



**TESTING FOR LINEAR AND NONLINEAR GRANGER
CAUSALITY IN THE STOCK RETURN AND STOCK TRADING
VOLUME RELATION: MALAYSIA AND SINGAPORE CASES**

Ong Sheue Li¹ and Ho Chong Mun

*School of Science and Technology
Universiti Malaysia Sabah*

Locked Bag 2073, 88999 Kota Kinabalu, Sabah, Malaysia.

Abstract

This study aims at examining the short-run linear and nonlinear Granger causality between stock return and trading volume in Malaysia and Singapore cases based on the Vector Autoregression (VAR) model and Taylor expansion of the nonlinear model, proposed by Péguin-Feissolle, *et al.* (2008), respectively. We find evidence of significant bidirectional nonlinear causality between returns and trading volume in Malaysia case while unidirectional nonlinear causality from trading volume to stock return in Singapore case, which may establish useful base for future empirical work in considering nonlinearity studies for the dynamic relationship of stock return and trading volume.

JEL Classification: *G11, G14*

Keywords: *Stock return and volume; Causality; Taylor series approximation*

1. Introduction

Most of the researches believe that stock prices and trading volume are two most important indicators for stock market performance. Both stock prices and trading volume may be affected by the same sort of risk and jointly determined by the same market fluctuations. Besides, the stock prices and aggregate trading volume could mainly reflect the expectations of investors on the future performance. Karpoff (1987) pointed out the four reasons of importance in studying the relation

¹ Corresponding author: School of Science and Technology, Universiti Malaysia Sabah, Locked Bag 2073, 88999 Kota Kinabalu, Sabah, Malaysia. Email: ongsheueli@hotmail.com / ongsheueli@yahoo.com. Tel: (+6016) 4553664

between stock prices and trading volume. First, the study of price-volume relation provides an insight into the structure of financial markets due to the predicted price-volume relation is depends on the rate of information flows, the way of information disseminated, and the size of the market and so on. Second, price-volume relation is important for event studies through the inferences made by the combination of price and volume data. Third, the price-volume relation is the main key for empirical distribution of speculative prices and the price-volume tests widely support the mixture of distribution hypothesis. Fourth, price-volume relations have significant implications for the research of futures markets. Hence, studies for the price-volume relation can provide useful information for financial advisors in asset markets.

Since the hypothesis of Osborne (1959) that securities prices could be as a lognormal distribution with the variance term dependent on the trading volume, researchers have been show their interest on the relations between price-volume for different financial products. After seven years, Ying (1966) examined the relationship between stock prices and volume, he found six significant results: (i) a small volume is usually associated with a fall in price, (ii) a large volume is usually associated with a rise in price, (iii) a large increase in volume is usually associated with either a large rise or a large fall in price, (iv) a large volume is usually associated behind a rise in price, (v) if the volume has been decreasing consecutively for a period of five trading days, then the price has a tendency to fall over the next four trading days, (vi) if the volume has been increasing consecutively for a period of five trading days, then the price has a tendency to rise over the next four trading days. In his results (i) and (ii), he suggests that volume and price change per se are positively correlated and result (iii) indicated that volume and absolute value of price change is also positively correlated. He was the first to document correlations between price and volume in the same data set. As a result, early studies focus on the contemporaneous correlation between price change and volume as well as the absolute value of the price change and volume (Granger and Morgenstern, 1963; Karpoff, 1987).

In year 1992, Gallant *et al.* indicated that more information can be obtained about price-volume relation through the study of joint dynamics of stock prices and trading volume. This supported by Silvapulle and Choi (1999) that, price-volume dynamic relation can be used as the basis of a trading strategy and as the facts for existence of efficiency or inefficiency of stock markets. Hence, in the more recent studies, researchers have switched their focus on the dynamic relationship between stock price and volume, especially the causal relationship (Rogalski, 1978; Chen *et al.*, 2001; Pisedtasalasai and Gunasekarage, 2007).

There are four categories of theoretical studies explain the presence of a dynamic causal relationship between stock prices and trading volume. The first theoretical explanation is from Copeland (1976). He proposed a model of asset trading under the assumption of Sequential Information Arrival. In his model, he found out that there is a positive causal relation between stock prices and trading volume in either direction. According to his explanation, new information flows into the market and is disseminated to investors one at a time in these asymmetric information models. Then, a sequence of momentary equilibrium with various stock price-volume combinations is produced before final, complete information equilibrium is achieved. Due to the sequential information flow, lagged trading volume could have predictive power for current absolute stock returns and vice versa.

The second theoretical explanation is from Clark (1973) and Epps (1975). They proposed the mixture of distributions models. However, they provide different explanations for their results. In Clark's mixture model, trading volume is a proxy for the speed of information flow and he found out that there is no true causal relationship between prices and trading volume. In Epps' mixture model, trading volume is used to measure disagreement among traders. When the new information reaches the market, traders will revise their reservation prices. The level of trading volume is larger when the degree of disagreement among traders is greater and they found out a positive causal relation is running from trading volume to absolute stock returns.

The third theoretical explanation is from Lakonishok and Smidt (1989). They proposed the tax- and non-tax-related trading motives. Tax-related motives include the optimal timing of capital gains and losses realized during the calendar year and have a negative causal relationship between prices and trading volume. Non-tax-related-trading motives include window dressing, portfolio rebalancing and contrarian strategies and have a positive causal relationship between prices and trading volume.

The fourth theoretical explanation is from DeLong *et al.* (1990). They proposed the noise-trader model which can reconcile the difference between the short- and long-run auto correlation properties of aggregate stock returns. They found out that positive bidirectional causality is exists between prices and volume. According to the assumption of the model, a positive causal relation from volume to stock returns is happened when the noise traders cause stock prices to move with their trading strategies and a positive causal relation from stock returns to volume is happened with the positive-feedback trading strategies of noise-traders, where the decision to trade is conditioned on past stock price movements.

Although numerous studies have been done on investigate the factors that affect the causal relationship among stock prices and trading volume, little studies have been done to explore the nonlinear relationship between stock prices and trading volume. According to Granger and Newbold (1986), nonlinear model is a proper way to model a real world that is ‘almost uncertainly nonlinear’. Besides, many empirical studies have revealed significant nonlinearities in stock prices (Hsieh, 1991; Peters, 1994; Ryden, *et al.* 1998). Large stock price move backward and forward and rapid changes in stock market volatility can only be properly modeled with nonlinear models. Hiemstra and Jones (1994) and Abdul Rashid (2007) also find evidence of significant nonlinearities in the causal relation between stock prices and trading volume. However, Diks and Panchenko (2006) showed that the Hiemstra and Jones (1994) test applied by them can severely over-reject if the null hypothesis of non-causality is true as the sample size increase. Hence, with the big sample of this study, Hiemstra and Jones (1994) test is not appropriate to be applied. As an alternative, Taylor expansion of the nonlinear model proposed by Péguin-Feissolle, *et al.* (2008) applied as nonlinear model to test the causal relation among stock return and trading volume. There are few advantages of employ this test. Firstly, Taylor expansion proposed by Péguin-Feissolle, *et al.* (2008) is easy to compute if compare with other nonparametric procedures. Secondly, it is applicable for both the small and large samples as indicated by the size simulations. Thirdly, this test does not require the knowledge of specific functional relationship between variables.

In Malaysia and Singapore context, the causal relationship between stock price and stock volume has been done by Pisedtasalasai and Gunasekarage (2007). However, they only investigate linear causality relationship in their study. Hence, the objective of this paper is to investigate the possible pattern of causal relationship between stock return and trading volume for Malaysia and Singapore cases in linear and nonlinear model, respectively. The rest of this study is organized as follows. Section 2 presents the data and methodology. Section 3 presents the empirical results, while the final section concludes this paper.

2. Data and Methodology

2.1 Data

This study employed the daily equity indices and the corresponding trading volume series for the stock markets in Malaysia and Singapore, namely Kuala Lumpur Composite Index (KLCI) and Straits Times Index (STI), respectively. Daily data is used because short horizon data are more appropriate to test the causal relationships between stock return and trading volume (Pisedtasalasai and Gunasekarage, 2007). The study

period for KLCI is from 28 April 1998 till 25 March 2011 whereas the study period for STI is from 5 January 1995 till 9 January 2008. These study periods is chosen for the availability of data obtained from the webpage of Yahoo Finance. KLCI is selected in our study due to it is a broad-based market capitalization weighted index for 100 stocks, is the main index for Bursa Malaysia whereas STI is a market value-weighted stock market index based on the stocks of 30 representative companies listed on the Singapore Exchange. The daily stock returns used in this study are continuous rates of return, computed as 100 times the difference of the natural logarithm of the daily stock price, R_t , that is $100 (\ln R_t - \ln R_{t-1})$. While the percentage in trading volume, V_t is expressed similarly, that is $100 (\ln V_t - \ln V_{t-1})$.

In order to test for the dynamic relationship between stock returns and percentage volume changes, we will first test the stationary of the series by using unit root test. In this study, Augmented Dickey-Fuller (ADF) test is used to test whether the series are stationary at their levels or at first differences.

Due to previous studies (Gallant *et al.*, 1992; Chen *et al.*, 2001) show the trend effects in time series of trading volume information, so, a two-step procedure (Gallant *et al.*, 1992) is used to remove systematic day-of-the-week and month-of-the-year calendar effects from stock returns and percentage volume changes. Both the mean and variance of the stock returns and trading volume series are adjusted to remove these effects. The two-step adjustment procedure for return series are computed as below involves estimating the following regression equations:

$$R_t = D_t \beta_R + \varepsilon_t \quad (\text{Mean Equation}) \quad (1)$$

$$\ln(\hat{\varepsilon}_t^2) = D_t \gamma_R + v_t \quad (\text{Variance Equation}) \quad (2)$$

where D_t is the vector of daily, monthly and recession dummy variables, β_R and γ_R are conformable parameter vectors, ε_t and v_t are error terms and $\hat{\varepsilon}_t$ is the ordinary least squares (OLS) estimated error in equation (1). Similar regressions are estimated for percentage volume changes.

The variance equation (2) is used to standardize the residuals from the mean equation (1) for each series. Hence, the calendar-adjusted, standardized stock return is computed as:

$$R_t^* = \frac{\hat{\varepsilon}_t}{\exp(D_t \hat{\gamma}_R / 2)} \quad (3)$$

where $\hat{\gamma}_R$ is the OLS estimate of γ_R . The calendar-adjusted, standardized stock returns, $\{R_t^*\}$ and analogous adjusted percentage volume change, $\{V_t^*\}$ are used in the following analysis.

The recession periods employed in this study are taken from the World Economic and Financial Survey (2009) conducted by International Monetary Fund (IMF), including financial stress, domestic banking crisis and export demand shock. In the survey report, they mentioned that recessions in Asia have had one common characteristic that the investment tends to decline during the recession, regardless of the shock that caused them. This is because investment is tied both to exports and domestic demand, so whenever the shocks happened on export demand, consumption or financial conditions, investment will be influenced. So, from the previous recessions defined by IMF since 1980, Malaysia has been experienced two recessions which start from 1998:1 till 1998:3 and 2001:1 till 2001:2 whereas Singapore has been experienced four recessions which start from 1985:2 till 1985:4, 1997:4 till 1998:3, 2001:1 till 2001:3 and 2002:3 till 2003:2. The first recession in Malaysia was identified with financial crisis and domestic banking crisis and the second recession was identified with export demand shock. In Singapore case, the first and the third recessions were identified with export demand shock while the second recession was identified with financial crisis. (see Table 1)

Table 1
Asia: Identification of Previous Recessions since 1980

Recessions identified with	Malaysia	Singapore
Financial Stress	1998Q1 – 1998Q3	1997Q4 – 1998Q3
Domestic Banking Crisis	1998Q1 – 1998Q3	-
Export Demand Shock	2001Q1 – 2001Q2	1985Q2 – 1985Q4 2002Q3 – 2003Q2

Source: World Economic and Financial Survey (IMF, 2009)

2.2 Methodology

2.2.1 Linear Causality Test

The linear causal relationship between calendar-adjusted stock returns (R_t^*) and percentage volume changes (V_t^*) is examined by following Vector Autoregression (VAR) model:

$$R_t^* = \alpha_0 + \sum_{i=1}^n \alpha_i R_{t-i}^* + \sum_{j=1}^n \beta_j V_{t-j}^* + \varepsilon_t \quad (4)$$

$$V_t^* = \lambda_0 + \sum_{i=1}^n \lambda_i R_{t-i}^* + \sum_{j=1}^n \gamma_j V_{t-j}^* + \eta_t \quad (5)$$

where n is the optimal lag length chosen by Akaike Information Criteria (AIC) and ε_t and η_t are the residuals. When V_t^* does not Granger cause R_t^* in equation (4), the null hypothesis is represented by $H_0 : \beta_1 = \dots = \beta_n = 0$.

2.2.2 Nonlinear Causality Test

The nonlinear causal relationship between calendar-adjusted stock returns (R_t^*) and percentage volume changes (V_t^*) is examined by following Taylor expansion of the nonlinear function in bivariate system:

$$\begin{aligned} R_t^* &= f_R(R_{t-1}^*, \dots, R_{t-p_R}^*, V_{t-1}^*, \dots, V_{t-q_R}^*; \theta_R) + \varepsilon_{Rt} \\ V_t^* &= f_V(R_{t-1}^*, \dots, R_{t-p_V}^*, V_{t-1}^*, \dots, V_{t-q_V}^*; \theta_V) + \varepsilon_{Vt} \end{aligned} \quad (6)$$

where $\theta_i, i = R, V$, are parameter vectors, $\varepsilon_{it} \sim nid(0, \sigma_i^2)$ and $E\varepsilon_{Rt}\varepsilon_{Vt} = 0$ for all t . The sequences $\{R_t^*\}$ and $\{V_t^*\}$ are weakly stationary and ergodic. The functional form of f is unknown but assumed that it is adequately represents the causal relationship between R_t^* and V_t^* . Besides, f is assumed to has a convergent Taylor expansion at any arbitrary point of the sample space for every $\theta_i \in \Theta$.

In this framework, V_t^* not Granger cause R_t^* (V_t^* NGC R_t^*) if

$$f_R(R_{t-1}^*, \dots, R_{t-p_R}^*, V_{t-1}^*, \dots, V_{t-q_R}^*; \theta_R) = f^*(R_{t-1}^*, \dots, R_{t=p_R}^*; \theta_R^*) \quad (7)$$

in equation (6). Similarly, R_t^* NGC V_t^* if

$$f_V(R_{t-1}^*, \dots, R_{t-p_V}^*, V_{t-1}^*, \dots, V_{t-q_V}^*; \theta_V) = f^{**}(V_{t-1}^*, \dots, V_{t=q_V}^*; \theta_V^*) \quad (8)$$

in equation (6).

To test equation (7) against equation (6), following Péguin-Feissolle, *et al.* (2008), f_R and f_V in equation (6) is linearized by approximating them with general polynomials. After approximating, merging terms and reparametrizing, the k th-order Taylor approximation of f_R has the following form:

$$\begin{aligned}
 R_t^* &= \beta_0 + \sum_{j=1}^{p_R} \beta_j R_{t-1}^* + \sum_{j=1}^{q_R} \gamma_j V_{t-1}^* + \\
 &\sum_{j_1=1}^{p_R} \sum_{j_2=j_1}^{p_R} \beta_{j_1 j_2} R_{t-j_1}^* R_{t-j_2}^* + \sum_{j_1=1}^{p_R} \sum_{j_2=1}^{q_R} \delta_{j_1 j_2} R_{t-j_1}^* V_{t-j_2}^* + \sum_{j_1=1}^{q_R} \sum_{j_2=j_1}^{q_R} \gamma_{j_1 j_2} V_{t-j_1}^* V_{t-j_2}^* + \dots + \\
 &\sum_{j_1=1}^{p_R} \sum_{j_2=j_1}^{p_R} \dots \sum_{j_k=j_{k-1}}^{p_R} \beta_{j_1 \dots j_k} R_{t-j_1}^* \dots R_{t-j_k}^* + \dots + \sum_{j_1=1}^{q_R} \sum_{j_2=j_1}^{q_R} \dots \sum_{j_k=j_{k-1}}^{q_R} \gamma_{j_1 \dots j_k} V_{t-j_1}^* \dots V_{t-j_k}^* + \epsilon_{Rt} \\
 &= T_R^k(R^*, V^*) + \epsilon_{Rt}
 \end{aligned} \tag{9}$$

where $\epsilon_{Rt} = \varepsilon_{Rt} + f_R - T_R^k(R^*, V^*)$ and $q_R \leq k$ and $p_R \leq k$ for notational convenience. Expansion (9) contains all possible combinations of lagged values of R_t^* and lagged values of V_t^* up to order k . In order to select the optimal lag lengths, we will follow Hsaio (1981) by first select the “optimal” univariate lag length, p_R , of the autoregressive null model, then, select the “optimal” lag length, q_R , conditional upon p_R . Two criteria are used in this study, namely Akaike’s (1979) criterion (AIC) and Schwarz’s (1978) criterion (SBIC). If the optimal lag length chosen is differs between criteria, the longest optimal lag lengths are chosen (Holmes and Patricia, 1988).

An analog expression can be defined for V_t^* and the testing is done within the system:

$$\begin{cases} R_t^* = T_R^k(R^*, V^*) + \epsilon_{Rt} \\ V_t^* = T_V^k(V^*, R^*) + \epsilon_{Vt} \end{cases} \tag{10}$$

where $T_V^k(V^*, R^*)$ and ϵ_{Vt} are defined analogously.

The assumption that V_t^* does not Granger cause R_t^* implies that all terms involving functions of lagged value of V_t^* in equation (9) must have zero coefficients. Hence, the null hypothesis of V_t^* not Granger causing R_t^* can be written as:

$$H_{02} : \begin{cases} \gamma_j = 0, j = 1, \dots, q_R \\ \delta_{j_1 j_2} = 0, j_1 = 1, \dots, p_R, j_2 = 1, \dots, q_R \\ \gamma_{j_1 j_2} = 0, j_1 = 1, \dots, q_R, j_2 = j_1, \dots, q_R \\ \vdots \\ \gamma_{j_1 \dots j_k} = 0, j_1 = 1, \dots, q_R, j_2 = j_1, \dots, q_R, \dots, j_k = j_{k-1}, \dots, q_R \end{cases} \tag{11}$$

According to Péguin-Feissolle, *et al.* (2008), there are two practical difficulties related to equation (9), namely numerical and amount of

information. Numerical problem arise due to the regressors in equation (10) tend to be highly collinear if k , p_R and q_R , as well as p_V and q_V are large. Another difficulty arise because the number of regressors increase rapidly with k , so the dimension of the null hypothesis become rather large. In order to solve these problems, Péguin-Feissolle, Strikholm and Teräsvirta suggests replace some matrices by their largest principal components. This can be done by divide the regressors into two groups, that are those being functions of lags of R_t only and the remaining ones. Then replace the second group of regressors by their first p^* principal components. Hence, the null hypothesis now is that the principal components have zero coefficients and yields the following test statistic:

$$General_{FB}^* = \frac{T}{p^*} (m - tr(\hat{\Omega}_1 \tilde{\Omega}_0^{-1})) \underset{\tilde{H}_0}{approx} F_{p^*, T} \quad (12)$$

where T is the number of observations, m is the number of equations in the system, matrices $\tilde{\Omega}_0 = \tilde{E}_0' \tilde{E}_0$ and $\hat{\Omega}_1 = \hat{E}_1' \hat{E}_1$ are the cross-product matrices of the residuals from estimating the model under the null and under the alternative, respectively. More particularly, $\tilde{E}_0 = (\tilde{\varepsilon}_1, \dots, \tilde{\varepsilon}_T)'$ and $\hat{E}_1 = (\hat{\varepsilon}_1, \dots, \hat{\varepsilon}_T)'$, where $\tilde{\varepsilon}_t$ and $\hat{\varepsilon}_t$, $t=1, \dots, T$, are the $(m \times 1)$ residuals vectors from the restricted and the unrestricted model, respectively.

3. Empirical Results

A descriptive statistics of stock returns and percentage volume change for Malaysia and Singapore were reported in Table 2. This table included mean, minimum and maximum values, standard deviation, skewness and excess kurtosis coefficients of daily stock returns and percentage volume change.

Augmented Dickey-Fuller (ADF) test is used to test the stationary of the variables. The results of the ADF tests are reported in Table 3. The results show that all stock return and percentages volume changes are stationary at the level.

Since the variables are stationary at level, Vector Autoregression (VAR) model is used to investigate the short-run dynamics of variables (see Table 4). The VAR test reveal that linear bidirectional causality relationship is exists between calendar-adjusted stock returns and percentage volume changes for Malaysia case and linear unidirectional causality relationship is exists from percentage volume changes to stock returns in Singapore case.

Table 2
Descriptive Statistics

Country	Malaysia		Singapore	
Index	Kuala Lumpur Composite Index		Straits Times Index	
Sample Period	28/4/1998 – 25/3/2011		5/1/1995 – 9/1/2008	
Observations	3157		3257	
	Stock Returns	Percentage Volume Changes	Stock Returns	Percentage Volume Changes
Mean	0.028	0.045	0.012	0.182
Minimum	-24.153	-262.393	-14.941	-396.581
Maximum	20.259	271.158	12.874	297.291
Std. Deviation	1.451	38.171	1.338	47.811
Skewness	-0.430	0.051	-0.258	-0.224
Kurtosis	70.874	10.936	15.209	12.763

Table 3
Augmented Dickey-Fuller Unit Root Test

Country	Malaysia		Singapore	
Level	Intercept	Trend & Intercept	Intercept	Trend & Intercept
Stock Returns	-13.221 (13)*	-13.220 (13)*	-14.647 (12)*	-14.677 (12)*
Percentage Volume Change	-23.370 (11)*	-23.366 (11)*	-16.046 (27)*	-16.054 (27)*

The lag length for the ADF test is given in parenthesis. An * denotes statistical significance at the 1% level.

Table 4
Linear Granger Causality Test Results
(Vector Autoregression Model)

Null Hypothesis, H_0 :	Number of lags in VAR	χ^2	Result
Malaysia			
R_t^* does not Granger cause V_t^*	14	27.691 (0.016)	C
V_t^* does not Granger cause R_t^*	14	31.068 (0.005)	C
Singapore			
R_t^* does not Granger cause V_t^*	14	22.793 (0.064)	NC
V_t^* does not Granger cause R_t^*	14	25.119 (0.033)	C

The numbers inside the parenthesis show the p-values for the computed χ^2 statistic used to test the null hypothesis of Granger noncausality. C indicates the presence of a causal relationship and NC indicates the absence of a causal relationship.

According to Péguin-Feissolle, *et al.* (2008), there are two practical difficulties related to the Taylor approximation. Firstly, the regressors tend to be highly collinear if both k , p_R , q_R , p_V and q_V are large, causes the numerical problem arises. Secondly, the number of regressors increases rapidly with k , may causes the number of degrees of freedom become rather small. Hence, in this study, second-order Taylor approximation was choosing for analysis and the maximum lag length is set to twenty five for both Akaike information criterion and Schwarz's criterion. The selected AR orders are given in Table 5. The Taylor expansion reveals that bidirectional nonlinear causality relationship exists between calendar-adjusted stock returns and percentage volume changes for Malaysia case and unidirectional nonlinear causality run from percentage volume changes to stock returns in Singapore case.

Table 5
Nonlinear Granger Causality Test Results (Taylor expansion)

Null Hypothesis, H_0 :	Number of lags	F-test	Result
Malaysia			
R_t^* does not Granger cause V_t^*	$p_V = 17, q_V = 12$	2.304 *	C
V_t^* does not Granger cause R_t^*	$p_R = 5, q_R = 11$	2.574 *	C
Singapore			
R_t^* does not Granger cause V_t^*	$p_V = 5, q_V = 22$	0.920	NC
V_t^* does not Granger cause R_t^*	$p_R = 14, q_R = 18$	1.835 *	C

* denotes significance at the 1% level. C indicates the presence of a causal relationship and NC indicates the absence of a causal relationship.

4. CONCLUSIONS

This study investigates the dynamic relationship between stock prices and aggregate trading volume using linear and nonlinear Granger causality tests. The tests are applied on daily stock returns and percentage volume changes for both Malaysia and Singapore stock markets, namely KLCI and STI. A two step procedure introduced by Gallant *et al.* (1992) is used to remove the systematic day-of-the-week and month-of-the-year calendar effects from stock returns and percentages volume changes in each case. Augmented Dickey-Fuller (ADF) test is applied to test the stationary of the variables and the results show that stock return and percentages volume changes for both Malaysia and Singapore cases are stationary at the level.

The findings of this paper show that both the linear and nonlinear Granger causality test reveal the same results. In Malaysia case, both the tests reveal that bidirectional causality relationship exists between calendar-adjusted stock returns and percentage volume changes. Whereas, unidirectional causality run from percentage volume changes

to stock returns in Singapore case. There are two possible explanations for the similar results obtained from the linear and nonlinear causality tests in this study. Firstly, the results can be explained from the perspective of the Taylor series expansion methodology. By the characteristic of the test, it is able to approximate the actual relationship start from order one to higher orders, therefore it nests the linear case even in higher order function. If the relationship consists of linear and nonlinear term, then it is not surprising that the linear and nonlinear Granger causality test can detect significant results.

Another possible explanation is that the trend effects and structural breaks effects in the time series have been removed at the beginning of analysis. Hence, without those disturbances, the linear Granger causality test is able to indicate significant result. Furthermore, the findings from the nonlinear Granger causality test provide additional support to the causality relationship. Removing the breaks effect at the beginning of the test is one of the limitations in this study. In fact, applying dummy variables whenever break is detected is an ad hoc and unsatisfied solution. If there is a structural break, a much more acceptable alternative is to apply a nonlinear specification model to approximate the downward and upward movement. The findings of this study suggest that future practice could consider nonlinear methodology when evaluating the dynamics of stock prices and trading volume instead of removing the trend and structural effects.

The significant causal relationship between stock return and trading volume in both Malaysia and Singapore cases indicate that information contained in these two variables may be useful in predicting each other (Granger, 1986). This provides useful guideline for the investors and corporations for investing in the equity. Through the guideline, investors can increase the hedge effect by using the information of past future price movements to forecasts current and future movements in trading volume, and vice versa. The presence of nonlinear causal relationship between stock return and trading volume indicates that stock returns and trading volume have nonlinear explanatory power to each others, although no guidance is provided regarding the source of nonlinear dependence.

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