Dynamic relationship between stock return, trading volume, and volatility in the Stock Exchange of Thailand: does the US subprime crisis matter?

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Abstract:

Using daily data from 2004 to 2015, this paper attempts to examine the relationship between return, volume and volatility in the Thai stock market. The main findings are that trading volume plays a dominant role in the dynamic relationships. Specifically, trading volume causes both return and return volatility when the US subprime crisis is taken into account. The results may give understanding on how investors make their trading decisions that can affect portfolio adjustment.

Keywords: Stock return, trading volume, volatility, VAR, subprime crisis

JEL Classification: G15, G14

1. Introduction

In previous empirical studies, the relationship between return and trading volume has been widely investigated in both well-developed and emerging stock markets.[1] Earlier studies emphasize the contemporaneous relationship between price changes and trading volume in the stock markets (Gallant et al., 1992, among others). In addition, there is an assertion that there is causal relationship between price changes and trading volume. Theoretically, there are competing models that explain why this notion exists. The sequential information arrival model asserts that the new information does not disseminate to all market participants at the same time. Therefore, lagged trading volume contains information that is useful in predicting current stock return and lagged stock return contains information that is useful in predicting current trading volume (Copeland, 1976, Jennings et al, 1981). Therefore, there should be at least a unidirectional causality between stock return and trading volume. The mixture of distribution model asserts that there should be a unidirectional causality running from trading volume to stock return (Epps and Epps, 1976). According to this model, trading volume is an important measure of disagreement among participants in the stock market. When new information arrives the stock market, the widening of disagreement occurs. Black (1976) indicates that returns of stocks listed in the Dow Jones industrial average are negatively correlated with volatility. Wang (1994) proposes a rational expectations model that links trading volume to stock price volatility under asymmetric information. Therefore, empirical studies emphasize the dynamic relationship between return and trading volume, trading volume and return volatility, and return and its volatility.

For volume-return relationship, Saatcioglu and Starks (1998) find that trading volume causes stock returns, but stock returns do not cause trading volume. Chen et al. (2001) examine the relation between returns, volume and volatility of stock indexes of nine international stock markets. They find evidence of positive correlation between trading volume and the absolute value of stock price change.

[1] Karpoff (1987) gives a thorough review of both theoretical and empirical works pertaining this relationship.

Furthermore, there is bidirectional causality between trading volume and stock returns. Their results also show that volatility is persistent even after accounting for current and lagged volume effects. Chuang et al. (2009) find bidirectional causality between trading volume and stock return with the dominant role of trading volume.

For the relation between trading volume, return and volatility, earlier empirical work of Christie (1982) finds evidence of a negative correlation between volume and volatility. Gallant et al. (1992) find the dominant role of trading volume in the return-volatility relationship. Using both linear and nonlinear causality tests, Brooks (1998) finds evidence of bidirectional causality between trading volume and volatility. Carroll and Kearney (2012) examine the role of trading volumes in a GARCH-based tests of the mixture of distribution hypothesis on firm-level data for 20 largest Fortune 500 stocks. They find that trading volumes and return volatility are positively correlated, and thus the evidence supports this hypothesis. Ong (2015) employs alternative approach rather than traditional linear and nonlinear causality tests, and finds that trading volume plays a dominant role in the dynamic relationship between return and volatility, and between trading volume and volatility for S&P500 stocks.

Some previous studies focus on Asian stock markets. Moosa and Al-Loughani (1995) employ monthly data to examine the price volume relationship in Malaysia, Philippines, Singapore and Thailand. They find evidence of causality running from trading volume to absolute price changes and from price changes to trading volume in these stock markets. In addition, nonlinear and linear causality tests seem to produce the similar results. Using daily data during 1990 and 2004, Pisedtasalasai and Gunasekarage (2007) examine the dynamic relationships among stock returns, return volatility and trading volume for Indonesia, Malaysia, Philippines, Singapore and Thailand. They find that stock returns in these economies are important in predicting their future dynamics as well as those of the trading volume, but trading volume has a very limited impact on future dynamics of stock returns. The trading volume in some markets seems to contain information for predicting future dynamics of return volatility. Gebka (2012) employs daily and weekly data from January 1990 to November 2003 to examine the dynamic relationship between returns, trading volume, and volatility in Hong Kong, Indonesia, Japan, South Korea, Malaysia, Singapore, Taiwan and Thailand, and finds weak evidence indicating that trading volume plays dominant role on return and volatility. Using daily data from January 1990 to June 2008, Lin (2013) investigates the dynamic relationship between returns and trading volume in Indonesia, Malaysia, Singapore, South Korea, Taiwan and Thailand and finds evidence showing that trading volume contains information to predict stock returns in most of the markets, except the case of Singapore. Using daily data of the Culcatta Stock Exchange in India, Bose and Rahman (2015) find that the contemporaneous or lagged trading volume as a proxy for latent information arrival to the market do not adequately convey information to induce traders' view of the desirability to trade.

The present study employs daily data during 2004 and 2015 to examine the dynamic relationship between stock return, trading volume and return volatility in the Thai stock market. The main finding is that trading volume plays an important part in the relationship between volume, return and volatility in the Stock Exchange of Thailand.

2. Data and Preliminary Results

2.1 Data

The dataset comprises the series of daily market and sectoral stock indexes and respective trading volume in the Thai stock market. The data are retrieved from SETSMART website. The period of study ranges from January 3, 2004 to December 30, 2015. There are 2,932 observations. The stock market index is a market capitalization-weighted index while the sectoral stock indexes are the capitalization-weighted equity sector indexes. The return series are the price changes. The trading volumes are expressed in millions of shares. The descriptive statistics are reported in Table 1.

Table 1 Descriptive statistics.

Panel A: Return series.				
	Mean	S. D.	Skewness	Kurtosis
Market	0.199	58.917	-0.230	15.140
Agro-industry	0.092	16.249	-1.369	18.481
Consumption	0.017	5.808	-1.518	28.532
Financials	0.023	8.909	-0.462	13.815
Industrials	-0.001	8.776	-1.665	30.709
Prop & Cons	0.015	6.449	-0.145	13.076
Resources	0.014	11.433	0.279	22.256
Services	0.092	11.590	-2.034	20.325
Technology	0.017	8.663	-0.443	14.655
Panel B: Trading volume series.				
	Mean	S. D.	Skewness	Kurtosis
Market	5341.105	4889.757	3.329	20.623
Agro-industry	101.128	102.111	4.281	38.776
Consumption	50.917	119.981	6.297	61.691
Financials	435.676	336.527	2.463	12.389
Industrials	447.569	634.194	6.030	62.225
Prop & Cons	1598.458	2177.880	6.865	93.266
Resources	241.293	193.011	2.393	13.379
Services	523.479	491.681	2.470	12.120
Technology	700.804	1048.762	8.926	128.958

Note: Prop & Cons stands for property and construction sector.

The descriptive statistics of the stock market return and those of eight sectors show that most of the returns are negatively skewed with excess kurtosis. The kurtosis values indicate that the returns are not normally distributed. For the trading volume, the high trading volumes compared with the market trading volume are those of property and construction, technology, services, industrials and financials. All trading volumes are positively skewed with excess kurtosis.

2.2 Trend and Unit Root Tests

Following Gallant et al. (1992), the trend stationary in trading volume is tested by regressing the series on a time trend and a nonlinear time trend. The test equation is expressed as:

$$TV_t = a + bt + ct^2 + e_t \qquad (1)$$

where TV_t is the raw trading volume and t is a linear time trend and t^2 is a nonlinear time trend. The results of this regression show that Eq. (1) performed quite well since the estimated coefficients of both linear and quadratic time trends are mostly significant at the 1 percent level.[2] As a result, the detrended trading volume is obtained for the market and each equity sector.

[2] The estimated coefficients of the quadratic time trend are not significant for the agriculture and property and construction sectors.

In testing for stationary property of the series, the augmented Dickey-Fuller (ADF) test and the Phillips and Perron (PP) test with constant are used. The results of unit root tests are reported in Table 2.

Table 2 Results of unit root tests.

Panel A: Return series.				
	ADF statistic	p-value	PP statistic	p-value
Market	-15.339 [25]	0.000	-160.875 [563]	0.000
Agro-industry	-19.147 [22]	0.000	-130.467 [492]	0.000
Consumption	-21.277 [22]	0.000	-142.628 [310]	0.000
Financials	-15.677 [25]	0.000	-256.179 [2040]	0.000
Industrials	-20.092 [22]	0.000	-156.213 [346]	0.000
Prop & Cons	-15.310 [25]	0.000	-213.463 [2930]	0.000
Resources	-20.628 [22]	0.000	-167.616 [353]	0.000
Services	-14.842 [25]	0.000	-134.859 [448]	0.000
Technology	-13.812 [25]	0.000	-122.629 [330]	0.000
Panel B. Detrended trading volume series.				
	ADF statistic	p-value	PP statistic	p-value
Market	-5.643 [23]	0.000	-33.784 [28]	0.000
Agro-industry	-7.058 [23]	0.000	-47.926 [27]	0.000
Consumption	-4.765 [27]	0.000	-53.865 [35]	0.000
Financials	-6.193 [20]	0.000	-42.125 [28]	0.000
Industrials	-7.127 [19]	0.000	-30.679 [19]	0.000
Prop & Cons	-4.376 [27]	0.000	-45.074 [28]	0.000
Resources	-7.074 [20]	0.000	-42.824 [26]	0.000
Services	-5.789 [26]	0.000	-41.688 [29]	0.000
Technology	-6.418 [27]	0.000	-42.313 [31]	0.000

Note: Prop & Cons stands for property and construction sector. The number in bracket is the optimal lag length for the ADF test determined by Akaike Information Criterion (AIC) and the optimal bandwidth for the PP test.

The data for returns and detrended trading volume exhibit stationarity property because the null hypothesis of unit root is rejected at the 1 percent level by both the ADF and PP tests. This is the necessary condition for the specified regression to obtain the contemporaneous relationships explained in the next sub-section.

2.3 Contemporaneous Relationships

The relationship between return and trading volume can be estimated by the following regression:

$$V_t = a_0 + b_0 R_t + e_t \qquad (2)$$

where V_t denotes detrended trading volume, and R_t denotes equity return. Eq. (2) is a simple regression. French (1980) and Hui (2005), among others, find evidence supporting the Monday effect. Therefore, the dummy variable that captures the impact of the Monday effect can be included in Eq. (2). However, the estimated coefficient of this dummy variable is insignificant in the relationship.

The estimated coefficient b_0 in Eq. (2) should be positive. The initial results of return-volume relationship are shown in Table 3.

Table 3 Contemporaneous return-volume relationship

	a_0	b_0
Market	-1.346	6.771***
	(-0.019)	(5.725)
Agro-industry	-0.054	0.582***
	(-0.032)	(5.679)
Consumption	-0.030	1.770***
	(-0.016)	(5.571)
Financials	-0.128	5.514***
	(-0.022)	(8.358)
Industrials	-0.004	2.894**
	(-0.001)	(2.362)
Prop & Cons	-0.428	28.672***
	(-0.012)	(5.177)
Resources	-0.025	1.716***
	(-0.008)	(5.975)
Services	-0.371	4.030***
	(-0.047)	(5.908)
Technology	-0.036	2.097
	(-0.002)	(1.016)

Note: Prop & Cons stands for property and construction sector. The number in parenthesis is t-statistic. *** and ** indicate significance at the 1 and 5 percent, respectively.

The results in Table 3 show that all coefficients of the intercept are insignificantly negative. The slope coefficients of most equity sectors are positive and significant at the 1 percent level, except for the coefficient of the industrial sector that is positive and significant at the 5 percent level. The technology sector is the only one sector that exhibits insignificant positive coefficient. For the overall market, the slope coefficient is positive and significant at the 1 percent level. Therefore, it can be argued that there is a significant contemporaneous correlation between return and trading volume in the Thai stock market.

3. Dynamic relationship between returns, volatility and trading volumes

3.1 Market analysis

Empirically, the error distribution of stock returns might not exhibit a constant variance. Therefore, the GARCH model of Bollerslev (1986) that encompasses heteroskedasticity should be suitable. If the positive contemporaneous relationship between trading volume and stock return exists after controlling for nonlinearity of error distribution, the GARCH (1,1) model can be estimated. The model is expressed as:

$$R_t = c_0 + c_1 V_t + \varepsilon_t ,$$

$$\varepsilon_t \approx N(0, h_t), \qquad (3)$$

$$h_t = \alpha_0 + \alpha_1 \varepsilon_t^2 + \beta_1 h_{t-1} + \delta_1 D_t$$

where D_t is the US subprime crisis dummy variable. This dummy variable takes the value of 1 during the crisis and zero otherwise.[3] The crisis is assumed to impose the immediate impact on the Thai stock market. Eq. (3) can detect the positive relationship between return and trading volume along with the return volatility series.

The GARCH (1,1) model expressed in Eq. (3) is first estimated for the stock market and the results are reported in Table 4.

Table 4 GARCH test of contemporaneous relationship

Variable	Estimated coefficient	t-statistic
c_0	-0.034***	-3.663
c_1	0.003***	20.821
α_0	1350.151***	25.303
α_1	0.428***	14.016
β_1	0.270***	10.773
δ_1	1353.115***	14.486
$Q(2)$ = 4.050 (p-value = 0.132)		
$Q^2(2)$ = 4.067 (p-value = 0.131)		
LR statistic = -15945.96		

Note: *** indicates significance at the 1 percent level.

As reported in Table 3, the coefficient of regressing stock market return on trading volume is positive and significant at the 1 percent level. This result confirms contemporaneous return-volume relationship even though the size of the estimated coefficient is much smaller. The result of GARCH model estimation in Table 4 shows that the LR statistic is very large in absolute value. The Ljung-Box statistics reveal that there are no serial correlation and further ARCH effect up to 2 lags. The coefficients of both ARCH and GARCH terms are positive and significant at the 1 percent level. The coefficient of the intercept is positive and significant at the 1 percent level. Furthermore, the sum of both coefficients is 0.698, which is less than 1. This indicates that the return volatility series is stationary. Therefore, the symmetric GARCH (1,1) model is an attractive representation of daily stock return behavior.[4] The coefficient of the US subprime crisis dummy variable is significantly positive and very large, which implies that the US subprime crisis imposes a positive impact on stock return volatility. The plot of the series of return volatility is shown in Fig. 1. In Fig. 1, the volatility is low before the crisis and significantly increased during the crisis. After the crisis, the volatility is decreased, but still larger than the volatility before the crisis.

[3] According to Dooley and Hutchison (2009), the range of the crisis is from February 27, 2007 to the end February 2009.

[4] The asymmetric GARCH model of Nelson (1991) is also estimated, but there is serial correlation in the error term of the mean equation.

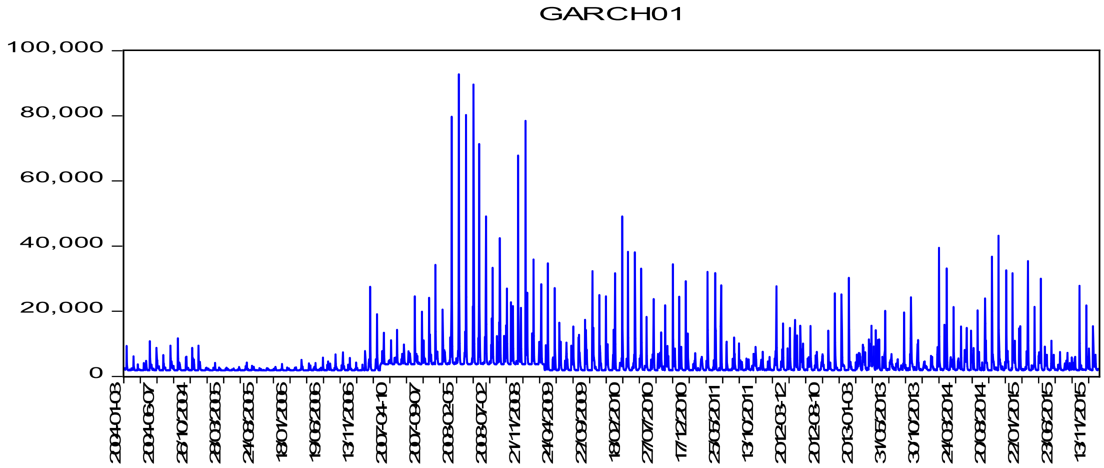

Fig. 1 Stock market return volatility.

The casual relationships among return, volatility and trading volume can be conducted using Granger causality test proposed by Granger (1969). Since all series are stationary, the test is conducted using the least squares method that includes the crisis dummy variable. In addition, the VAR (p) model can be used to examine the relationships among variables. The results of pairwise Granger causality test with the US subprime crisis dummy variable are reported in Table 5.

Table 5 Results of Granger causality test.

Null hypothesis	F-statistic	Coefficient of dummy
$R_t \Rightarrow V_t$	1.275	6.079
	(0.252)	(0.966)
$V_t \Rightarrow R_t$	3.669***	-1.865
	(0.000)	(0.502)
$V_t \Rightarrow VOL_t$	3.156***	2997.431
	(0.003)	(0.000)
$VOL_t \Rightarrow V_t$	1.360	-125..079
	(0.209)	(0.438)
$R_t \Rightarrow VOL_t$	3.574***	2909.652
	(0.000)	(0.000)
$VOL_t \Rightarrow R$	1.173	-5.598*
	(0.312)	(0.078)

Note: VOL_t denotes return volatility. ***, ** and * indicate significance at the 1, 5 and 10 percent, respectively. The null hypothesis is that one variable does not cause another variable.

The results in Table 5 show causality between each pair of variables. The first pairwise causality is that stock market return does not Granger causes trading volume, but trading volume Granger causes stock market return. This implies that stock return does not precede trading volume, but trading volume precedes stock market return.[5] However, the US subprime crisis does not affect these causal relationships. For the pairwise causality between trading volume and return volatility, return volatility does not Granger cause trading volume, but trading volume causes return volatility. The US subprime crisis strongly affect this pairwise causality in one direction, i.e., causality that runs from trading volume to return volatility. For the pair of return and its volatility, return volatility does not cause

[5] In spite of the existence of contemporaneous relationship between trading volume and stock return, stock return does not cause trading volume in Granger causality sense.

return, but return causes its own volatility. The subprime crisis strongly strengthens the unidirectional causality running from return to return volatility.

It should be noted that trading volume causes stock return at a 1 percent significance level. This result is compatible with the existence of contemporaneous relationship reported in Table 4. In addition, trading volume also significantly causes return volatility. Therefore, it can be argued that trading volume helps predict both return and return volatility. In this sense, trading volume contains information about return and has the ability to predict return volatility at the same time. The third finding is that return helps predict volatility, but volatility does not help predict return.

Using the VAR (p) model proposed by Sim (1980), the relationships among variables can be examined. The optimal lag length, p, can be determined by information criterion. The VAR (8) is estimated using AIC to determine the order of lag length. The estimation of the VAR (8) model allows for an analysis of impulse response functions and variance decompositions. The results of impulse response analysis are shown in Fig. 2.

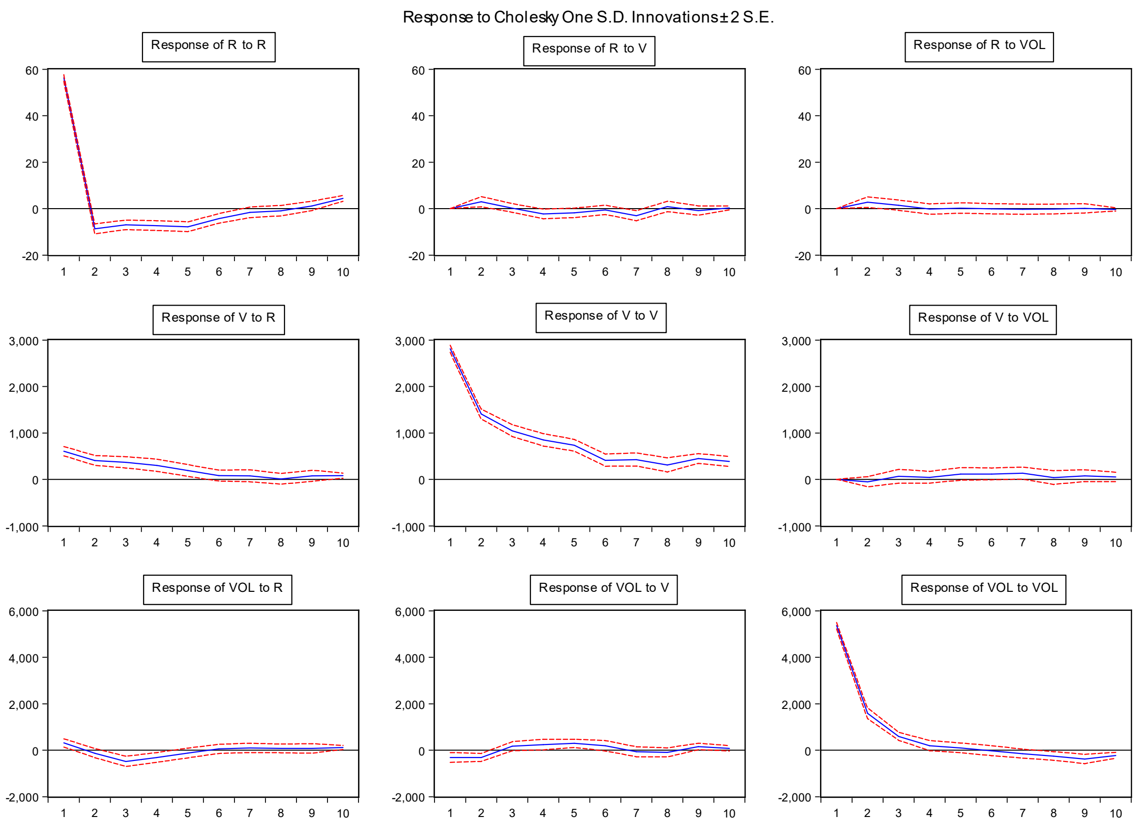

Fig. 2 Impulse response functions

Fig. 2 shows the impulse response functions and the Monte Carlo simulated at 95 percent intervals. The response of stock market return (R) to a shock of trading volume (V) shows both positive and negative impacts. Stock market return begins to rise on the next day following the contemporaneous effect of that shock and lasts for ten days. The response of stock market return to a shock of return volatility is temporary because this response dissipates quickly. The response of trading volume to a shock in return decreases within 6 days following the effect of that shock. However, trading volume does not respond to a shock in stock return at all. For the response of volatility to a shock in return, the volatility decreases the next day after the shock and increases the next day and dissipates within two days. Finally, the response of trading volume to a shock in stock market return dissipates within six days. It can be concluded that trading volume plays a more important role compared to other variables.

Variance decompositions that are used to ascertain how important the innovations of other variables are in explaining the fraction of each variable at different step-ahead-forecast variance. The results of variance decompositions analysis are illustrated in Fig. 3

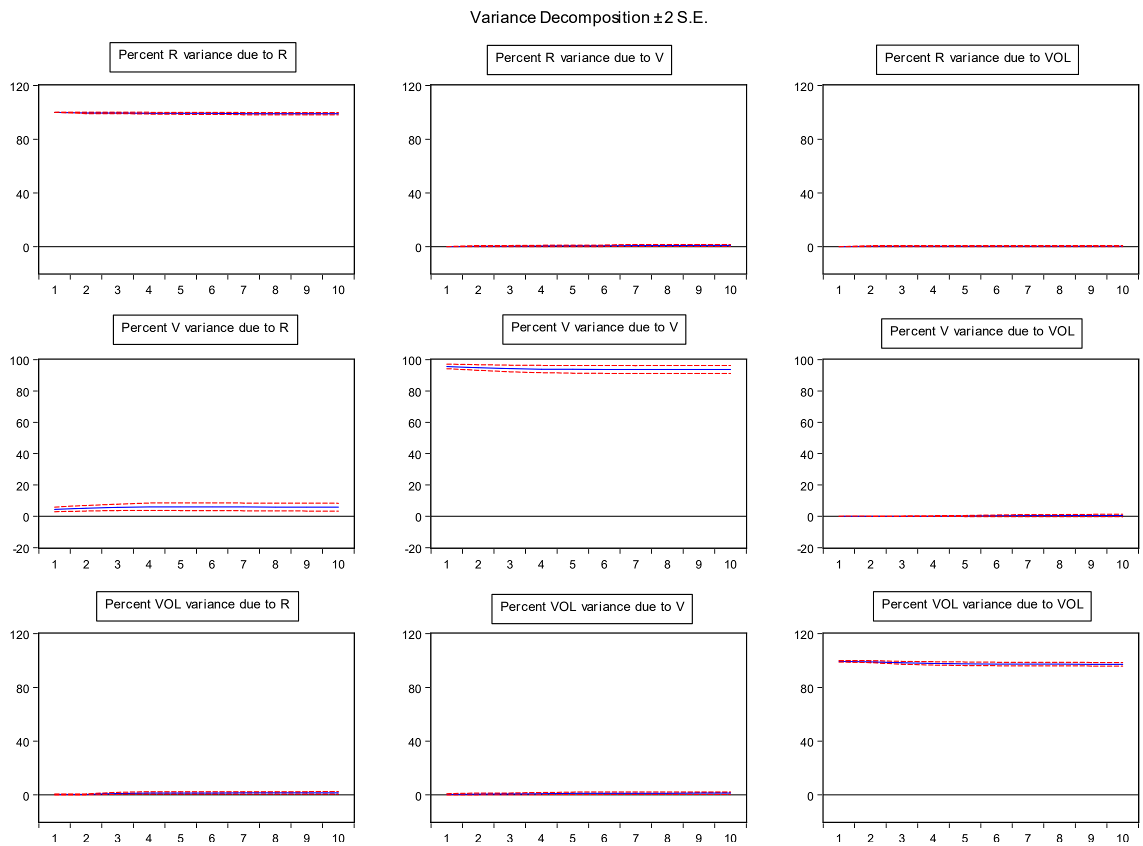

Fig. 3 Variance decompositions

The dashed lines in Fig. 3 represent the Monte Carlo simulated at the 95 percent confidence intervals. The results provide evidence for the independency of trading volume because its variance is mainly caused by its own innovations. The impact of stock return on trading volume is small while the impact of return volatility on trading volume is negligible. In addition, stock return has no impact on return volatility. Finally, return volatility imposes no impact on trading volume.

3.2 Sector analysis

The results in Table 3 show that only one sector does not exhibit contemporaneous relationship. However, the causal relationship between trading volume and sector return can be analyzed using the causality test.[6] The results are reported in Table 6.

[6] The impact of the subprime crisis is also included in each test equation.

Table 6 Results of Granger causality test for equity sectors.

Sector	$R_t \Rightarrow V_t$	$V_t \Rightarrow R_t$
Agro-industry	5.973***	3.363***
	(0.000)	(0.001)
Consumption	6.623***	1.499
	(0.000)	(0.159)
Financials	2.182**	4.062***
	(0.026)	(0.000)
Industrials	1.104	1.167
	(0.357)	(0.315)
Prop & Cons	1.904*	4.889***
	(0.055)	(0.000)
Resources	2.560***	1.519
	(0.010)	(0.145)
Services	3.740***	2.647***
	(0.000)	(0.007)
Technology	0.797	1.367
	(0.605)	(0.206)

Note: ***, ** and * indicate significance at the 1, 5 and 10 percent, respectively. P-value is in parenthesis.

There are only three sectors (consumption, financials and resources) are affected by the subprime crisis. Therefore, the subprime crisis does not affect the market. The dynamic or causal relationship between volume and return are observed in most sectors. Bidirectional causality is found in three sectors (agro-industry, financials, and services) while no causality is found in two sectors (industrials and technology. The overall results seem to support the results from the market analysis.

3.3 Discussion

Some points are worth discussing. Firstly, there is contemporaneous relationship between trading volume and return in the Thai stock market even though one out of eight equity sectors does not exhibit this relationship. The results of causality test indicate that trading volume significantly causes stock return. This finding is contradictory to the results found by Lee and Rui (2002) for some advanced stock markets and Pisedtasalasai and Gunasekarage (2007) for five emerging stock markets in Southeast Asia. This finding is also consistent with some theoretical models that there is information content of trading volume for future returns, e. g. the result of bidirectional causality found by Chuang et al (2009) and Lin (2013). The second finding reveals that there is a dynamic or causal causation from trading volume to return volatility is not compatible with the result found by Gebka (2012), which shows only weak evidence of the role of trading volume on return. Specifically, trading volume helps predict both return volatility and stock market return. Finally, the finding that return negatively causes return volatility is in line with the find by Christie (1982) and Black (1976).

4. Concluding Remarks

In this paper, empirical dynamic or causal relationship between trading volume, return and volatility is investigated by using daily data during 2004 and 2015. The results found in this paper are compatible with some theoretical models that assert that trading volume play a dominant role, i.e., trading volume Granger causes stock market return in the Thai stock market. In addition, the inter-linkages among stock return, return volatility, and trading volume are observed. Specifically, trading volume seems to contain information about return and has the ability to predict return volatility at the same time. This study also takes into account of the impact of the US subprime crisis on stocks listed in the stock exchange of Thailand. The US subprime crisis strongly affect this pairwise causality in one direction, i.e., causality that runs from trading volume to return volatility. For the pair of return and its volatility, return volatility does not cause return, but return causes its own volatility. The subprime crisis strongly strengthens the unidirectional causality running from return to return volatility. The findings in this paper may give some insight to how investors will make trading decisions, which can affect portfolio adjustment.

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