against trading volume. The analysis focuses on the Indonesian Stock Exchange for the period of after economic crisis until before sub-prime mortgage crisis, i.e. from year 2000 to 2007. It is expected that Indonesia capital market has a significant change from its condition before the crisis. In terms their relationships, traders are expected to deploy information contained in trading volume more wisely after crisis.

The study of return–volume and volatility–volume needs to consider the use of ARCH–autoregressive conditional heteroskedasticity–and its derivatives because there is a possibility that variances influence the return and volatility behaviour. Considering that traders may behave differently to positive and negative information, it is appropriate to employ TARCH–thresholds autoregressive conditional heteroskedasticity–to extract and to accommodate that asymmetric behaviour 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.

Besides the conditional variances and trading volume, the use of the lags of dependent variables in the models is very important. Such a use is quite common for time series data, especially for stock price and return. This study proves that the use of the lags is statistically viable for both return and volatility. For Indonesia Stock Exchange, lag of ten days is still considerably important for traders to be taken care of in the analysis. The use of lags reveals the price reversal at the next two trading days.

In terms of return–volume relationships, there is a quite strong indication that the increase (decrease) in trading volume or activities encourages the increase (decrease) in return. An active market tends to attract traders into the market to trade. Within the period under study, they influence the buying pressure more strongly than selling pressure that push the price up. When trading activities decrease, traders may think that the market is not attractive any longer. This encourages selling pressure that leads to prices to go down.

Traders tend to respond and to correct market price quickly based on current and yesterday's trading volume. While current trading volume change encourages the price movement at the same direction, yesterday's trading volume change leads traders to re-evaluate and correct the price. There is a possibility that traders realize their overreaction to the information contained in the trading volume. The correction on the next day indicates that the way they manage information is significantly efficient.

In terms of volatility–volume relationships, the use of Abs [Return$_t$] seems to be slightly better than [Return$_t$]$^2$. This study reveals that trading volume still considerably has value on explaining the behaviour of volatility. The magnitude of explanation, however, is quite low. Traders prefer more to employ past volatility and behave accordingly than to employ trading volume.

Apart from the evidence that return–volume hypothesis is proven to be accepted and volatility–volume hypothesis cannot be accepted, it is important to note that the coefficient of determinants for all models are considerably low, i.e. less than 10%. This indi-

cates that the use of independent variables in the model is not enough. There must be other information to be considered to improve the power of explanation of the models. Those information, mainly public information, need to be identified and accommodated into the models to improve the ability of traders to explain the return and volatility behaviour. By doing so, traders may have weapon to beat the market. This is a next interesting topic to be explored.

## REFERENCES

Admati, A., and P. Pfleiderer, 1988. "A Theory of Intraday Petterns: Volume and Price Volatility". *Review of Financial Studies,* 1, 3–40.

Amihud, Y., and H. Mendelson, 1991. "The Volatility, Efficiency, and Trading: Evidence from the Japanese Stock Market". *The Journal of Finance,* 46 (5), 1765–1789.

Andersen, T. G., 1996. "Return Volatility and Trading Volume: AN Information Flow Interpretation of Stochastic Volatility". *The Journal of Finance,* 51 (1), 169–204.

Bierens, H. J., 1993. "Higer-Order Sample Autocorrelation and Unit Root Hypothesis'. *Journal of Econometrics,* 57, 137–160.

Blume, L., D. Easly, and M. O'Hara, 1994. "Market Statistics and Technical Analysis: The Role of Volume". *The Journal of Finance,* 49 (1), 153 – 181.

Brailsford, T. J., 1994. "The Empirical Relationship Between Trading Volume, Returns, and Volatility". University of Melbourne. Available at: 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, accessed December 11th 2010.

Brown, J. H., D. K. Crocker, and S. R. Foster, 2009. "Trading Volume and Stock Investments". *Financial Analysts Journal,* 65 (2), 67 – 85.

Campbell, J. Y., S. J. Grossman, and J. Wang, 1993. "Trading Volume and Serial Correlation in Stock Returns". *The Quarterly Journal of Economics,* 108 (4), 905 – 939.

Chan, L. K., and J. Lakonishok, 1993. "Institutional Trade and Intraday Stock Price Behaviour". *Journal of Financial Economics,* 33, 173 – 199.

Choi, W., K. Hoyem, and J. W. Kim, 2009. "Analyst Forecast Dispersion, Trading Volume, and Stock Return". *Seoul Journal of Economics,* 22 (2), 263 – 287.

Chowdury, M., J. S. Howe, and J. C. 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,* 12 (4), 563 – 578.

Easley, D., and M. O'Hara, 1987. "Price, Trade Size, and Information in Securities Markets". *Journal of Financial Economics,* 19, 69 – 90.

Easely, D., and M. O'Hara, 1992. "Adverse Selection and Large Trade Volume: The Implication for Market Efficiency". *Journal of Financial and Quantitative Analysis,* 27 (2), 185 – 208.

Easley, D., N. M. Kiefer, M. O'Hara, and J. B. Papermen, 1996. "Liquidity, Information, and Infrequently Trade Stocks". *The Journal of Finance,* 51 (4), 1405 – 1436.

Epps, T.W., 1975. "Security Price Changes and Transaction Volume: Theory and Evidence". *American Economic Review,* 65, 586 – 597.

Faff, R. W., and M. D. McKenzie, 2007. "The Relationship between Implied Volatility

and Autocorrelation". *International Journal of Managerial Finance,* 3 (2), 191 – 196.

Foster, F. D., and S. Vismanathan, 1994. "Strategic Trading with Asymmetrically Informed Traders and Long-Lived Information". *Journal of Financial and Quantitative Analysis,* 29 (4), 499 – 518.

Gemmil, G., 1994. "Transparency and Liquidity: A Study of Large Trades on the London Stock Exchange under Different Publication Rules", research paper, Office of Fair Trading, London, 7.

Girard, E., and M. Omran, 2009. "On the Relationship between Trading Volume and Stock Price Volatility in CASE". *International Journal of Managerial Finance,* 5 (1), 110 – 134.

Glosten, L., and P. Milgrom, 1985. "Bid, Ask, and Transaction Prices in a Specialist Market with Heterogeneously Informed Traders". *Journal of Financial Economics,* 14 (1), 77 – 100.

Hrazdil, K., 2009. "The Price, Liquidity, and Information asymmetry Changes Associated with New S&P 500 Additions". *Managerial Finance,* 35 (7), 579 - 605

Keim, D. B. and A. Madhavan, 1996. "The Upstairs Market for Large-Block Transactions: Analysis and Measurement of Price Effects". *The Review of Financial Studie*s, 9 (1), 1 – 36.

Kim, J., A. Kartsaklas, and M. Karanasos, 2006. "The volume–volatility relationship and the opening of the Korean stock market to foreign investors after the financial turmoil in 1997". *Asia-Pacific Financial Market,* 12 (3), 245 - 271

Kim, K., and P. Schmidt, 1993. "Unit Root Test with Conditional Heteroskedasticity". *Journal of Econometrics,* 59 (3), 287 – 300.

Kymaz, H., and E. Girard, 2009. "Stock Market Volatility and Trading Volume:

AN Emerging Market Experience". *IUP Journal of Applied Finance,* 15 (6), 5 – 32.

Lakonishok, J., and S. Schmidt, 1986. "Volume for Winners and Losers: Taxation and other motives for Stock Trading". *The Journal of Finance,* 41 (4), 951 – 974.

Lamoureux, C. G., and W. D. Lastrapes, 1990. "Heteroskedasticity in Stock Return Data: Volume versus GARCH Effects". *The Journal of Finance,* 45 (1), 221 – 229.

Lin, C. Y., H. Rahman, and K. Yung, 2010. "Investor Overconfidence in REIT Stock Trading". *Journal of Real Estate Portfolio Management,* 16 (1), 9 – 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 M. Qiu, 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,* 15 (7), 24 - 39

Smirlock, M., and L. Starks, 1988. "An Empirical Analysis of the Stock Price – Volume Relationship". *Journal of Banking and Finance,* 12, 31 – 41.

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 M. H. Chen, 2010. "Open Interest, Volume, and Volatility: Evidence from Taiwan Futures Markets". *Journal of Economics and Finance,* 34 (2), 113 – 141.