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On Asymmetric Causality Between Stock Prices and Trading Volume for Some Developed and Emerging Stock Markets: A Preliminary Analysis

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Abstract: This study aims to present some evidence for the presence of a causal relationship between price and volume in six international stock markets. The econometric methodology used in this paper allows us to determine the symmetric and asymmetric Granger causality between the price index and the trading volume, and it helps us to discriminate between competing theories on how information is disseminated in the stock markets. Among the main results, it is found that, with the exception of the Nikkei 225, the past information on trading volume is helpful in predicting the behavior of the stock price, indicating that stock markets are inefficient. The DeLong et al. (1990) noise-trader model is applicable to the CAC 40 and Hang Seng index. For the FTSE 100, S&P 500 and TSEC weighted index, the results provide evidence that the stock prices and trading volume of the four markets are simultaneously subject to the influence of the sequential information arrival model and the noise-trader model. A feedback loop is found to prevail with an arbitrary sign of correlation between price and volume.

Key words: Price, Volume; Asymmetric causality; Stock market
JEL: G14; C32

1. Introduction

Since the seminal work of Osborne (1959), untangling the price-volume relationships of financial markets has long been the focus of much attention from academics, the government and investors. According to Karpoff (1987), there are at least four reasons why it is important to understand the relationship between the stock prices and trading volume. The first reason is that the empirical relationship between price and volume helps discriminate between competing theories as to how information is disseminated in stock or futures markets. Second, it is important for event studies. This is because the power of statistical tests increases by incorporating the price-volume relationship, if the changes in price and volume are jointly determined. Third, the price-volume relationship is critical in assessing the distribution of prices or returns themselves. Fourth, a better understanding of the statistical structure of volume and returns can help explain the technical analysis. Blume et al. (1994) also emphasize that trading volume captures important information about speculators' trading activities and, hence, movements in trading volume may be useful in the forecasting of stock price dynamics.

Theoretically, there are several explanations for the presence of the causal relationship between price and volume in the literature. The most widely cited hypotheses, albeit competing ones, are the sequential information arrival model (hereafter SIA) and the mixture of distribution model (hereafter MD). The first was proposed by Copeland (1976) and Jennings et al. (1981) and the latter by Clark (1973) and Epps and Epps (1976). Empirically, the SIA hypothesis indicates that there is bi-directional causality between the trading volume and stock returns.[1]The mixture model of Epps and Epps (1976) indicates that a positive causal relationship runs from the trading volume to absolute stock returns. On the other hand, the MD hypothesis of Clark (1973) predicts that a neutral relationship exists between the trading volume and stock returns.[2]

Two other related models are the noise-trader model of DeLong et al. (1990) and the heterogeneous investor model of Wang (1994). The former predicts that "the positive causal relationship running from price to volume is consistent with the positive-feedback trading strategy of noise traders who base their decisions on past price movements. Moreover, the model predicts that a positive causal relationship from volume to price is consistent with the

[1]The terms "price" and "return" are used interchangeably in this paper.

[2]Readers are referred to, for example, Hiemstra and Jones (1994), Moosa and Silvapulle (2000) and Rashid (2007) for the rationale underlying the price-volume relations of these theoretical models.

hypothesis that price changes are caused by the actions of noise traders" (Moosa and Silvapulle, 2000, p. 14). The latter postulates that the trading volume is always positively correlated with the absolute price change.[3]

A significant number of studies have devoted many efforts to this issue, especially in the stock market. Early studies use the conventional linear Granger causality technique to examine the price-volume relationship (see, for example, Smirlock and Starks, 1988; Chordia and Swaminathan, 2000; Chen et al., 2001; Campbell et al., 1993; Lee and Rui, 2000, 2002; Lee et al., 2004; Gurgul and Majdosz, 2005; and Pisedtasalasai and Gunasekarage, 2007). Two important features characterize these studies. First, the findings are mixed, if not contradictory, which means that there is no corroborative conclusion vis-a-vis the causal relationship between the stock price and trading volume. Second, a majority of studies overlook the non-linear property inherent in the stock market (Savit, 1988; Abhyankar, 1998) and only apply the traditional method in testing for the Granger causality of stock price and trading volume.

A group of researchers have turned their attention to test for the non-linear causal relationship between the stock price index and trading volume. From an economic point of view, many studies (e.g., Savit, 1988; Hsieh, 1991; Moosa and Silvapulle, 2000) point out that non-linear dependence may be present if price and volume are generated by non-linear processes. These non-linearities are normally attributed to the non-linear transaction cost functions, the role of noise traders, and market microstructure effects (Abhyankar, 1998). From an econometric point of view, the relationship is motivated by the statistical power of the advances in the non-linear Granger causality tests (Hiemstra and Jones, 1994; Diks and Panchenko, 2005, 2006). An increasing number of authors, e.g., Abhyankar (1998), Moosa and Silvapulle (2000), Rashid (2007) and Chen (2008), have applied new non-linear tools to test the price-volume relationship of stock markets.

The purpose of this paper is to contribute to the empirical literature by examining the price-volume relationship for six international stock markets. In keeping with the previous literature, we take non-linearity into consideration in this study. However, most of the previous studies adopt the non-parametric non-linear Granger causality test (Hiemstra and Jones, 1994; Diks and Panchenko, 2005, 2006) to test for the price-volume relationship. This

[3]Other theoretical contributions to this debate can be found in Lakonishok and Smidt (1989), Campbell et al. (1993), and He and Wang (1995).

paper differs from theirs. Instead, we test for the existence of asymmetric causal effects by conducting new causality tests, championed by Hatemi-J (2012a), that separate the effect of positive shocks from the negative ones.[4] It allows us to untangle the symmetric and asymmetric causal relationship between the stock price index and the trading volume and helps us to discriminate between competing theories on how information is disseminated in stock markets. We focus our attention on six international stock markets, i.e., the CAC 40, Nikkei 225, FTSE 100, S&P 500, Hang Seng index and TSEC weighted index, in this study.[5]

The major findings of this study are previewed as follows. First, for the Nikkei 225, the stock price does not Granger cause the trading volume and vice versa, indicating that the mixture of the distribution model of Clark (1973) is applicable to Japan. Second, the DeLong et al. (1990) noise-trader model is applicable to the CAC 40 and Hang Seng index. Third, there is a feedback relationship between the stock prices and trading volume for the FTSE 100, S&P 500 and TSEC weighted index. These results provide evidence that the stock prices and trading volume of the four markets are subject to the influences of the sequential information arrival model and the noise-trader model simultaneously. Finally, with the exception of the Nikkei 225, the past information on trading volume is helpful in forecasting the behavior of the stock price, indicating that the stock markets are not efficient.

The remainder of this paper is organized as follows. The next section reviews the existing literature. Section 3 briefly introduces the econometric methodology that we employ. Section 4 describes the data and discusses the empirical test results. Section 5 presents the conclusions that we draw from this research.

2. Selective Literature Review

There are numerous price-volume nexus studies in the literature. As mentioned in the introduction, early studies adopt the conventional linear Granger causality technique to examine the price-volume relationship. For example, Saatcioglu and Starks (1998) examine the stock price-volume relation in a set of Latin American markets by using a vector autoregression (VAR) analysis to test for Granger causality. They fail to find strong

[4]Of course there are many different types of asymmetric forms, not just positive versus negative shocks. For example, the impacts of the big and small shocks are often thought to be different. Good news and bad news are also different.

[5]Hatemi-J (2012b) applies this method to assess the degree of integration or segmentation of the UAE stock market with the U.S. market. The results show that the degree of integration is stronger when the markets are falling than when they are rising.

evidence on stock price changes leading volume. Chen et al. (2001) find a significant positive correlation between trading volume and the absolute value of the stock prices for nine national markets, viz. New York, Tokyo, London, Paris, Toronto, Milan, Zurich, Amsterdam, and Hong Kong.

Some researches employ the non-linear Granger causality test, proposed by Hiemstra and Jones (1994), to examine the stock price and trading volume relation. For example, by using Karachi Stock Exchange (KSE) data, Rashid (2007) find that volume has significant nonlinear explanatory power for stock returns in general, whereas stock returns have linear explanatory power for trading volume. Chen (2008) also tries to untangle the nexus of stock price and trading volume for Chinese stock market by employing Diks and Panchenko's (2006) non-parametric nonlinear Granger causality test.[6] Chen and Liao (2005) try to replicate the causal relation between stock returns and trading volume via the agent-based stock markets. They show that the appearance or disappearance of the price-volume relation can never be complete if the feedback relation between individual behavior and aggregate outcome is neglected.

Besides, Yoruk et al. (2006) apply a Taylor expansion of the non-linear model, as proposed by Peguin-Feissolle and Terasvirta (1999), to examine the dynamic relationship between the daily Turkish banking sector stock price and trading volume. Evidence is found of significant linear and nonlinear causality between these two series. Yuan et al. (2012) use multifractal detrended fluctuation analysis (MF-DFA) and multifractal detrended cross-correlation analysis to examine the price-volume relation of Chinese stock markets. Their empirical evidences find that both Shanghai and Shenzhen stock markets show pronounced long-range cross-correlations between stock price and trading volume.

Recently, Chuang et al. (2009), Lin (2013) and Gebka and Wohar (2013) have investigated the causal relationships between stock returns and volume for the NYSE, S&P 500, FTSE 100 and emerging Asian markets based on quantile regressions. For example, Chuang et al. (2009) show that for the NYSE, S&P 500 and FTSE 100 indices past trading volume exerts a positive (negative) impact on returns from the top (bottom) of return distribution. Lin (2013) empirically examines the dynamic stock return-volume relations for six emerging Asian markets: Indonesia, Malaysia, Singapore, South Korea, Taiwan, and

[6] Commenting on Hiemstra and Jones' (1994) method, Diks and Panchenko (2006) argue that it lacks consistency, and in its place, they propose a new test statistic for non-linear Granger causality.

Thailand. Evidence is found that trading volume Granger causes stock return in quantiles and the causal effects of volume are heterogeneous across quantiles.

It is of interest to note that Matilla-Garcıa et al. (2014) propose a new nonparametric information based *permutation entropy* test for causality which is valid when the data exhibit causal dependence either of linear or nonlinear nature, and causality might appear either in the mean and/or in the variance. Bouezmarni, Rombouts, and Taamouti (2012) derived a nonparametric test based on Bernstein copulas and tested using high frequency data for causality between stock returns and trading volume.

Studies on the price-volume relationship have also been extended to the bond and futures markets (Tauchen and Pitts, 1983; Grammatikos and Saunders, 1986), the foreign exchange market (Chung and Joo, 2005; Chen and Chen, 2006), the crude oil future market (Foster, 1995; Moosa and Silvapulle, 2000), and to the agricultural futures market (Malliaris and Urrutia, 1998). For example, by using the non-linear Granger causality test proposed by Hiemstra and Jones (1994), Abhyankar (1998) finds a significant bi-directional non-linear causal relationship between the FTSE 100 index futures and cash markets. Asimakopoulos, Ayling and Mahmood (2008) examine the relationship between currency futures returns and find that there is an unidirectional non-linear causality relationship in four cases. However, after filtering the returns using a GARCH (1,1) model they find insignificant and statistically weaker non-linear causality relationships.

3. Methodology

We briefly outline Hatemi-J's (2012a) asymmetric Granger causality test in this section and the content of this section draws heavily from his paper. Readers are referred to Hatemi-J's (2012a) paper for details. Our interest is focused on investigating the causal relationship between two integrated variables $y_{1t}$and $y_{2t}$with each being defined as the following random walk process:

$$y_{1t}=y_{1t-1} + \varepsilon_{1t}=y_{10} + \sum_{\mathrm{i}=0}^{\mathrm{t}} \varepsilon_{1i} \quad (1)$$

and

$$y_{2t}=y_{2t-1} + \varepsilon_{2t}= y_{20} + \sum_{\mathrm{i}=0}^{\mathrm{t}} \varepsilon_{2i} \quad (2)$$

where t = 1, 2, ..., T, the constantsy_{10}, and $y_{20}$are the initial values, and the variablesε_{1i} and ε_{2i}signify white noise disturbance terms. Positive and negative shocks are defined as follows:

$$\varepsilon_{1t}^{+}= \max(\varepsilon_{1i},0)\ ,\varepsilon_{1t}^{-}= \min(\varepsilon_{1i},0)\ ,\quad \varepsilon_{2t}^{+}= \max(\varepsilon_{2i},0)\ ,\varepsilon_{2t}^{-}= \min(\varepsilon_{2i},0) \qquad (3)$$

Therefore, Eqs (1) and (2) can be rewritten as follows:

$$y_{1t}= y_{10}+\sum_{i=1}^{t}\varepsilon_{1i}^{+} + \sum_{i=1}^{t}\varepsilon_{1i}^{-} \qquad (4)$$

and

$$y_{2t}= y_{20}+\sum_{i=2}^{t}\varepsilon_{2i}^{+} + \sum_{i=2}^{t}\varepsilon_{2i}^{-} \qquad (5)$$

the positive and negative shocks of each variable can be defined in cumulative form as

$$y_{1t}^{+}=\sum_{i=1}^{t}\varepsilon_{1t}^{+},\ y_{1t}^{-} = \sum_{i=1}^{t}\varepsilon_{1t}^{-},\ y_{2t}^{+} = \sum_{i=1}^{t}\varepsilon_{2t}^{+},\ y_{2t}^{-} =\sum_{i=1}^{t}\varepsilon_{2t}^{-}, \qquad (6)$$

It should be noted that, by construction, each positive as well as negative shock has a permanent impact on the underlying variable. The next step is to test the causal relationship between these components. In the following, we outline the case whereby we test for the causal relationship between negative cumulative shocks. Assuming that $y_t^{-} =(y_{1t}^{-}, y_{2t}^{-})$, the test for causality can be implemented by using the following vector autoregressive model of order *p*, VAR (*p*):

$$y_t^{-}=\text{v}+A_1 y_{t-1}^{-} +\ldots+ A_p y_{t-p}^{-} + u_t^{-}, \qquad (7)$$

where y_t^{-} is the 2 × 1 vector of the variables, *n* is the 2 × 1 vector of the intercepts, and u_t^{-} is a 2 × 1 vector of error terms (corresponding to each of the variables representing the cumulative sum of negative shocks). The matrix *AR* is a 2×2 matrix of parameters for lag order *r*(*r* = 1, ..., *p*). After determining the optimal lag order via minimizing the information criterion, the null hypothesis that the *k*th element of y_t^{-} does not Granger-cause the *j*th element of y_t^{-} is tested. This nullhypothesis is defined as follows:

*H*0 : the row *j*, column *k* elements in *Ar* are equal to zero for *r* = 1, ..., *p*. (8)

Following Hatemi-J (2012b), we also include an additional unrestricted lag in the VAR model in order to neutralize the effect of one unit root on the distribution of the underlying test statistic as suggested by Toda and Yamamoto (1995). By making use of some notation, it is possible to represent the VAR (*p*) model more compactly as follows:

$$Y = DZ +\delta, \qquad (9)$$

The following Wald test can be used to test the null hypothesis of non-Granger causality defined as *H*0: $C\beta= 0$:

$$Wald = (C\hat{\beta})'[C((Z'Z)^{-1} \otimes SU)C']^{-1}(C\hat{\beta}) \qquad (10)$$

where $\hat{\beta}= \text{vec}(\widehat{D})$ and vec denotes the column-stacking operator; $\otimes$represents the Kronecker product, and *C* is a *p* ×*n*(1+*np*) indicator matrix with elements of ones for restricted parameters and zeros for the rest of the parameters. *SU* is the variance-covariance matrix of the unrestricted VAR model estimated as $SU = \hat{\delta}_u' \hat{\delta}_u /(T - q)$, where q is the number of parameters in each equation of the VAR model. When the assumption of normality is fulfilled, the Wald test statistic above has an asymptotic chi-square distribution with the number of degrees of freedom being equal to the number of restrictions to be tested (in this case equal to p).

4. Data and Results

4.1 Data Description and Basic Statistics

Our empirical study on the price-volume relationship focuses on six stock price indices: the CAC40 (France), Nikkei 225 (Japan), FTSE 100 (the UK), S&P 500 (the US), the Hang Seng index (Hong Kong) and the TSEC weighted index (Taiwan). All data are obtained from the website of Yahoo Finance. *PRt* and *VOt* are the abbreviations of the stock price index and trading volume, respectively. The sample period was determined primarily based on the availability of the data. For all variables the weekly data are for periods with different starting dates but they all end on January 7, 2013. The starting date is October 11, 2004 for the CAC 40; March 17, 2003 for the Nikkei 225; December 2, 2002 for the FTSE 100; January 7, 2002 for the S&P 500 and Hang Seng index; and January 6, 2003 for the TSEC weighted index. All of the variables used are expressed in natural logarithms.

As a preliminary analysis, we apply a battery of linear unit root tests to determine the order of integration of the stock price index and trading volume. We consider the Augmented Dickey- Fuller (ADF) test, as well as the ADF-GLS test of Elliott et al. (1996) in this study. Vougas (2007) highlights the usefulness of the Schmidt and Phillips (1992) (SP hereafter) unit root test in practice. Therefore, we also employ it in this study. These authors propose some modifications of existing linear unit root tests in order to improve their power and size. For the ADF and ADF-GLS tests, an auxiliary regression is run with an intercept and a time trend. To select the lag length (k) we use the 't-sig' approach proposed by Hall (1994). That is, the number of lags is chosen for which the last included lag has a marginal significance level that is less than the 10% level.

The results of applying these tests are reported in Tables 1 and 2. In the case of *VO*, we find that, with the exception of the CAC 40 and Nikkei 225, the null hypothesis of a unit root cannot be rejected at the 5% significance level for the ADF statistics. Based on the well-known low power problem of the ADF test, we turn our attention to other statistics. The

SP test (see Schmidt and Phillips, 1992), with parametric correction, cannot reject the unit root hypothesis with both a linear and quadratic trend at the five percent significance level.[7] The results of the DF-GLS (see Elliott et al., 1996) suggest that the null hypothesis of a unit root can be rejected for all of the stock markets, suggesting that the trading volumes for these markets are stationary processes. As Perron (1989) pointed out, in the presence of a structural break, the power to reject a unit root decreases if the stationary alternative is true and the structural break is ignored. To address this, we use Zivot and Andrews' (1992) sequential one trend break model and Lumsdaine and Papell's (1997) two trend breaks model to investigate the order of the trading volume. We use the 't-sig' approach proposed by Hall (1994) to select the lag length (k). We set $kmax$ = 12 and use the approximate 10% asymptotic critical value of 1.60 to determine the significance of the t- statistic for the last lag. We use the 'trimming region' [0.10T, 0.90T] and select the break point endogenously by choosing the value of the break that maximizes the ADF t-statistic. We report the results in Table 1. The results suggest that the null hypothesis of a unit root can be rejected at the 5% significance level for all of the trading volumes. These findings fully echo those obtained from the SP and DF-GLS linear unit root tests.

In the case of *PR* (see Table 2), we find strong evidence in favor of the unit root hypothesis based on these unit root statistics in their respective level data. When we apply these unit root tests to the first difference of stock price indexes, again, we are able to reject the null hypothesis of a unit root at the 5% level or better. Therefore, we conclude that these stock price indexes are I(1) processes.

4.2 Results of the Asymmetric Causality Test

Next, we conduct diagnostic tests for the multivariate normality and multivariate ARCH effects in the VAR model. The results of these multivariate diagnostic tests are presented in Table 3, and indicate that the null hypothesis of multivariate normality is strongly rejected in all six cases. The null hypothesis of no multivariate ARCH effect is, however, rejected only in the case of (*VO*, *PR*)in all six stock markets. In the case of the S&P 500, the null hypothesis of no multivariate ARCH effect is rejected for the VAR models of (*VO*+, *PR*−) and (*VO*−, *PR*−).[8]As highlighted by Hatemi-J (2012a), given that the

[7]The terms SP(1) and SP(2) denote the Schmidt-Phillips t tests with the linear and quadratic trend, respectively.

[8]The term *VO* is the logarithmic value of the trading volume, and the term *PR* is the logarithmic value of the stock price index. The cumulative positive sum of each variable is denoted by + and the cumulative negative sum is denoted by −.

residuals are not normality distributed, it is important to make use of bootstrapping in order to generate reliable critical values for the causality tests. In this paper, the bootstrapping is utilized for both the symmetric and asymmetric Granger causality tests. The steps for implementing the bootstrap simulation are outlined in Hatemi-J (2012a, 2012b). For the readers' information, we replicate these steps in the Appendix.[9]

The results from Table 2 show that each stock price index contains one unit root. This is evident from the time series plots in Figures.[10] Although the results of Table 1 suggest that the trading volumes for these markets are stationary processes, their positive and negative cumulative sums exhibit obviously upward and downward trends, respectively. Separating the impact of positive shocks from negative ones is important, especially in the financial markets, because people tend to react more to negative shocks than to positive ones even in cases where the size of the shock is the same in absolute terms.

The symmetric and asymmetric Granger causality test results for these stock markets are presented in Tables 4 to 9, respectively. Starting with the CAC 40 (see Table 4), with the exception of ($VO \not\Rightarrow PR$), the null hypothesis that the trading volume is not causing the price index cannot be rejected at the 5% significance level, indicating that the asymmetric Granger causality does not hold from the trading volume to the price index. The null hypothesis that the price index does not Granger-cause the trading volume cannot be rejected at any conventional significance level. This indicates that there is no symmetric and asymmetric Granger-causal effect running from the stock price index to the trading volume.

For the Nikkei 225 (see Table 5), it is clear that in the results of the symmetric and asymmetric Granger causality, the evidence shows that there is neutrality between the stock price and trading volume with or without the asymmetric effect. Therefore, the mixture of the distribution model of Clark (1973) is applicable to the price-volume relationship in the stock market of Japan.

In moving to the FTSE 100 (see Table 6), the results show that there is a bi-directional symmetric Granger-causal relationship between the stock price and trading volume. However, the asymmetric causality tests reveal that the null hypothesis of a negative shock in the trading volume not causing the negative component of the stock price, i.e., ($VO-$

[9] All computations are implemented using the GAUSS program available from Professor Hatemi-J. We thank him for making his computer code publicly available on the Internet

[10] We do not show the graphs of the stock price index and trading volume as well as their positive and negative cumulative sums for the these markets because of space limit consideration. These graphs are available from the authors upon request.

$\nRightarrow$*PR*−), is rejected at the 10% significance level. Moreover, the results of the asymmetric causality tests indicate that there is unidirectional asymmetric Granger causality running from the positive shock of the price index to the negative component of trading volume (*PR*+ $\nRightarrow$*VO*−).

Turning to the S&P 500 (see Table 7), with the exception of (*VO*+ $\nRightarrow$*PR*−), there is symmetric Granger causality running from the trading volume to the price index. The negative component of the trading volume exerts an asymmetric Granger-causal effect on the positive and negative components of the price index. There is unidirectional asymmetric causality running from the positive component of the trading volume to the positive component of the stock price index. In addition, the negative shock of the price index has an asymmetric Granger-causal effect on the positive and negative components of the trading volume, respectively.

The empirical results for the Hang Seng index (see Table 8) show that the null hypothesis of the negative shock of the trading volume not causing the positive component of the price index is rejected at the 5% significance level. Likewise, the negative component of the price index has an asymmetric Granger-causal effect on the positive component of the trading volume. Finally, in the case of the TSEC weighted index (see Table 9), the results show that there is a bi-directional symmetric Granger-causal relationship between the stock price and trading volume. Likewise, there is a bi-directional asymmetric Granger-causal relationship between the negative component of the price index and the negative component of trading volume. Moreover, there is a uni-directional asymmetric Granger-causal effect running from the positive (negative) shock of the trading volume to the negative (positive) component of the price index.

For the readers' information, we summarize the symmetric and asymmetric Granger causality tests in Table 10. Generally speaking, with the exception of the Nikkei 225, the past information on trading volume is helpful in predicting the behavior of the stock price. These results are in line with Gallant et al. (1992) and Blume et al. (1994). Blume et al. (1994) have stressed that trading volume inherits important information regarding speculators' trading activities, and hence, movements in trading volume are useful in forecasting of the stock price dynamics. Gallant et al. (1992) claim that more can be learned about the stock market behavior by studying the joint dynamics of stock prices and trading volume rather than by focusing on only one of them.

Based on these findings, we can determine which theoretical explanation holds for the presence of the causal relationships between the stock price and the trading volume (see Table 11). First, it is clear that the mixture of distribution model of Clark (1973) is applicable to the price-volume relationship in the Nikkei 225 of Japan because a neutral relationship between trading volume and stock prices is accepted in the sense of symmetric and symmetric Granger causality. Second, the DeLong et al. (1990) noise-trader model is applicable to the CAC 40 and Hang Seng index . This is because, for the former, there is symmetric uni-directional Granger causality running from the trading volume to the price index and, for the latter, there is an asymmetric unidirectional Granger-causality running from the stock price to the trading volume. Third, for the FTSE 100, S&P 500 and TSEC weighted index, there is a feedback relationship between the stock prices and trading volume. These results provide evidence that the stock prices and trading volume of the four markets are subject to the influences of the sequential information arrival model and the noise-trader model simultaneously, and that a feedback loop will prevail with an arbitrary sign of correlation between the price and volume. Finally, the mixture distribution model of Epps and Epps (1976) is not applicable to any of the six stock markets.

5. Concluding Remarks

This paper examines the nature of the stock price-volume relationship in six international stock markets. In order to untangle the symmetric and asymmetric causal relationship between the stock price index and the trading volume and to help us to discriminate between competing theories on how information is disseminated in stock markets, we adopt the asymmetric Granger causality test with bootstrap simulation, as proposed by Hatemi-J (2012a), to achieve this goal. Since the data appears to deviate from the normal distribution, bootstrapping is utilized to generate correct critical values for each null hypothesis. For the readers' information, we summarize our empirical results in Tables 10 and 1.

This study reaches the following key conclusions. First, by using a battery of univariate unit root tests, the stock price indexes of these markets are characterized as a unit root process, while the trading volumes are suggested to be the stationary processes. Second, there is neutrality between the stock prices and trading volume with or without an asymmetric effect for the Nikkei 225 and, therefore, the mixture of distribution model of

Clark (1973) is applicable to Japan. Third, the DeLong et al. (1990) noise-trader model is applicable to the CAC 40 and Hang Seng index because, for the former, there is symmetric uni-directional Granger causality running from the trading volume to the price index. For the latter, there is asymmetric uni-directional Granger causality running from the stock prices to the trading volume. Fourth, for the FTSE 100, S&P 500 and TSEC weighted index, there is a feedback relationship between the stock prices and trading volume. These results provide evidence that the stock prices and trading volume of the four markets are subject to the influences of the sequential information arrival model and the noise-trader model simultaneously and that a feedback loop will prevail with an arbitrary sign of the correlation between stock prices and trading volume. Finally, the mixture distribution model of Epps and Epps (1976) is not applicable to all six stock markets.

In general, the results presented in this study are consistent with the predictions of the sequential information arrival hypothesis and the noise-trader model. This conclusion is similar to Moosa and Silvapulle (2000) who apply the linear and non-linear Granger causality to the crude oil futures market. Our results are useful for market participants and the efficiency of the stock market. For market investors or speculators, the results are useful since they imply that volume can be used to predict prices, lending support to technical analysis. Finally, the results imply that the market is inefficient due to the fact that traders may make abnormal profits by predicting their prices based on previous volumes.

Appendix: The Bootstrap Simulation

As a remedy for the residuals that are not normally distributed, we make use of the bootstrap simulation technique by implementing the following steps:

1. The first step is to estimate the restricted regression model (9), i.e., the model is estimated when the restrictions under the null hypothesis are imposed.

2. The next step is to simulate the bootstrap data, Y_t^*, via the following expression:

$$Y^* = \widehat{D}Z + \delta_{,}^* \tag{11}$$

It should be mentioned that the bootstrapped residuals ($\delta_{,}^*$) are produced by T random draws with replacement from the regression's modified residuals. Each independent draw has an equal likelihood of $1/T$. Since the theoretical condition for a good model is to have the expected value of the residuals equal to zero, we mean-adjust the bootstrapped residuals in each replication in order to make sure that the mean value of the residuals is zero in that bootstrap replication. This will be achieved by subtracting the mean value of the resulting set of drawn modified residuals from each of the modified residuals in that set. The modified residuals are the regression's original residuals that are adjusted via leverages in order to have constant variance.

3. The bootstrap simulations are repeated 100,000 times and each time the Wald test statistic, as presented in Eq. (10), is estimated based on each underlying bootstrap sample. In this way, the empirical distribution of the test statistic is generated, whatever that distribution might be and in spirit of it, not necessarily being normal. Thus, the bootstrap generated critical value at the α-level of significance (c_{α}^{*}) is obtained by taking the (α)th upper quantile of the distribution of the bootstrappedWald test statistic.

4. The final step in the bootstrap approach is to estimate the Wald test statistic using the original data, which is compared to the bootstrap critical value. The null hypothesis of non-Granger causality is rejected at the αlevel of significance if the Wald test statistic (that is estimated in the final step) is larger than the bootstrap critical value (c_{a}^{*}) at that significance level. The bootstrap critical values of the test statistic are generated for the 1%, 5%and 10% significance levels, respectively.

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Table 1: Results of the linear unit root tests (*VO*)

	Linear trend		
	ADF	**SP(1)**	**DF-GLS**
CAC 40	−3.464**	−8.798**	−8.885**
Nikkei 225	−4.991**	−5.482**	−5.844**
FTSE 100	−2.776	−11.571**	-9.054**
S&P 500	−0.736	−4.646**	−6.588**
Hang Seng	−1.530	−3.857**	−5.654**
TSEC Weighted	−3.026	−5.390**	−5.567**

	Quadratic trend and breaks test		
	SP(2)	**ZA, Model C**	**LP, Model C**
CAC 40	−9.840**	−7.311**	−6.513*
Nikkei 225	−9.295**	−6.786**	−7.513**
FTSE 100	−12.365**	−9.290**	−6.643*
S&P 500	−6.893**	−6.623**	−6.440
Hang Seng	−5.187**	−6.822**	−6.520*
TSEC Weighted	−5.240**	−7.236**	−6.904*

(1) *, **, *** denote significance at the 10%, 5% and 1%, respectively. (2) ADF, SP(1) and DF-GLS denote the augmented Dickey-Fuller test, Schmidt-Phillips *t* test with linear trend and Elliott et al. (1996) DF-GLS test, respectively. (3) SP(2), ZA and LP denote the Schmidt-Phillips *t* test with quadratic trend, Zivot and Andrews (1992) and Lumsdaine and Papell (1997) tests, respectively. (4) The 5% critical values for the ADF, SP(1) and DF-GLS tests are −3.43, −3.04 and −2.89, respectively. (5) The 5% critical values for the SP(2), ZA and LP tests are −3.55, −5.08 and −6.75, respectively.

Table 2: Results of the linear unit root tests (*PR*)

	Linear trend		
	ADF	**SP(1)**	**F-GLS**
CAC 40	−2.446	−1.499	−1.554
Nikkei 225	−2.497	−1.320	−1.106
FTSE 100	−2.151	−1.910	−2.030
S&P 500	−2.269	−2.042	−1.928
Hang Seng	−3.073	−2.090	−2.041
TSEC Weighted	−3.787**	−2.244	−1.898

	Quadratic trend and breaks tests		
	SP(2)	**ZA, Model C**	**LP, Model C**
CAC 40	−2.001	−3.449	−4.718
Nikkei 225	−2.019	−3.810	−5.570
FTSE 100	−2.162	−4.285	−5.401
S&P 500	−1.849	−5.214*	−6.288
Hang Seng	−2.209	−3.993	−6.427
TSEC Weighted	−2.414	−3.762	-6.223

(1) *, **, *** denote significance at the 10%, 5% and 1%, respectively. (2) ADF, SP(1) and DF-GLS denote the augmented Dickey-Fuller test, Schmidt-Phillips *t* test with linear trend and Elliott et al. (1996) DF-GLS test, respectively. (3) SP(2), ZA and LP denote the Schmidt-Phillips *t* test with quadratic trend, Zivot and Andrews (1992) and Lumsdaine and Papell (1997) tests, respectively. (4) The 5% critical values for the ADF, SP(1) and DF-GLS tests are −3.43, −3.04 and −2.89, respectively. (5) The 5% critical values for the SP(2), ZA and LP tests are −3.55, −5.08 and −6.75, respectively.

Table 3: Tests for multivariate normality and ARCH in the VAR model

Variables in the VAR model	CAC 40 Multivariate normality	CAC 40 Multivariate ARCH	Nikkei 225 Multivariate normality	Nikkei 225 Multivariate ARCH	FTSE 100 Multivariate normality	FTSE 100 Multivariate ARCH
(VO, PR)	<0.001***	<0.001***	<0.001***	<0.001***	<0.001***	<0.001***
(VO^+, PR^+)	<0.001***	0.985	<0.001***	0.995	<0.001***	0.874
(VO^-, PR^+)	<0.001***	0.705	<0.001***	0.611	<0.001***	0.406
(VO^+, PR^-)	<0.001***	0.889	<0.001***	0.896	<0.001***	0.925
(VO^-, PR^-)	<0.001***	0.999	<0.001***	0.151	<0.001***	0.920

Variables in the VAR model	S&P 500 Multivariate normality	S&P 500 Multivariate ARCH	Hang Seng Multivariate normality	Hang Seng Multivariate ARCH	TSEC Multivariate normality	TSEC Multivariate ARCH
(VO, PR)	<0.001***	<0.001***	<0.001***	<0.001***	<0.001***	<0.001***
(VO^+, PR^+)	<0.001***	0.727	<0.001***	0.709	<0.001***	0.871
(VO^-, PR^+)	<0.001***	0.123	<0.001***	0.681	<0.001***	0.363
(VO^+, PR^-)	<0.001***	<0.001***	<0.001***	0.903	<0.001***	0.879
(VO^-, PR^-)	<0.001***	<0.001***	<0.001***	0.988	<0.001***	0.644

(1) *, **, *** denote significance at the 10%, 5% and 1%, respectively. (2) The test suggested by Doornik and Hansen (2008) was used for testing the null hypothesis of multivariate normality. (3) The p values for the diagnostic tests are presented.

Table 4: The results for causality using the bootstrap simulations (CAC 40)

Null hypothesis	Test value	Bootstrap CV at 1%	Bootstrap CV at 5%	Bootstrap CV at 10%
$VO \nRightarrow PR$	11.309***	9.122	6.240	4.671
$VO^+ \nRightarrow PR^+$	1.110	7.612	4.221	2.963
$VO^- \nRightarrow PR^-$	0.599	8.490	3.567	2.388
$VO^+ \nRightarrow PR^-$	0.124	6.888	3.986	2.658
$VO^- \nRightarrow PR^+$	0.024	7.648	4.036	2.738
$PR \nRightarrow VO$	3.491	9.330	6.586	4.876
$PR^+ \nRightarrow VO^+$	0.062	7.784	4.034	2.584
$PR^- \nRightarrow VO^-$	0.045	7.250	3.772	2.481
$PR^+ \nRightarrow VO^-$	0.903	8.169	4.405	2.912
$PR^- \nRightarrow VO^+$	1.192	8.140	3.812	2.575

(1) The denotation $A \nRightarrow B$ means that variable A does not cause variable B. (2) *, **, *** denote significance at the 10%, 5% and 1%, respectively.

Table 5: The results for causality using the bootstrap simulations (Nikkei 225)

Null hypothesis	Test value	Bootstrap CV at 1%	Bootstrap CV at 5%	Bootstrap CV at 10%
$VO \nRightarrow PR$	0.772	11.725	8.046	6.417
$VO^{+} \nRightarrow PR^{+}$	0.200	7.194	4.094	3.002
$VO^{-} \nRightarrow PR^{-}$	1.886	6.804	3.663	2.613
$VO^{+} \nRightarrow PR^{-}$	1.179	14.833	8.652	6.671
$VO^{-} \nRightarrow PR^{+}$	0.021	7.233	3.668	2.591
$PR \nRightarrow VO$	2.182	10.857	7.961	6.233
$PR^{+} \nRightarrow VO^{+}$	1.843	6.780	3.878	2.599
$PR^{-} \nRightarrow VO^{-}$	0.092	7.848	3.791	2.669
$PR^{+} \nRightarrow VO^{-}$	0.953	6.133	4.061	2.700
$PR^{-} \nRightarrow VO^{+}$	2.060	12.338	8.511	6.213

(1) The denotation $A \nRightarrow B$ means that variable *A* does not cause variable *B*. (2) *, **, *** denote significance at the 10%, 5% , and 1%, respectively.

Table 6: The results for causality using the bootstrap simulations (FTSE 100)

Null hypothesis	Test value	Bootstrap CV at 1%	Bootstrap CV at 5%	Bootstrap CV at 10%
$VO \nRightarrow PR$	11.690**	13.044	7.784	6.227
$VO^{+} \nRightarrow PR^{+}$	0.045	8.589	3.667	2.555
$VO^{-} \nRightarrow PR^{-}$	2.514*	9.583	3.624	2.222
$VO^{+} \nRightarrow PR^{-}$	0.047	9.421	3.441	2.326
$VO^{-} \nRightarrow PR^{+}$	1.863	7.638	3.427	2.555
$PR \nRightarrow VO$	10.988**	12.659	7.822	6.350
$PR^{+} \nRightarrow VO^{+}$	1.546	6.857	4.237	2.805
$PR^{-} \nRightarrow VO^{-}$	2.239	8.436	3.871	2.496
$PR^{+} \nRightarrow VO^{-}$	6.368**	8.159	4.117	2.647
$PR^{-} \nRightarrow VO^{+}$	3.555	11.666	4.603	2.807

(1) The denotation $A \nRightarrow B$ means that variable *A* does not cause variable *B*. (2) *, **, *** denote significance at the 10%, 5% and 1%, respectively.

Table 7: The results for causality using the bootstrap simulations (S&P 500)

Null hypothesis	Test value	Bootstrap CV at 1%	Bootstrap CV at 5%	Bootstrap CV at 10%
$VO \nRightarrow PR$	19.507***	12.841	9.930	7.805
$VO^{+} \nRightarrow PR^{+}$	6.572**	7.168	4.179	2.847
$VO^{-} \nRightarrow PR^{-}$	6.795*	12.305	7.726	6.193
$VO^{+} \nRightarrow PR^{-}$	6.055	14.253	8.076	6.496
$VO^{-} \nRightarrow PR^{+}$	5.453**	5.610	3.592	2.397
$PR \nRightarrow VO$	3.510	12.993	9.820	8.030
$PR^{+} \nRightarrow VO^{+}$	0.351	7.842	4.188	2.698
$PR^{-} \nRightarrow VO^{-}$	6.987*	12.267	7.968	6.270
$PR^{+} \nRightarrow VO^{-}$	2.889	6.746	3.940	2.558
$PR^{-} \nRightarrow VO^{+}$	6.886*	12.996	8.133	6.367

(1) The denotation $A \nRightarrow B$ means that variable A does not cause variable B. (2) *, **, *** denote significance at the 10%,5% and 1%, respectively.

Table 8: The results for causality using the bootstrap simulations (Hang Seng)

Null hypothesis	Test value	Bootstrap CV at 1%	Bootstrap CV at 5%	Bootstrap CV at 10%
$VO \nRightarrow PR$	1.833	10.371	7.914	6.199
$VO+ \nRightarrow PR+$	3.274	7.425	4.068	2.676
$VO- \nRightarrow PR-$	4.840	11.006	8.090	6.379
$VO+ \nRightarrow PR-$	0.252	8.421	4.018	2.675
$VO- \nRightarrow PR+$	6.597**	8.753	5.194	3.889
$PR \nRightarrow VO$	0.831	11.646	8.198	6.577
$PR+ \nRightarrow VO+$	0.006	7.871	3.991	2.794
$PR- \nRightarrow VO-$	7.317*	12.710	8.050	6.051
$PR+ \nRightarrow VO-$	2.182	9.874	6.327	4.742
$PR- \nRightarrow VO+$	1.765	7.708	3.728	2.721

(1) The denotation $A \nRightarrow B$ means that variable A does not cause variable B. (2) *, **, *** denote significance at the 10%,5% and 1%, respectively.

Table 9: The results for causality using the bootstrap simulations (TSEC)

Null hypothesis	Test value	Bootstrap CV at 1%	Bootstrap CV at 5%	Bootstrap CV at 10%
$VO \nRightarrow PR$	24.409***	8.968	6.301	4.803
$VO^{+} \nRightarrow PR^{+}$	3.261	5.942	3.735	2.665
$VO^{-} \nRightarrow PR^{-}$	11.238***	10.605	7.906	6.329
$VO^{+} \nRightarrow PR^{-}$	9.447**	13.298	8.747	6.026
$VO^{-} \nRightarrow PR^{+}$	4.694**	6.324	3.786	2.578
$PR \nRightarrow VO$	4.976*	8.291	5.838	4.424
$PR^{+} \nRightarrow VO^{+}$	0.082	5.955	3.700	2.785
$PR^{-} \nRightarrow VO^{-}$	7.466*	11.603	8.098	6.348
$PR^{+} \nRightarrow VO^{-}$	0.002	7.245	3.820	2.627
$PR^{-} \nRightarrow VO^{+}$	4.234	11.622	8.019	6.364

(1) The denotation $A \nRightarrow B$ means that variable A does not cause variable B. (2) *, **, *** denote significance at the 10%,5% and 1%, respectively.

Table 10: Summary of symmetric and asymmetric Granger causality tests

Null hypothesis	CAC 40	Nikkei 225	FTSE 100	S&P 500	Hang Seng	TSEC
$VO \not\Rightarrow PR$	Reject		Reject	Reject		Reject
$VO^{+} \not\Rightarrow PR^{+}$				Reject		
$VO^{-} \not\Rightarrow PR^{-}$			Reject	Reject		Reject
$VO^{+} \not\Rightarrow PR^{-}$						Reject
$VO^{-} \not\Rightarrow PR^{+}$				Reject	Reject	Reject
Null hypothesis	**CAC 40**	**Nikkei 225**	**FTSE 100**	**S&P 500**	**Hang Seng**	**TSEC**
$PR \not\Rightarrow VO$			Reject			Reject
$PR^{+} \not\Rightarrow VO^{+}$						
$PR^{-} \not\Rightarrow VO^{-}$				Reject	Reject	Reject
$PR^{+} \not\Rightarrow VO^{-}$			Reject			
$PR^{-} \not\Rightarrow VO^{+}$				Reject		

(1) The denotation *A*6⇒*B* means that variable *A* does not cause variable *B*. (2) "Reject" denotes the null hypothesis ofno causality is rejected at the 10% significance level or better.

Table 11: Corresponding to theoretical model

	Copeland SIA	Clark MD	Epps & Epps MD	DeLong et al. Noise-trader
	$PR \Leftrightarrow VO$	$PR \not\Leftrightarrow VO$	$PR \Rightarrow VO$	$PR \Rightarrow VO$ **or** $VO \Rightarrow PR$
CAC 40				hold (S)
Nikkei 225		hold		
FTSE 100	hold (S)			hold (A)
S&P 500	hold (A)			hold (A)
Hang Seng				hold (A)
TSEC Weighted	hold (S,A)			hold (A)

(1) Term "hold" indicates that the condition is sustainable. (2) Term "hold (S)" indicates that the condition is sustainable with symmetric Granger causality. (3) Term "hold (A)" indicates that the condition is sustainable with asymmetric Granger causality. (4) Term "hold (A, S)" indicates that the condition is sustainable with symmetric and asymmetric Granger causality. (5) Terms SIA and MD indicate the sequential information arrival and mixture distribution models, respectively.