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The Empirical Relationship between Stock Return and Trading Volume based on Stock Market Cycles

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In this paper, we analyze the empirical relationship between stock return and trading volume based on stock market cycles. Using daily data for Jakarta Composite Index (JCI) closing price and trading volume from 2010 to 2014, we identify the bull and bear phases, then we analyze the return–volume relationship in both contemporaneous and dynamic context. We find that (1) there is a positive contemporaneous return–volume relationship in both bull and bear markets, which is only significant in bull markets; (2) no evidence of asymmetry in contemporaneous relationship is found; and (3) there exists a positive unidirectional causality from stock return to trading volume. Our research has two implications. First, in the bull market, overconfidence may grow with long-lasting past success and there is also momentum or positive feedback trading. Second, stock return is able to forecast trading volume. In addition, our findings are robust for different sample period and data frequency.

Keywords: *Stock return; Trading volume; Stock market cycles; Contemporaneous relationship; Dynamic relationship; Markov switching; Granger causality*

JEL classification: G12; C32

Introduction

In finance, there exists a long history of stock return predictability. It is important for making decision of portfolio allocation and for understanding the risk–return trade off and market inefficiency as well. Therefore, enormous literature have documented that stock returns are predictable by economic variables such as dividend-price rations, nominal interest rates, etc. Although there is still some controversy on the predictability of stock return, the prevailing tone in the literature is that stock return have a predictable component (Zhu & Zhu, 2013).

Based on market folklore, it is generally believed that trading volume is positively associated with stock return (Chen, 2012). There are much literature investigating contemporaneous correlation between stock return and trading volume. Harris and Gurel (1986) examines the daily data for price changes and trading volume of 479 common stocks from 1976 to 1977 and finds that price changes is positively associated with trading volume. The same result is founded by Richardson, Sefcik, and Thompson (1987) who investigate the weekly data of 106 common stocks from 1973 to 1982. Furthermore, Karpoff (1987) shows that trading volume is positively correlated with the magnitude of price changes.

However, since the 1990s, the focus has moved to dynamic (causal) correlation between

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stock return and trading volume. In other words, studies have started to examine the causal relation by asking questions such as, "does volume help forecast stock return" or "do investors trade more when prices goes up"? In general, bivariate vector autoregressive (VAR) models and Granger causality tests are applied in most studies investigating the dynamic return–volume relation (Chen, 2012). Some examples are the following.

Using the daily data for trading volume and stock return of three stock markets (New York, Tokyo, and London), Lee and Rui (2002) find that trading volume does not Granger-cause stock return. In addition, Statman, Thorley, and Vorkink (2006) examine the NYSE/AMEX monthly data from 1962-2001 and show that trading activity is positively related to lagged returns for many months. Using data from six Latin American markets, Saatcioglu and Starks (1998) fail to find strong evidence of stock price changes leading to volume changes, yet they find that volume seems to lead to stock price changes. Furthermore, Chuang, Kuan, and Lin (2009) use quantile regressions to investigate the causal relations between stock return and volume. They show that causal effects of volume on return are usually heterogenous across quantiles and those of return on volume are more stable.

In contrast to previous studies, Chen (2012) examines whether the return–volume relation differs during different phases of stock market cycles (bull and bear markets). According to Chen (2012), there are two intuivite reasons for questioning such an asymmetric relation. First, cyclical variations in stock returns are widely reported in the literature. Second, as the return–volume relation reflects the structure of financial markets, and various factors (such as how investors behave) may change in bull and bear markets, we should expect that the return–volume relation would also change across different phases of market cycles.

Using monthly data for S&P 500 price index and trading volume from 1973M2 to 2008M10, Chen (2012) finds that in regard to contemporaneous correlation, return and volume are negatively (positively) correlated in bear (bull) markets. Furthermore, the asymmetric contemporaneous return–volume relation is statistically significant. In regard to dynamic correlation, strong evidence that stock return is able to forecast volume in both and bear markets is found. On the other hand, the evidence regarding the information content of trading volume to forecast stock return is weaker because its forecastability is found only in bear markets.

In this paper, we investigate the return–volume relation in Indonesia stock market by using the daily data of JCI closing price and trading volume from 2010 to 2014. According to Tran (2016), emerging stock markets generally provide investors with relatively high returns compared to developed markets. It is due to the fact that emerging economies have developed rapidly after undertaking many important reforms including financial liberalization.The financial liberalization helped these markets to integrate into the world capital market and hence, promoted a sharply increase in capital inflows which resulted in positive consequences to the economic growth (Bekaert & Harvey, 2000). However, a surge of capital inflows may lead to asset price bubbles (Kim & Yang, 2009). Hence, the high returns in emerging stock markets may imply the presence of bubbles. In fact, during 1990s, many financial crises have been witnessed in emerging markets, such as the Mexican financial crisis in 1994 or the Asian crisis in 1997. Although they did not have global effects as strong as the subprime crisis in the United States in 2007, their consequences were very severe (Tran, 2016).

Following Chen (2012), we first use Markov-switching models to identify the bull and bear regimes in the stock market and contemporaneous return–volume relation. Then, we examine its possible asymmetry by using Wald test. Finally, using bivariate VAR model and Granger causality test, we investigate the dynamic (causal) return–volume relation. We would like to know if lagged volume (lagged return) is able to predict stock return (trading volume). According to Chen (2012), there are two reasons as the motivation for investigating return–volume relation in dynamic context. First, it is important to know if trading volume provides

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useful information content that would improve stock return forecasts. Second, it is also of interest to ask if investor trade more when market have done well in the past. As argued in Griffin, Nardari, and Stulz (2007), answering such a question may help in obtaining forecasts of trading intesity, and devising efficient trading strategies.

Literature Review

Karpoff (1987) shows the strong evidence of a positive correlation between trading volumes and changes in prices in the US equity market. Mixture of Distribution Hypothesis (MDH) and Sequential Information Arrival Hypothesis (SIAH) attempt to explain the relationship between those two variables. The MDH is proposed by Clark (1973) and it indicates the securities' return is drawn from a joint distribution of volume prices conditional on the current information. Prices and trading volume changes are driven by the same underlying information arrival process. Hence, volume and volatility are correlated. Andersen (1996), Gallo and Pacini (2000), Kim and Kon (1994), and Lamoureux and Lastrapes (1990) find evidence in support of a contemporaneous volume volatility relation from the U.S. stock market. First, there is no conditional volatility on volume and the failure to indicate volatility persistence after including volume. Second, Fong (2003) and Xu, Chen, and Wu (2006) argue that MDH model do not allow for serial dependence in return volatility and volume.

SIAH (Copeland 1976) assumes that new information is disseminated sequentially to the informed and uninformed traders. Dissemination of information flow sequentially causes return to be able to predict trading volume and vice versa, which imply bidirectional causality between volume and volatility. Brooks (1998), Campbell, Grossman, and Wang (1993), and Hiemstra and Jones (1994) also find the presence of bidirectional Granger causality between volume and volatility. However, Gallant, Rossi, and Tauchen (1992) and Silvapulle and Choi (1999) only find Granger causality from volume to volatility in US and Korean stock markets. Furthermore, Lee and Rui (2002) find trading volume do not Granger-cause return in Chinese and Japanese market respectively.

Statman et al. (2006) use monthly data from the NYSE/AMEX and provide evidence that trading activity is positively related to lagged returns for many months. Xu et al. (2006) use time-consistent VAR model to test the dynamic return volatility-volume relationship, and find that volatility and volume are persistent and highly correlated with past volatility and volume.In addition, Pisedtasalasai and Gunasekarage (2007) investigate the dynamic relationship among the stock returns, volatility and trading volume in five emerging stock market and find that returns can predict trading volume and trading volume has very limited impact in predicting stock returns. Furthermore, Kumar, Singh, and Pandey (2009) investigate the nature of relationship between price and trading volume for Indian stock market and show that there is a weak dynamic relationship between stock returns and trading volume.

Bheenick and Brooks (2010) examine the Austrilian market and find that there exists a positive return–volume relation. Focusing on the level of trading volume and thin trading in the market, their results suggest that trading volume does seem to have strong predictive power for high volume firms and in certain industries of the Australian market. However, it does not apply for smaller firms. Louhichi (2011) investigate the relationship between volume and volatility on Euronext in France exchange to determine which component of trading volume (trade size or number of transactions) drives this relation for the CAC40 Index as well as for individual stocks. First, it is confirmed there is a strong positive relationship between volume and volatility. Second, including volume in the conditional variance of stock returns significantly reduces the persistence of volatility. Third, it is showed that the well-known positive relationship between volatility and volume is generated by the number of trades.

Chuang, Liu, and Susmel (2012) investigate the contemporaneous and causal relationship between stock returns and trading volume and find that there is significant correlation in major Asian stock markets. Furthermore, by employing various econometric tests, Azad, Azmat, and Edirisuriya (2014) provide strong evidence of South-Asian market inefficiency. This finding extracts the evidence of legal cases manipulation period and the analysis of price–volume relationship. The first argument is that a price increase accompanied by a high volume is an indication of bullish sentiments. Second, a price decline accompanied by volume is an indication of bearish sentiments. Their study draws the regulators' attention to the need for appropriate reforms in order to prevent market manipulation in these markets. Such manipulations harm public confidence in capital markets and prevent their growth and development. In addition, Gebka and Wohar (2013) analyze the causality between past trading volume and index returns in the Pacific Basin countries. Nevertheless, their OLS results indicate no causal link between trading volume and returns.

In contrast to previous studies, Chen (2012) examines whether the return–volume relation differs during different phases of stock market cycles (bull and bear markets). According to Chen (2012), there are two intuivite reasons for questioning such an asymmetric relation. First, cyclical variations in stock returns are widely reported in the literature. See Perez-Quiros and Timmermann (2000) for example. Hence, it is empirically evident that nonlinear models of the stock return with switches across bull and bear market regimes fit the data better than do linear models. Second, as the return–volume relation reflects the structure of financial markets, and various factors (such as how investors behave) may change in bull and bear markets, we should expect that the return–volume relation would also change across different phases of market cycles. For instance, in a bull market, overconfidence may grow with long-lasting past success in the market, which would result in a strong positive return–volume correlation.

Using monthly data for S&P 500 price index and trading volume from 1973M2 to 2008M10, Chen (2012) finds that in regard to contemporaneous correlation, return and volume are negatively (positively) correlated in bear (bull) markets. Furthermore, the asymmetric contemporaneous return–volume relation is statistically significant. In regard to dynamic correlation, strong evidence that stock return is able to forecast volume in both and bear markets is found. On the other hand, the evidence regarding the information content of trading volume to forecast stock return is weaker because its forecastability is found only in bear markets.

In this paper, our hypotheses based on empirical results of previous studies by Chen (2012) are as follows:

Return–volume contemporaneous relationship based on stock market cycles

H_0 : There is positive (negative) relationship between return and volume in bear (bull) markets.

H_{1a} : There is negative relationship between returns and volume in bear markets. ($\beta_0 < 0$)

H_{1b} : There is positive relationship betwee returns and volume in bull markets. ($\beta_1 > 0$)

Asymmetric return–volume contemporaneous relationship in bull and bear markets

H_0 : There is no asymmetric contemporaneous correlation between return and volume in bull and bear markets. ($\beta_0 = \beta_1$)

H_2 : There is asymmetric contemporaneous correlation between return and volume in bull and bear markets. ($\beta_0 \neq \beta_1$)

Return–volume dynamic relationship

H_0 : Return (volume) is not able to predict volume (return)

H_{3a}: Return is able to predict volume

H_{3b}: Volume is able to predict return

Research Methods

Data

We use the daily JCI closing price and trading volume from 2010 to 2014, all of which are collected from Datastream database. The sample period is chosen in order to exclude the global financial crisis period. First of all, unit root test are conducted to investigate whether these series are stationary. Because of the non-stationarity property of the closing price and

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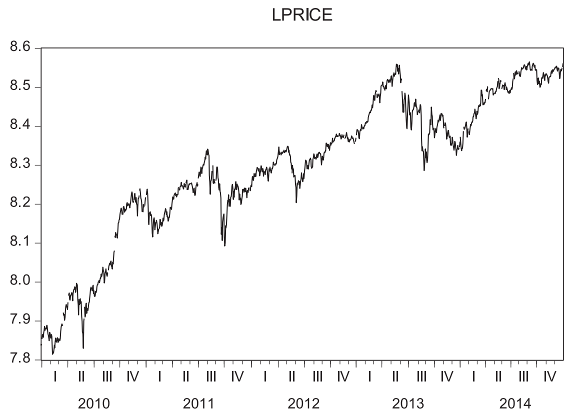

Figure 1. Closing price JCI (in Log)

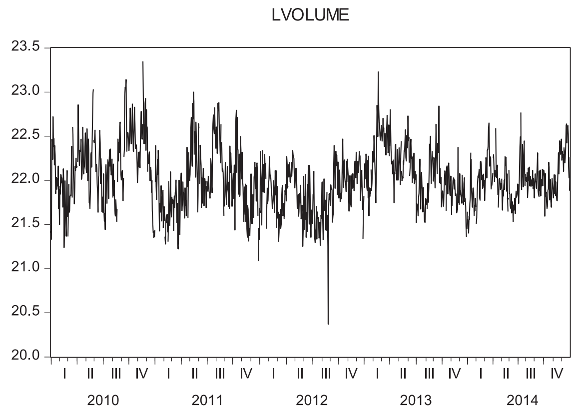

Figure 2. Trading volume JCI (in Log)

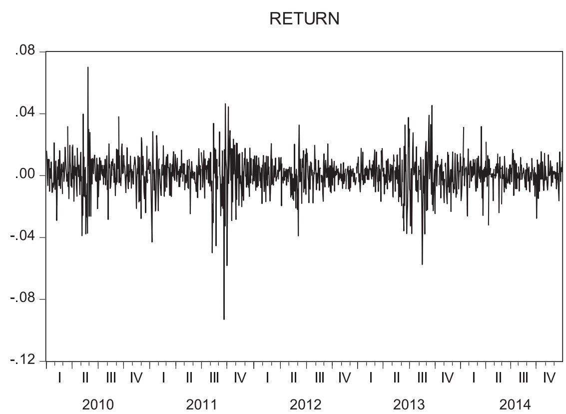

Figure 3. Return JCI

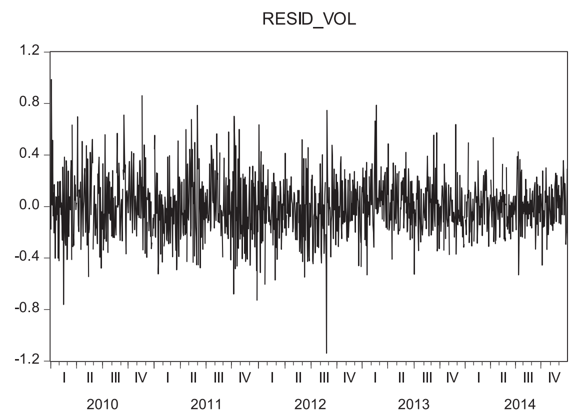

Figure 4. Unexpected volume JCI

trading volume series, in this paper we consider stock return (r_t) calculated as follows:

$$r_t\text{-}\log(p_t/p_{t-1}) \tag{1}$$

and unexpected volume (v_t) estimated from the following model:

$$\log(V_t) = \alpha+\beta_t V_{t-1}+\theta_t v_{t-1}+v_t \tag{2}$$

The results of Augmented Dickey-Fuller (ADF) test are reported in Table 1. From 2010 to 2014, the increasing trend is observed in closing price JCI (Figure 1), whereas high volatilty is reflected in trading volume JCI (Figure 2). We can also see from the graphs that the stock return (Figure 3) and unexpected volume (Figure 4) series are stationary.

Models

Following Chen (2012), several models are used to analyze the empirical relationship between stock return and trading volume based on stock market cycles. Before investigating the return–volume relation, we identify the bull and bear phases in Indonesia stock market using a two-state Markov autoregressive switching model of stock return of order q (MS-AR(q)). According to Maheu and McCurdy (2000) and Perez-Quiros and Timmermann (2000), the high-return stable and low-return volatile states in stock return are conventionally labeled as bull markets and bear markets, respectively.

$$\varphi(L)r_t = \mu_{s_t} + \beta_{s_t}v_t + \epsilon_t,$$
$$\epsilon_t \sim \text{i.i.d.}\mathcal{N}\left(0,\sigma_{s_t}^2\right) \tag{3}$$

Where $\varphi(L) = 1-\varphi_1 L-\varphi_2 L^2-\ldots-\varphi_q L^q$ and L is the lag operator. Term μ_{s_t} and $\sigma_{s_t}^2$ are the state-dependent mean and the variance, respectively. The unobserved state variable s_t is a latent dummy variable set at either 0 or 1. Stock return are assumed to follow a two-state Markov process with a fixed transition probabilities matrix:

$$P = \begin{bmatrix} p^{00} & 1-p^{11} \\ 1-p^{00} & p^{11} \end{bmatrix},$$

where $p^{00} = P(s_t = 0|s_{t-1} = 0)$ and
$vp^{11} = P(s_t = 1|s_{t-1} = 1)$

Then, we can investigate the return–volume relation. We also estimate both the linear model (random walk model) and Markov switching model to show the superior performance of a Markov switching model over a linear model in fitting stock return data. According to Chen (2012), we use two models with several adjustments: (1) MS-AR(q) and Wald test and (2) bivariate VAR model and Granger causality test. We use MS-AR(q) and Wald test to investigate the return–volume contemporaneous relationship based on stock market cycles plus its possible asymmetry, with the following model:

$$\varphi(L) r_t = \mu_{s_t} + \beta_{s_t} v_t + \epsilon_t, \quad \epsilon_t \sim \text{i.i.d.}\mathcal{N}\left(0, \sigma^2_{s_t}\right) \tag{4}$$

where r_t = JCI return at time t and r_t = unxpected volume of JCI at time t. Term μ_{s_t} and $\sigma^2_{s_t}$ are the state-dependent mean and the variance, respectively. The unobserved state variable s_t is a latent dummy variable set at either 0 or 1. We also use bivariate VAR model and Granger causality test to invetigate the return–volume dynamic relationship, with the following model:

$$r_t = \mu + \Sigma_{i=1}^{k} \varphi_i r_{t-i} + \Sigma_{i=1}^{k} \lambda_i v_{t-i} + \varepsilon_t, \quad \varepsilon_t \sim \text{i.i.d. } N(0,\sigma^2) \tag{5}$$

$$v_t = \mu + \Sigma_{i=1}^{k} \phi_i r_{t-i} + \Sigma_{i=1}^{k} \theta_i v_{t-i} + \eta_t, \quad \mu_t \sim \text{i.i.d. } N(0,\sigma^2) \tag{6}$$

where r_t = return JCI pada periode t, r_{t-1} = return JCI pada periode t-i, v_t = unexpected volume JCI pada periode t, v_{t-i} = unexpected volume JCI pada periode t-i, and k is the lag length.

Results and Discussions

Model Comparison: Linear versus Markov-switching

Following Chen (2012), we also estimate both the linear model (random walk model) and Markov switching model (MS-AR(0)) to show the superior performance of a Markov switching model over a linear model in fitting stock return data. The estimation results of random walk and MS-AR(0) models are shown in Table 1 column (1) and (2), respectively. Performance of a model can be measured from its log-likelihood value, which will be used to calculate its likelihood ratio (LR). According to Garcia (1998), LR test follows the chi-square distribution with critical values = 14.02 at α = 1%. Obviously, the LR value = 1,153.44 and significant at the 1% level. This finding is consistent with Chen (2012), which means that H_0 (linear model has superior performance) is rejected, and MS-AR (0) model, which has superior performance, is used to analyze the return–volume relationship in this paper.

Return–Volume Contemporaneous Relationship

Linear Setting

As shown in Table 1 column (3), the return–volume correlation is statistically positive (β > 0). This finding is inconsistent with Chen (2012), yet consistent with Lee and Rui (2002), who use Generalized Method of Moments (GMM) and daily data to analyze the return–volume contemporaneous relationship in U.S., Japan, and U.K. stock markets. However, we should notice that the results from linear regressions are sensitive to the sample period chosen. Therefore, we will conduct robustness test for different sample period in the next section.

Based on Stock Market Cycles

In this section, we first identify the stock market cycles using MS-AR(3) model. Information critera is used to determine the optimal lag length. As shown in Table 1 colum (4), where unexpected volume is included as the regressor, MS-AR(3) model identifies bear markets regime (μ_0= -0.002 and σ_0= 0.020) and bull markets regime (μ_1 = 0.001 and σ_1= 0.008) well, consistent with the characteristics of bear

Table 1. Contemporaneous relationship

	(1)	(2)	(3)	(4)
Intercept	-0.001		**0.001***	
	(-0.012)		(1.650)	
Mean (bear)		-0.002		**-0.002***
		(-1.329)		(-1.724)
Mean (bull)		**0.001*****		**0.001*****
		(4.362)		(5.850)
Variance (bear)		**0.021*****		**0.020*****
		(-64.885)		(-68.842)
Variance (bull)		**0.008*****		**0.008*****
		(-147.316)		(-152.295)
Return t-1			0.039	
			(1.355)	
Return t-3				**-0.118*****
				(-4.021)
Unexpected Volume			**0.008*****	
			(5.269)	
Unexpected Volume (bear)				0.002
				(0.186)
Unexpected Volume (bull)				**0.010*****
				(8.173)
LogLikelihood	3287.69	**3864.41**	3700.83	3897.72

Note: t-stat and z-stat are in parentheses.

and bull markets identified by Maheu and McCurdy (2000) and Perez-Quiros and Timmermann (2000). In addition, this finding is also supported by Figure 5. The smoothing probabilities of bull markets regime fits the movement of return (Figure 3.) well. For instance, from 2012 to 2013 the return volatility is relatively low (Figure 3.) and it is identified as bull markets regime in Figure 5. Furthermore, from the transition probabilities (Appendix 2), it is obvious that bull markets regime is more persistent than bear markets regime. Bull markets on average last for $1/(1-p^{11}) = 1/(1-0.98) \approx 42$ days, whereas bear markets on average last for $1/(1-p^{00}) = 1/(1-0.91) \approx 11$ days.

Next, we analyze the return–volume contemporaneous relationship. Based on Table 1 column (4), it is obvious that the return–volume correlation is positive in both bull and bear markets. Consistent with Chen (2012), that positive correlation is statistically significant in bull markets. According to Chen (2012), two reasons for this finding are as follows. First, in the bull market, overconfidence may grow with long-lasting past success in the market, which would result in a strong positive return–volume correlation. For instance, Hong, Scheinkman, and Xiong (2006) have shown that overconfidence can lead to a stock market bubble with heterogenous beliefs and short-sales constraints. Second, momentum or positive feedback trading (buy high and sell low) may also cause a positive return–volume relation under short-sales constrains. However, generally, momentum investing is based on the belief that an extended bull market is in effect. Hence, we would expect a positive correlation between price changes and volume in a bull market.

On the other hand, we find a statistically insignificant positive correlation between return and volume in bear markets, which is inconsistent with Chen (2012). We argue that the possible explanation for this finding is the opposite of Chen (2012) explanation. The main characteristic of the bear market is that the stock price increases while trading volume decreases. Chen (2012) finds a statistically significant negative correlation between return and volume in bear markets and argues that the driving foce behind stock price changes is reduction in supply, rather than increases in demand. Thus, the return–volume correlation is negative. It is contrast with our finding, which indicates that the driving force behind stock price changes is increases in demand by investors with contrarian strategy.

Furthermore, we also investigate whether there is asymmetric return–volume contemporaneous relationship in bull and bear markets by conducting Wald test. Based on Appendix

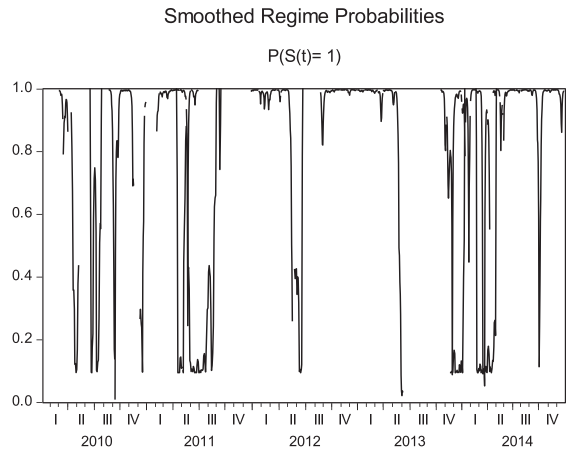

Figure 5. Smoothing Probabilities Bull Markets Regime

1, we cannot find asymmetric return–volume contemporaneous relationship in bull and bear markets. This result is inconsistent with Chen (2012), who finds asymmetric return–volume contemporaneous relationship in bull and bear markets. We argue that there are of some contrarian investors in bear markets, thereby increasing demand andeventually, stock price. Hence, our finding indicates there are positive return–volume contemporaneous relationship in both bull and bear markets.

Return–Volume Dynamic Relationship

In this section, we analyze the return–volume dynamic relationship by using bivariate VAR model and Granger causality test. The estimation results are shown in Table 2, where column (1) represents the return equation (equation 3) and column (2) represents the volume equation (equation 4). Consistent with Clark (1973), Lee and Rui (2002), and Tauchen and Pitts (1983), we find that unexpected volume does not Granger-cause return (p-value (1) > α = 0.05), while return Granger-causes unexpected volume (p-value (2) < α = 0.05). Hence, we can conclude that stock return is able to predict trading volume (H_{3a}), but not vice versa. Our argument is based on MDH and SIAH. Trading volume does not represent return-related information directly, but through the return volatility. This indicates that information available in market is not perfect, thereby causing trading volume cannot predict stock return. The return-volume relationship is seen as "it is related to the role of information in price formation..." (Wiley & Daigler, 1999). On the other hand, return is the result of combination of perfect information in the market. That is why we find strong evidence that stock return is able to predict trading volume.

Investors' motive to trade is solely dependent on their trading activity; it may be to speculate on market information or portfolios diversification for risk sharing, or else the need for liquidity. These different motives to trade are a result of processing different available information. In consequence, trading volume may originate from any of the investors who may have different information sets. As various studies reported, the information flow into the market is linked to the trading volume and volatility (see Gallant et al. (1992)).

Accordingly, since the stock return changes when new information arrives, there exists a relation between prices, volatility and trading volumes (see He & Wang (1995) and Lamoureux & Lastrapes (1990)). Since there is a stock-return relationship, it proves that stock return contains information to predict trading volume. As the rational investor behavior, especially at the bull condition, where investor trying to keep getting returns in bad economic condition, especially in emerging market country, as one of it, Indonesia. At the bull condition, where the market and condition of economic cannot be predicted, stock returns is the best predictor for investor to getting information in the market than another predictor (fundamental and technical analysis).

However, we should notice that these results are sensitive to the sample period chosen. Therefore, we will conduct robustness test for

Table 2. Dynamic Relationship: Granger causality test

	(1)	(2)
χ-stat	8.424	**17.716*****
p-Value	0.134	0.003

Table 3. Robustness Tests: Contemporaneous Relationship

	(1)	(2)
Mean (bear)	**-0.002****	0.003
	(-2.184)	(0.0892)
Mean (bull)	**0.002*****	**0.028*****
	(6.266)	(57.445)
Variance (bear)	**0.026*****	**0.044*****
	(-85.275)	(-27.736)
Variance (bull)	**0.009*****	**0.001*****
	(-187.167)	(-23.494)
Return t-1	0.040	
	(1.951)	
Return t-4		**-0.154*****
		(-21.173)
Unexpected Volume (bear)	0.003	0.006
	(1.302)	(0.596)
Unexpected Volume (bull)	**0.004*****	**0.160*****
	(4.877)	(83.267)

Notes: z-stat is in parentheses

different sample period in the next section.

Robustness Tests

In this section, we consider several modifications to check the robustness of our main empirical results. First, we use different sample period (2006-2014). Second, we also use different of data frequency (monthly).

Sample Period: 2006-2014

Table 3 column (1) shows the regression results using daily data from 2006 to 2014. MS-AR(1) model is used to investigate the return–volume contemporaneous relationship in bull and bear markets.We find that the return–volume correlation is positive in both bull and bear markets, but only statistically significant in bull markets. By conducting Wald test, we also find that there is no asymmetric return–volume contemporaneous relationship in bull and bear markets. In regard to dynamic relationship, the regression results are shown in Table 4 column (1) and (3). Without considering the stock market cycles, we find that unexpected volume does not Granger-cause return, while return Granger-causes unexpected volume. In other words, stock return is able to predict trading volume, but not vice versa. These results are similar to our main empirical results. Therefore, our main empirical results are robust to different sample period.

Data Frequency: Monthly

Table 3 column (2) shows the regression results using monthly data from 2010 to 2014. MS-AR(3) model is used to investigate the return–volume contemporaneous relationship in bull and bear markets.We find that the return–volume correlation is positive in both bull and bear markets, but only statistically significant in bull markets. In contrast with one of our main empirical results, we find that there is asymmetric return–volume contemporaneous relationship in bull and bear markets. This is probably caused by insufficient numbers of observations. There are 1224 observations when the daily data is used, whereas only 60 observations when the monthly data is used. In regard to dynamic relationship, the regression results are shown in Table 4 column (2) and (4). Without considering the stock market cycles, we find that unexpected volume does not Granger-cause return, while return Granger-causes unexpected volume. In other words, stock return is able to predict trading volume, but not vice

Table 4. Robustness Tests: Dynamic Relationship

	Return Equation		Volume Equation	
	(1)	(2)	(3)	(4)
χ-stat	6.383	2.0040	24.645***	4.429**
p-value	0.604	0.1567	0.002	0.035

versa. These results are not substantially change from our main empirical results. Therefore, our main empirical results are robust to different data frequency.

Conclusions

In this paper, we use Markov switching autoregressive model and bivariate VAR model to analyze the empirical relationship between stock return and trading volume based on stock market cycles. Using daily data for the JCI closing price and trading volume from 2010 to 2014, we identify the bull and bear phases in Indonesia stock market, then we analyze the return–volume relationship in both contemporaneous and dynamic context. We find that (1) there is a positive contemporaneous return–volume relationship in both bull and bear markets, which is only significant in bull markets. These kind of information which represented by stock return, proving us related to the anomaly effect (such as Monday effect) happen because there is still insider investor whose have special information than others investor which influencing trading volume in the stock market. In other words, information created by stock return does not the real information needed by the investor, especially when there is bull market. Where there is bull market, there will only some investor which gaining benefit from these kind of information (using stock return) or other word the stock return is not a good predictor for trading volume especially for bull market; (2) no evidence of asymmetry in contemporaneous relationship is found; and (3) there exists a positive unidirectional causality from stock return to trading volume. Our research has two implications for Indonesian stock market. First, regarding contemporaneous relationship, in the bull market, overconfidence may grow with long-lasting past success and there is also momentum or positive feedback trading. Second, regarding dynamic relationship, stock return is able to forecast trading volume. In addition, our findings are robust for different sample period and data frequency.

For further research, we suggest to analyze the crisis (for example, the 2008 global financial crisis) effect on return-volume relationship. It is important because many financial crises which have been witnessed in emerging markets (Tran, 2016). It is also interesting to include all ASEAN countries stock indexes (regarding the ASEAN Economic Community implemented in 2016) and compare the results with each other to know if there is any differences related to stock return or trading volume forecastability.

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Appendix

Appendix 1. Transition Probabilities

Equation: CONTEMP_MS_AR3_CHOSEN
Date: 12/06/15 Time: 17:59
Transition summary: Constant Markov transition probabilities and expected durations
Sample (adjusted): 1/07/2010 12/30/2014
Included observations: 1221 after adjustments

Constant transition probabilities:
P(i, k) = P(s(t) = k | s(t-1) = i)
(row = i / column = j)

		1	2
1		**0.976300**	0.023700
2	0	.091941	**0.908059**

Constant expected durations:

	1	2
	42.19480	**10.87657**

Appendix 2. Wald Test

Wald Test:
Equation: CONTEMP_MS_AR3_CHOSEN

Test Statistic	Value d	f	Probability
t-statistic 0	.820236	1212	**0.4122**
F-statistic 0	.672787 (	1, 1212) 0	.4122
Chi-square	0.672787 1	0	.4121

Null Hypothesis: C(2)=C(5)
Null Hypothesis Summary:

Normalized Restriction (= 0)	Value S	td. Err.
C(2) - C(5)	0.008447 0	.010298

Restrictions are linear in coefficients.

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