ELSEVIER Journal of Banking & Finance 26 (2002) 51–78

Journal of BANKING & FINANCE

www.elsevier.com/locate/econbase

The dynamic relationship between stock returns and trading volume: Domestic and cross-country evidence

Bong-Soo Lee [a], Oliver M. Rui [b,*]

[a] *Department of Finance, College of Business Administration, University of Houston, Houston, TX 77204-6282, USA*

[b] *Department of Accountancy, Hong Kong Polytechnic University, Hung Hom, Kow Loon, Hong Kong*

Received 14 October 1999; accepted 24 August 2000

Abstract

This paper examines the dynamic relations – causal relations and the sign and magnitude of dynamic effects – between stock market trading volume and returns (and volatility) for both domestic and cross-country markets by using the daily data of the three largest stock markets: New York, Tokyo, and London. Major findings are as follows: First, trading volume does not Granger-cause stock market returns on each of three stock markets. Second, there exists a positive feedback relationship between trading volume and return volatility in all three markets. Third, regarding the cross-country relationships, US financial market variables, in particular US trading volume, contains an extensive predictive power for UK and Japanese financial market variables. Fourth, sub-sample analyses show evidence of stronger spillover effects after the 1987 market crash and an increased importance of trading volume as an information variable after the introduction of options in the US and Japan. © 2002 Elsevier Science B.V. All rights reserved.

JEL classification: G15; G14

Keywords: Spillover; Trading volume; VAR

* Corresponding author. Tel.: +852-2766-7081; fax: +852-2365-4303.
E-mail address: acmrui@inet.polyu.edu.hk (O.M. Rui).

PII: S0378-4266(00)00173-4

1. Introduction

Numerous studies have examined the return correlation among different markets and the relationship between stock returns and trading volume. In an extensive review of theoretical and empirical research into the relationship between stock price changes and trading volume, Karpoff (1987) cites several reasons why the price–volume relationship is important and observes that much of the previous research has been about the *contemporaneous* relationship using correlations. Gallant et al. (1992) also point out that previous empirical work on the price–volume relationship has focused primarily on the *contemporaneous* relationship between price changes and volume.

Although some previous studies may have some implications for dynamic relations between returns of different national markets and between trading volume and stock returns in a domestic stock market and between different national markets, few studies examine dynamic (causal) relations between trading volume and returns (and volatility) both domestically and across countries to confirm or reject these implications. For example, referring to an old Wall Street adage that "It takes volume to make prices move", Karpoff (1987) states that one can question the asserted causality. Hamao et al. (1990) point out that volatility spillovers between different countries' stock markets could represent a causal phenomenon across markets that trade sequentially. [1]

However, in a dynamic context, an important issue should be whether information about trading volume is useful in improving forecasts of price changes (i.e., returns) and return volatility. The purpose of this paper is to empirically examine the dynamic (causal) relationship between trading volume and stock market returns (and volatility). Given recent interest in cross-country spillovers, we examine the causal relations not only for domestic stock markets but also for cross-country markets using the data of the three largest stock markets: New York, Tokyo and London. We include volatility in our analysis as well as return and volume in part because it is possible that the dynamic relation between return and volume may be affected by volatility effects associated with information flow and in part because volatility is a key ingredient of the risk-return tradeoff that permeates modern financial theories. [2] In addition,

[1] Hamao et al. (1990) find evidence of price volatility spillovers from New York to Tokyo, London to Tokyo, and New York to London but no evidence of spillover effects in other directions for the period prior to the 1987 crash.

[2] A thorough understanding of the determinants of the volatility process is critical for issues related to the functioning of markets and the implementation and evaluation of both asset pricing theories and option pricing theories. Bessembinder and Seguin (1993) find that linking volatility to trading volume does not extract all information. Hiemstra and Jones (1994) also find that after controlling for volatility effects, the dynamic relation between trading volume and stock return is not affected.

we examine dynamic effects, in particular the sign and magnitude, of trading volume changes on stock market returns and volatility, domestically and internationally, when there exist causal relations.

We believe it is important to distinguish contemporaneous relationships among variables from dynamic causal relationships. An objective of this paper is to understand whether the finding of a relationship between two variables such as US returns and Japanese volume is a result of causal or contemporaneous factors. There are also reasons why we should expect both contemporaneous and causal relationships across national markets. The dynamic causal relation between volume in one market and return in another is important because a finding of an empirical link between, for example, return in US stocks and volume in the Japanese market may be a result of US returns affecting Japanese returns and Japanese returns affecting Japanese volume rather than US returns affecting Japanese volume directly. Perhaps this is due to the fact that international markets operating at different times allow more continuous trading and therefore uninterrupted transmission of information as reflected by returns, volume and volatility. In addition, the US, UK and Japanese markets list many of the same securities.

We find that US financial market variables, in particular US trading volume, contains an extensive predictive power for UK and Japanese financial market variables. Our sub-sample analyses show evidence of stronger spillover effects after the 1987 market crash and an increased importance of trading volume as an information variable after the introduction of options in the US and Japan.

1.1. Review of the literature on direct spillover effects from one national market to another

Numerous studies on national equity markets have focused on the return correlations among different markets. Agmon (1972, 1974) for example, finds that these correlations are generally insignificant or unstable. However, Jaffe and Westerfield (1985a,b) find that the correlations are positive and significant among national markets. Using vector autoregressions, Eun and Shim (1989) find substantial cross-country interactions and an influential role for the US market. Copeland and Copeland (1998) explore the contemporaneous and lead–lag relations of market returns using the Dow Jones global industry indexes. [3] Arshanapalli and Doukas (1993) examine the linkages and dynamic interactions among stock price indices in the major world stock exchanges taking account of cointegration among the indices.

[3] They find that there is a strong contemporaneous relationship among regional exchanges that open at the same time and that the US leads Europe and the Pacific by one day.

The finding that stock returns in different countries are correlated is not surprising in itself in view of international capital asset pricing models. Some studies provide alternative explanations. In an attempt to explain why, in October 1987, many stock markets in different countries fell together despite widely differing economic circumstances, King and Wadhwani (1990) propose a contagion theory, where a "mistake" in one market is transmitted to other markets. This theory posits that traders in one market draw inferences about shocks to stock price fundamentals from observed price movements in other markets. Even price moves that are not generated by fundamentals can affect many markets. Regarding the conditional variance of stock returns, Hamao et al. (1990) find spillover effects from the US and the UK stock markets to the Japanese market. Although they suspect that such volatility spillovers could represent a causal relation across markets, they do not further pursue the causal relations. The spillover effect of information by trading volume of one country to trading volume of another has been rarely discussed in the past. We find substantial cross-country interactions of trading volumes and an influential role of US trading volume.

1.2. Review of the literature on cross-variable spillover effects cross-country

Recently, some theoretical studies investigate the dynamic relationship between trading volume and stock returns, which may have some causal relationship implications. Copeland (1976) and Jennings et al. (1981) derive the sequential information arrival model. They suggest a positive causal relationship between stock prices and trading volume in either direction. [4] In the mixture of distributions model of Epps and Epps (1976), trading volume is used to measure disagreement as traders revise their reservation prices based on the arrival of new information into the market. The greater the degree of disagreement among traders, the larger the level of trading volume. Their model suggests a positive causal relationship running from trading volume to absolute stock returns. [5] Campbell et al. (1993) present a model whose implications include that price changes accompanied by high volume will tend to be reversed, and this will be less true of price changes on days with low volume. Blume et al. (1994) present a model in which traders can learn valuable information about a security by observing both past price and past volume information. In their model, volume provides data on the quality or precision of

[4] Due to the sequential information flow, lagged trading volume could have predictive power for current stock returns, and lagged stock returns could have predictive power for current trading volume.

[5] In Clark (1973) mixture model, trading volume is a proxy for the speed of information flow, a latent common factor that affects contemporaneous stock returns and volume. There is no causal relation from trading volume to stock returns in Clark's common-factor model.

information about past price movements, and thus traders who include volume measures in their technical analysis perform better in the market than those who do not. Wang (1994) analyzes dynamic relationships between volume and returns based on a model with information asymmetry. His model shows that volume may provide information about expected future returns. [6]

The dynamic relation between volume in one market and return in another should be interesting in that it may help better understand contemporaneous relations. This is because there is some overlapping trading period and multiple listings of the same securities. As such, international markets allow more continuous trading and uninterrupted transmission of information as reflected by returns, volume and volatility.

The relationship between stock returns and trading volume has interested empirical financial economists for a number of years. For example, previous studies have investigated the relationships between price indices and aggregate exchange trading volume (Granger and Morgenstern, 1963), between absolute price change and trading volume (Crouch, 1970; Karpoff, 1987), and between price change and trading volume (Tauchen and Pitts, 1983; Wood et al., 1985; Karpoff, 1987). However, these empirical studies on the price–volume relationship have focused primarily on the contemporaneous relationship between price changes and volume (see Karpoff, 1987; Gallant et al., 1992). Although some models imply a dynamic relationship between price and volume using cross-correlation, they do not further pursue causal relationships.

Rogalski (1979), Smirlock and Starks (1988), and Jain and Joh (1988) test for a linear causal relation between stock prices and trading volume. Hiemstra and Jones (1994) investigate the dynamic relation between daily aggregate stock prices and trading volume using linear and nonlinear causality tests. [7] Chordia and Swaminathan (2000) examine the interaction between trading volume and the predictability of short horizon stock returns. They find that daily returns of stocks with high trading volume lead daily returns of stocks with low trading volume. They attribute this to the tendency of high volume stocks to respond promptly to market-wide information. They conclude that trading volume plays a significant role in the dissemination of market-wide information. These studies focus on domestic relations but do not examine cross-country dynamic relations.

[6] We thank the referee for suggesting that we organize the introduction this way.

[7] They find evidence of uni-directional Granger causality from Dow Jones stock returns to NYSE trading volume, but bi-directional nonlinear causality between returns and volume. However, using daily S&P 500 index stock returns and NYSE trading volume, Gallant et al. (1992) find evidence of strong nonlinear impacts from lagged stock returns to current and future trading volume but only weak evidence of a nonlinear impact from lagged volume to current and future stock returns.

Several studies examine the relation between volatility and trading volume. Some investigate relations between the variance of price change and trading volume (e.g., Epps and Epps, 1976), others between squared price change and trading volume (e.g., Harris, 1986; Clark, 1973). Tauchen and Pitts (1983) examine the relationship between the variability of price change and volume on the speculative markets. Foster and Viswanathan (1995) derive a speculative trading model with endogenous informed trading that yields a conditionally heteroscedastic time series for volume and volatility. Andersen (1996) develops an empirical return volatility–volume model from a microstructure framework.

In the current paper, we use a methodology developed by Sims (1972, 1980) based on both bivariate and multivariate vector autoregression (VAR). Using daily data, we examine causal relations not only between volume and price changes but also between volume and volatility of returns both in domestic and international markets and investigate dynamic effects among these variables.

The remainder of the paper is organized as follows: Section 2 discusses data and preliminary results. Dynamic relationships among returns, volatility, and trading volume are presented in Section 3. Section 4 concludes the paper.

2. Data and preliminary results

2.1. Data

The data set comprises *daily* market price index and trading volume series for the three largest stock exchanges: New York, Tokyo and London. For the US Stock Exchange, we use the S&P 500 index. The index covers the period of 2 January 1973–1 December 1999, and consists of 6784 observations for each series. [8] For the Tokyo Stock Exchange, we use the Tokyo Stock Exchange Price Index (TOPIX). The index covers the period of 7 January 1974–1 December 1999, and consists of 6525 observations. For London, we use the Financial Times–Stock Exchange (FT–SE) 100 index. The index covers the period of 27 October 1986–1 December 1999, and consists of 3310 observations for each variable. We collected the data from Datastream database and stock returns are expressed in percent.

The S&P 500 index is a market capitalization-weighted index that tracks the daily total return performance of 500 common stocks of large capitalization companies that are listed on the NYSE, AMEX, and NASDAQ. The S&P 500 accounts for about 64% of the market value of shares listed on the three exchanges. Base value is 10 for the period 1941–1943. The TOPIX is a broad-based capitalization-weighted index that tracks the performance of all domestic

[8] The sample does not include the dates when trading volume is not available.

common stocks listed on the first section of the Tokyo Stock Exchange. The first section is comprised of larger, established companies that have generally been in existence for five years or more and meet more stringent eligibility criteria relating to the size and business conditions of the issuing company as well as the liquidity of its securities. Base value is 100 on 4 January 1968. The FT–SE 100 index was started on 3 January 1984, by the Stock Exchange (SE) and Financial Times (FT), incorporating the top 100 UK companies, accounting for about 70% of the total market value of all UK equities. The FT–SE 100 index is a market value-weighted index that tracks the daily total return performance of the 100 highly capitalized British stocks traded on the London Stock Exchange. The index consists of shares that must qualify for inclusion in the FT–SE Actuaries All-Share Index. Base value is 1000 at the opening of business on 3 January 1984 (see Shilling, 1996, for details). All these series of index and trading volume are matched.

2.2. Trend and unit root tests

The vector autoregression model we use for causality tests assumes that the variables in the system are stationary. As such, we test for the stationarity of stock returns and trading volume data. There are two ways to achieve stationarity. Some series need to be detrended (called the *trend-stationary* process), and others need to be differenced (called the *difference-stationary* or *integrated of order one*, I(1), process, or *unit root* process).

Previous works report strong evidence of both linear and nonlinear time trends in trading volume series (e.g., Gallant et al., 1992). As such, trend stationarity in trading volume is tested by regressing the series on a deterministic function of time. To allow for a nonlinear time trend as well as a linear trend, we include a quadratic time trend term

$$V_t = \alpha + \beta t + \chi t^2 + \varepsilon_t, \tag{1}$$

where V_t is (raw) trading volume in each stock market.

To test for a unit root (or the difference stationary process), we employ both the augmented Dickey and Fuller (1979), (i.e., D–F) test and the Phillip and Perron (1988), (i.e., P–P) test:

(a) Augmented Dickey–Fuller regression

$$\Delta x_t = \rho_0 + \rho x_{t-1} + \sum_{i=1}^{n} \delta_i \Delta x_{t-i}. \tag{2}$$

(b) Phillips–Perron regression

$$x_t = \alpha_0 + \alpha x_{t-1} + u_t. \tag{3}$$

The difference between the two unit root tests lies in their treatment of any “nuisance” serial correlation. The P–P test tends to be more robust to a wide range of serial correlation and time-dependent heteroskedasticity. In these tests, the null hypothesis is that a series is nonstationary (i.e., difference stationary): $\rho = 0$ and $\alpha = 1$.

The test result shows that the coefficients (with t-ratios in parentheses) of regressing trading volume on a linear time trend alone are 0.008 (111.74), 0.004 (18.71), and 0.12 (68.15) in the US, Japanese, and UK stock markets, respectively, and they are all significant at 1%. When we add a quadratic time trend term, its coefficient is very significant in all three markets. [9] Therefore, we use trading volumes adjusted for both linear and nonlinear trends for the three markets. The test result also shows that the null hypothesis that the stock return series and detrended trading volume series are nonstationary (i.e., have a unit root) is strongly rejected in all three stock exchanges whether we allow for three lags or five lags. This confirms that detrended trading volume and stock return series are both stationary. The detailed test results are available upon request. For the estimation of the VAR, we use five lags considering both the Akaike information criterion (AIC) and the Schwarz criterion, which amounts to allowing for week-long information in the regression.

2.3. Contemporaneous relationships

As mentioned above, the contemporaneous relationship between stock returns and trading volume has been extensively studied from a variety of perspectives (see Karpoff, 1987). We investigate the relationship using an instrumental variable estimator as a GMM estimator to avoid problems of simultaneity bias. In addition, the use of a GMM framework produces heteroskedasticity-consistent estimates by correcting the covariance matrix of the (consistent) instrumental variable estimator (see Foster, 1995). Panel A of Table 1 reports that the coefficients of regressing stock returns on trading volume (trading volume on stock returns) are 0.383 (0.001), 1.255 (0.039), and 1.010 (0.005) in the US, Japanese, and UK stock markets, respectively, and they are all significant. Therefore, there exists a positive contemporaneous relationship between trading volume and returns in all three stock markets. Our finding about the US market is consistent with previous studies. [10]

[9] For the sub-sample period up to 1995, only US trading volume has a significant quadratic trend. It is noted that Japanese trading volume has a negative quadratic trend when we include recent data (e.g., post-1995).

[10] The results of the regression of stock returns on expected and unexpected trading volumes are available upon request. To compute expected and unexpected trading volume, we use a VAR consisting of each market's return, volatility, and volume and use innovations in trading volume as unexpected volume. In practice, we regress trading volume on a constant, past returns, past volatilities, and past volumes for each market and use the regression residuals as unexpected volume and the rest as expected volume.

Table 1
Contemporaneous relationship between daily trading volume and stock returns[a]

	US	t-ratio coefficient	Japan	t-ratio coefficient	UK	t-ratio coefficient
Panel A. GMM robust test of contemporaneous relationship $R_t = b_0 + b_1 V_t + b_2 V_{t-1} + b_3 R_{t-1} + \varepsilon_t$, $V_t = a_0 + a_1 R_t + a_2 V_{t-1} + a_3 V_{t-2} + u_t$, where V_t is the detrended trading volume at time t, and R_t is the return at time t						
b_0	0.033	(2.798)*	0.023	(1.971)**	0.043	(2.378)**
b_1	0.383	(1.780)***	1.255	(17.942)*	1.010	(4.287)*
b_2	−0.194	(−0.701)	−0.968	(−13.670)*	−0.627	(−2.660)*
b_3	0.075	(6.197)*	0.091	(7.451)*	0.074	(4.283)*
a_0	0.001	(0.096)	−0.001	(−0.483)	−0.001	(−0.127)
a_1	0.001	(1.866)***	0.039	(9.174)*	0.005	(4.276)*
a_2	0.631	(53.777)*	0.657	(5.331)*	0.411	(23.924)*
a_3	0.253	(21.534)*	0.178	(15.041)*	0.133	(7.686)*
Panel B. GARCH robust test of contemporaneous relationship $R_t = b_0 + b_1 V_t + \varepsilon_t$, $\varepsilon_t \mid (\varepsilon_{t-1}, \varepsilon_{t-2}, \ldots) \sim N(0, h_t)$, $h_t = a_0 + a_1 \varepsilon_{t-1}^2 + a_2 h_{t-1}$						
b_0	0.051	(5.295)*	0.064	(8.158)*	0.062	(4.252)*
b_1	0.282	(2.153)**	0.414	(16.148)*	1.096	(7.281)*
a_0	0.011	(8.181)*	0.013	(11.429)*	0.022	(5.369)*
a_1	0.067	(43.935)*	0.151	(42.264)*	0.078	(10.348)*
a_2	0.923	(194.205)*	0.849	(186.849)*	0.898	(87.711)*
LR statistic	8677		7677		4278	
Panel C. GARCH robust test of contemporaneous relationship $R_t = b_0 + \varepsilon_t, \varepsilon_t \mid (\varepsilon_{t-1}, \varepsilon_{t-2}, \ldots) \sim N(0, h_t)$, $h_t = a_0 + a_1 \varepsilon_{t-1}^2 + a_2 h_{t-1} + a_3 V_t$						
b_0	0.045	(4.673)*	0.047	(6.146)*	0.057	(3.917)*
a_0	0.031	(13.049)*	0.013	(11.255)*	0.025	(5.776)*
a_1	0.075	(38.324)*	0.154	(37.131)*	0.083	(9.492)*
a_2	0.889	(188.579)*	0.845	(177.060)*	0.888	(76.885)*
a_3	0.185	(11.539)*	0.011	(3.084) *	0.093	(2.057)**
LR statistic	8616		7690		4285	

[a] For panels A–C, sample periods are 01/02/73–12/01/99 for the US, 01/07/74–12/01/99 for Japan, and 10/27/86–12/01/99 for the UK.
* Represent the causal relationship being significant at 1%.
** Represent the causal relationship being significant at 5%.
*** Represent the causal relationship being significant at 10%.

A preliminary normality test shows that the error distribution of stock returns does not exhibit a constant variance. The GARCH model encompasses an autocorrelation correction and is robust to underlying nonnormality. The GARCH model also incorporates heteroskedasticity in a sensible way and can be extended to include other effects on conditional variances. Thus the model offers considerable flexibility in robust modeling of stock returns. To test whether the positive contemporaneous relationship between trading volume and stock returns still exists after controlling for nonnormality of error distribution, the following GARCH (1,1) model is estimated:

$$\begin{aligned} R_t &= b_0 + b_1 V_t + \varepsilon_t, \\ \varepsilon_t &| (\varepsilon_{t-1}, \varepsilon_{t-2}, \ldots) \sim N(0, h_t), \\ h_t &= a_0 + a_1 \varepsilon_{t-1}^2 + a_2 h_{t-1}. \end{aligned} \tag{4}$$

As reported in Panel B of Table 1, the coefficients of regressing returns on trading volume are all positive and significant using the GARCH (1,1) model. The LR statistics in the three countries are very large, which implies that the GARCH model is an attractive representation of daily stock return behavior, successfully capturing the temporal dependence of return volatility. The presence of GARCH effects suggests the daily time dependence in the rate of information arrival to the aggregate markets. The positive contemporaneous relationship between trading volume and return remains after taking heteroskedasticity into account. When we incorporate trading volume into the volatility equation while excluding contemporaneous trading volume in the estimation of the returns equation, the GARCH effect still remains for aggregate market returns (see Panel C of Table 1). This implies, among other things, that the volatility of returns is not totally explained by trading volume. This evidence appears inconsistent with findings of Lamoureux and Lastrapes (1990), but compatible with findings of Bessembinder and Seguin (1993) that linking volatility to trading volume does not extract all information. [11]

3. Dynamic relationship

3.1. Causal relationship between trading volume and return

The empirical procedure in this section tests whether trading volume precedes stock returns, and vice versa. This is the notion behind causality testing

[11] Lamoureux and Lastrapes (1990) find that ARCH effects tend to disappear when volume is included in the variance equation for a sample of 20 actively traded individual stocks. Bessembinder and Seguin (1993) find the above evidence by examining a sample of eight futures markets.

in Granger (1969), and it is based on the premise that the future cannot cause the present or the past. If an event x occurs before an event y, then we can say that x causes y. Formally, if the prediction of y using past x is more accurate than the prediction without using past x in the mean square error sense (i.e., if $\sigma^2(y_t|I_{t-1}) < \sigma^2(y_t|I_{t-1} - x_t)$, where I_t is the information set), x Granger-causes y, denoted by $x \overset{\text{G.C}}{\rightarrow} \text{y}$.

The following bivariate autoregression is used to test for causality between the two variables among trading volume, stock returns and volatility of stock returns:

$$\begin{aligned} x_t &= \alpha_0 + \sum_{i=1}^{m} \alpha_i x_{t-i} + \sum_{i=1}^{n} \beta_i y_{t-i} + \varepsilon_t, \\ y_t &= \gamma_0 + \sum_{i=1}^{m} \gamma_i x_{t-i} + \sum_{i=1}^{n} \delta_i y_{t-i} + \eta_t. \end{aligned} \tag{5}$$

Suppose that x_t and y_t are trading volume and returns, respectively. If the β_i coefficients are statistically significant, inclusion of past values of return (y), in addition to past history of volume (x), yields a better forecast of future volume, and we say returns cause volume. If a standard F-test does not reject the hypothesis that $\beta_i = 0$ for all i, then returns do not cause volume. Similarly, in the second equation, if causality runs from volume to returns, the γ_j coefficient will jointly be different from zero. If both β and γ are different from zero, there is a feedback relation between returns and trading volume. [12]

Table 2 presents the results of domestic causal relationship tests based on a bivariate model, along with F-statistics and corresponding significance levels. The following observations, among other things, are noted. First, at a 5% significance level, trading volume does not Granger-cause stock market returns on each of the US, Japanese, and UK stock exchanges when we use the whole sample periods. This implies that, although there is a positive contemporaneous correlation between volume and returns, trading volume does not add significant predictive power for future returns in the presence of current and past returns. This finding is consistent with Clark (1973) mixture model that predicts no causal relation from trading volume to stock returns. This is also consistent with the findings of Gallant et al. (1992), who use nonlinear impact analysis, but at odds with the findings of Hiemstra and Jones (1994), who use Dow Jones stock returns. This finding contradicts some theoretical models that imply information content of volume for future returns (e.g., the sequential

[12] Given the importance of the predictability of stock returns, we are primarily interested in the causal relation from volume to returns.

Table 2
Tests of causal relationship among stock returns, volatility and trading volume: Domestic data[a]

$$\begin{bmatrix} x_t \\ y_t \end{bmatrix} = \begin{bmatrix} d_1 \\ d_2 \end{bmatrix} + \begin{bmatrix} A_{11}(L) & A_{12}(L) \\ A_{21}(L) & A_{22}(L) \end{bmatrix} \begin{bmatrix} x_{t-1} \\ y_{t-1} \end{bmatrix} + \begin{bmatrix} u_{1t} \\ u_{2t} \end{bmatrix},$$

where $A_{ij}(L) = \sum_{s=1}^{5} a_{ij}(s)L^{s-1}$ for $i, j = 1$ and 2

Hypothesis	Comments	F-statistic (significance level) V_t = detrended volume	F-statistic (significance level) V_t = expected volume	F-statistic (significance level) V_t = unexpected volume
Panel A1. $[x_t\ y_t]' = [USR\ USV]'$				
Whole period				
$H_0: A_{12}(L) = 0$	USV $\overset{G.C}{\to}$ USR	1.586 (0.160)	2.034 (0.071)***	1.660 (0.141)
$H_0: A_{21}(L) = 0$	USR $\overset{G.C}{\to}$ USV	4.386 (0.000)*	13.758 (0.000)***	0.006 (0.999)
Before introduction of index option on NYSE[1]				
$H_0: A_{12}(L) = 0$	USV $\overset{G.C}{\to}$ USR	0.761 (0.578)	0.667 (0.648)	0.269 (0.930)
$H_0: A_{21}(L) = 0$	USR $\overset{G.C}{\to}$ USV	5.871 (0.000)*	91.151 (0.000)*	129.903 (0.000)*
After introduction of index option on NYSE and before 1987 crash				
$H_0: A_{12}(L) = 0$	USV $\overset{G.C}{\to}$ USR	0.284 (0.921)	0.277 (0.924)	0.260 (0.934)
$H_0: A_{21}(L) = 0$	USR $\overset{G.C}{\to}$ USV	21.214 (0.000)*	33.337 (0.000)*	46.132 (0.000)*
After 1987 crash				
$H_0: A_{12}(L) = 0$	USV $\overset{G.C}{\to}$ USR	2.330 (0.040)**	2.533 (0.026)**	2.090 (0.063)***
$H_0: A_{21}(L) = 0$	USR $\overset{G.C}{\to}$ USV	5.164 (0.000)*	5.068 (0.000)*	2.847 (0.014)**
Panel A2. $[x_t\ y_t]' = [USR^2\ USV]'$				
Whole period				
$H_0: A_{12}(L) = 0$	USV $\overset{G.C}{\to}$ USR^2	3.097 (0.008)*	2.208 (0.051)***	1.552 (0.170)
$H_0: A_{21}(L) = 0$	USR^2 $\overset{G.C}{\to}$ USV	13.647 (0.000)*	128.744 (0.000)*	0.253 (0.938)
USR^2 = conditional volatility filtered by the GARCH model				
$H_0: A_{12}(L) = 0$	USV $\overset{G.C}{\to}$ USR^2	20.676 (0.000)*	1.781 (0.112)	22.040 (0.000)*
$H_0: A_{21}(L) = 0$	USR^2 $\overset{G.C}{\to}$ USV	4.993 (0.000)*	18.573 (0.000)*	0.305 (0.909)
Before introduction of index option on NYSE				
$H_0: A_{12}(L) = 0$	USV $\overset{G.C}{\to}$ USR^2	0.547 (0.741)	0.698 (0.625)	1.737 (0.123)
$H_0: A_{21}(L) = 0$	USR^2 $\overset{G.C}{\to}$ USV	11.607 (0.000)*	71.191 (0.000)*	29.316 (0.000)*
After introduction of index option on NYSE and before 1987 crash				
$H_0: A_{12}(L) = 0$	USV $\overset{G.C}{\to}$ USR^2	3.161 (0.007)*	4.182 (0.000)*	1.475 (0.194)
$H_0: A_{21}(L) = 0$	USR^2 $\overset{G.C}{\to}$ USV	53.709 (0.000)*	150.090 (0.000)*	31.711 (0.000)*
After 1987 crash				
$H_0: A_{12}(L) = 0$	USV $\overset{G.C}{\to}$ USR^2	10.288 (0.000)*	11.641 (0.000)*	2.937 (0.012)**
$H_0: A_{21}(L) = 0$	USR^2 $\overset{G.C}{\to}$ USV	21.407 (0.000)*	57.104 (0.000)*	15.719 (0.000)*
Panel B1. $[x_t\ y_t]' = [JPR\ JPV]'$				
Whole period				
$H_0: A_{12}(L) = 0$	JPV $\overset{G.C}{\to}$ JPR	2.033 (0.071)***	1.413 (0.215)	1.463 (0.198)
$H_0: A_{21}(L) = 0$	JPR $\overset{G.C}{\to}$ JPV JPV	23.672 (0.000)*	265.196 (0.000)*	0.059 (0.997)

Table 2 (*continued*)

Hypothesis	Comments	F-statistic (significance level) V_t = detrended volume	F-statistic (significance level) V_t = expected volume	F-statistic (significance level) V_t = unexpected volume
Before 1987 crash				
$H_0: A_{12}(L) = 0$	$JPV \overset{G.C}{\to} JPR$	2.551 (0.025)**	2.599 (0.023)**	3.041 (0.009)*
$H_0: A_{21}(L) = 0$	$JPR \overset{G.C}{\to} JPV$	22.816 (0.000)*	153.608 (0.000)*	6.195 (0.000)*
After 1987 crash and before introduction of index option on OSAKA[2]				
$H_0: A_{12}(L) = 0$	$JPV \overset{G.C}{\to} JPR$	0.423 (0.832)	1.321 (0.254)	1.107 (0.355)
$H_0: A_{21}(L) = 0$	$JPR \overset{G.C}{\to} JPV$	1.050 (0.387)	10.296 (0.000)*	0.457 (0.808)
After introduction of index option on OSAKA				
$H_0: A_{12}(L) = 0$	$JPV \overset{G.C}{\to} JPR$	2.2603 (0.046)**	1.216 (0.298)	1.707 (0.129)
$H_0: A_{21}(L) = 0$	$JPR \overset{G.C}{\to} JPV$	15.036 (0.000)*	198.877 (0.000)*	2.949 (0.011)**
Panel B2. $[x_t y_t]' = [JPR^2\ JPV]'$				
Whole period				
$H_0: A_{12}(L) = 0$	$JPV \overset{G.C}{\to} JPR^2$	1.867 (0.096)***	2.354 (0.038)**	1.442 (0.204)
$H_0: A_{21}(L) = 0$	$JPR^2 \overset{G.C}{\to} JPV$	6.332 (0.000)*	39.256 (0.000)*	0.004 (0.999)
JPR^2 = conditional volatility filtered by the GARCH model				
$H_0: A_{12}(L) = 0$	$JPV \overset{G.C}{\to} JPR^2$	3.529 (0.003)*	3.907 (0.002)*	4.789 (0.002)*
$H_0: A_{21}(L) = 0$	$JPR^2 \overset{G.C}{\to} JPV$	2.511 (0.028)**	7.443 (0.000)*	0.878 (0.494)
Before 1987 crash				
$H_0: A_{12}(L) = 0$	$JPV \overset{G.C}{\to} JPR^2$	10.768 (0.000)*	13.700 (0.000)*	8.719 (0.000)*
$H_0: A_{21}(L) = 0$	$JPR^2 \overset{G.C}{\to} JPV$	1.788 (0.111)	11.068 (0.000)*	3.087 (0.005)*
After 1987 crash and before introduction of index option on OSAKA				
$H_0: A_{12}(L) = 0$	$JPV \overset{G.C}{\to} JPR^2$	1.422 (0.215)	1.757 (0.121)	0.457 (0.807)
$H_0: A_{21}(L) = 0$	$JPR^2 \overset{G.C}{\to} JPV$	0.477 (0.793)	1.884 (0.096)***	0.446 (0.815)
After introduction of index option on OSAKA				
$H_0: A_{12}(L) = 0$	$JPV \overset{G.C}{\to} JPR^2$	1.683 (0.353)	3.323 (0.005)*	1.182 (0.315)
$H_0: A_{21}(L) = 0$	$JPR^2 \overset{G.C}{\to} JPV$	9.329 (0.000)*	63.926 (0.000)*	2.333 (0.039)**
Panel C1. $[x_t y_t]' = [UKR\ UKV]'$				
Whole period				
$H_0: A_{12}(L) = 0$	$UKV \overset{G.C}{\to} UKR$	0.547 (0.972)	1.645 (0.144)	0.687 (0.632)
$H_0: A_{21}(L) = 0$	$UKR \overset{G.C}{\to} UKV$	0.951 (0.446)	19.437 (0.000)*	0.002 (0.999)
Before 1987 crash				
$H_0: A_{12}(L) = 0$	$UKV \overset{G.C}{\to} UKR$	0.711 (0.616)	0.659 (0.654)	0.735 (0.596)
$H_0: A_{21}(L) = 0$	$UKR \overset{G.C}{\to} UKV$	0.348 (0.882)	6.869 (0.000)*	0.359 (0.875)
After 1987 crash				
$H_0: A_{12}(L) = 0$	$UKV \overset{G.C}{\to} UKR$	0.407 (0.884)	0.362 (0.874)	0.367 (0.871)
$H_0: A_{21}(L) = 0$	$UKR \overset{G.C}{\to} UKV$	2.016 (0.073)***	37.726 (0.000)*	0.104 (0.991)

(*continued on next page*)

Table 2 (*continued*)

Hypothesis	Comments	F-statistic (significance level) V_t = detrended volume	F-statistic (significance level) V_t = expected volume	F-statistic (significance level) V_t = unexpected volume
Panel C2. $[x_t y_t]' = [UKR^2\ UKV]'$				
Whole period				
$H_0 : A_{12}(L) = 0$	UKV $\overset{G.C}{\rightarrow}$ UKR^2	4.009 (0.001)*	0.221 (0.954)	3.545 (0.003)*
$H_0 : A_{21}(L) = 0$	UKR^2 $\overset{G.C}{\rightarrow}$ UKV	5.809 (0.000)*	96.087 (0.000)*	0.005 (0.999)
UKR^2 = conditional volatility filtered by the GARCH model				
$H_0 : A_{12}(L) = 0$	UKV $\overset{G.C}{\rightarrow}$ UKR^2	20.193 (0.000)*	1.570 (0.165)	19.138 (0.000)*
$H_0 : A_{21}(L) = 0$	UKR^2 $\overset{G.C}{\rightarrow}$ UKV	2.144 (0.057)***	12.416 (0.000)*	0.007 (0.999)
Before 1987 crash				
$H_0 : A_{12}(L) = 0$	UKV $\overset{G.C}{\rightarrow}$ UKR^2	0.385 (0.858)	0.558 (0.731)	0.415 (0.838)
$H_0 : A_{21}(L) = 0$	UKR^2 $\overset{G.C}{\rightarrow}$ UKV	0.464 (0.802)	2.426 (0.036)**	0.274 (0.926)
After 1987 crash				
$H_0 : A_{12}(L) = 0$	UKV $\overset{G.C}{\rightarrow}$ UKR^2	3.506 (0.003)*	2.663 (0.021)**	2.938 (0.011)**
$H_0 : A_{21}(L) = 0$	UKR^2 $\overset{G.C}{\rightarrow}$ UKV	2.951 (0.011)**	73.726 (0.000)*	0.856 (0.509)

[a] $X \overset{G.C}{\rightarrow} Y$ denotes that X Granger-causes Y R_t = returns; V_t = detrended trading volumes; R_t^2 = volatility of returns. The whole sample periods are 01/02/73–12/01/99 for the US, 01/07/74–12/01/99 for Japan, and 10/27/86–12/01/99 for the UK. The NYSE composite index options were introduced on 23 September 1983. The Nikkei 225 options were introduced on 12 June 1989.

* Represent the causal relationship being significant at 1%.

** Represent the causal relationship being significant at 5%.

*** Represent the causal relationship being significant at 10%.

information arrival models of Copeland (1976) and Jennings et al. (1981) and the mixture of distributions model of Epps and Epps (1976)) but confirms the difficulty of improving the predictability of returns by adding public information about trading volume. However, returns Granger-cause trading volume in the US and Japanese markets but not in the UK market.

Second, between trading volume and return volatility, there is a feedback relation in all three markets. That is, volume helps predict return volatility and vice versa. Taken together, trading volume helps predict the volatility of returns but not the level of returns. In this sense, trading volume contains information about returns indirectly through its predictability of return volatility, but not directly of return itself. This finding seems consistent with Clark (1973) latent common-factor model in that trading volume may serve as a proxy for daily information flow in the stochastic process generating stock return variance.

Once we establish causal relations, it is natural to examine the dynamic effects, in particular the sign and magnitude of effects, of a variable on the other variable over different (forecasting) horizons. Since we find that volume does not help predict returns, we do not consider the response of returns to volume shocks. Specifically, we examine the response of volatility and trading volume to a one-standard deviation shock in either volume or volatility. Some common response patterns emerge from the three stock markets. Trading volume shock initially has a positive effect on volatility in the three stock markets, but its effect dissipates very quickly. The volatility shock initially has a positive effect on trading volume in all the three stock markets, and its effect declines gradually over time. In short, there is a positive feedback relation between volume and volatility in all three stock markets. [13]

An important distinction in investigating the trading volume and volatility relation may be to distinguish between expected and unexpected trading volume (e.g., Bessembinder and Seguin, 1992, 1993). For example, Bessembinder and Seguin (1993) find that in a sample of eight futures markets, unexpected volume shocks have a larger effect on volatility. Table 2 presents the causal relations between stock returns and expected/unexpected trading volumes, which are computed based on a VAR model (see Footnote 10). [14] By construction, stock returns should not Granger-cause unexpected volume. Hence, we focus on the causal relation from expected/unexpected volume to either returns or volatility. Table 2 shows that neither expected nor unexpected volume has a significant causal effect on stock returns, which is in line with the observation that trading volume does not have a significant causal effect on returns. In addition, the table shows that expected volume Granger-causes volatility in US and Japanese markets, but unexpected volume has a significantly stronger causal effect on volatility in the UK market.

3.2. Tests of robustness

3.2.1. Calendar effects

In recent years there has been a proliferation of empirical studies documenting anomalous seasonal regularities in security returns. These include calendar effects related to the time of day (Harris, 1986), the day of the week (French, 1980; Jaffe and Westerfield, 1985a,b; Keim and Stambaugh, 1984; Lokonishok and Levi, 1982), the turn of month (Ariel, 1990), and the turn of the year (Lakonishok and Smidt, 1984). These patterns appear to conflict with the theoretical notions of efficiency and rational expectations in the market for securities.

[13] Figures showing dynamic effects based on impulse responses are available upon request.

[14] The computation of unexpected volume using a VAR residual implies that unexpected volume will not be predicted by domestic returns and volatilities by construction. It is noted that a VAR model, which can be thought of as a multivariate ARIMA model, employed in this paper provides a natural framework to decompose volumes into expected and unexpected components.

We employ a three-step procedure developed by Gallant et al. (1992) to adjust for seasonal regularities. [15] Then, we use these adjusted data to test for the robustness of the dynamic relations. It turns out that using the adjusted data results in exactly the same causal relationship as those using raw data. As such, to save space, we report only the results using raw data.

3.2.2. Sub-sample analyses

Some studies find structural changes in the stock markets (e.g., international co-movements in stock prices) after the 1987 stock market crash, [16] while others find changes in stock prices and volatility after introducing the trade of index options into the markets. [17] The introduction of index options may bring more private information to the market and thus allow a quicker dissemination of information. As such, it may lead to a stronger dynamic relation among returns, volume, and volatility. Poon (1994) hypothesizes that upon the introduction of option trading, there is a structural shift in the relation between stock return volatility and trading volume. This is because the greater leverage and lower transaction costs provided by the option market would attract more investors who would not have otherwise traded without the availability of

---

[15] There is some weak evidence about seasonal regularities of trading volume. Lokonishok and Maberly (1990) document some interesting regularity in trading patterns of individual and institutional investors related the to day of the week. They find that NYSE trading volume on Monday is lower than on other days of the week. We employ the same procedure to adjust for seasonal regularities of trading volume. It turns out that using the adjusted data results in almost the same causal relationship as those using raw data. To save space, we do not report the results.

[16] Several studies find an increase in comovements among national stock prices after the 1987 crash. Arshanapalli and Doukas (1993) examine the linkages and dynamic interactions among stock price indices in the major world stock exchanges, taking into account cointegration among the indices. They find that the degree of international co-movements in stock price indices has changed significantly since the market crash of October 1987, with the Nikkei index the only exception. In this paper, we are mainly concerned with causal relations and dynamic interactions among returns, trading volume, and volatility. See also Lee and Jeon (1995), Arshanapalli et al. (1995) and Masih and Masih (1997).

[17] The introduction of options may have different effects on the volatility of the underlying shares. The existence of options may increase the volatility of stock returns due to more speculation and the hedging activity of option traders. On the other hand, introducing options expands the investment opportunity set and may make markets more liquid and efficient. In contrast, introduction of options can reduce volatility of underlying stocks by providing low cost state-contingent strategies which enable investors to minimize portfolio risk, and by introducing positive information externalities and by transferring speculators from spot markets to option markets. Two studies by the Chicago Board Options Exchange (CBOE, 1975, 1976) find that a statistically significant decline in price volatility occurred following the options listing date. Utilizing daily data for varying periods around the listing date, Skinner (1989) finds, among other things, the volatility, as measured by variance of returns, falls after options listing, whereas beta remained unchanged. Previous studies, however, have not examined dynamic relations among returns, volume, and volatility.

options. We examine whether either the market crash or the introduction of options affects the dynamic interactions by dividing the whole sample period into sub-periods and conducting causality tests for each sub-period separately.

The NYSE composite index options were introduced on 23 September 1983. Nikkei 225 options were introduced on 12 June 1989, on the Osaka exchange, and the FT–SE 100 stock index options were first traded in May 1984 on the London-traded options market. Since our sample period of the UK market covers the period between 27 October 1986, and 1 December 1999, we do not have a long enough sample period to compare the causal relations between the pre- and post-option periods.

To isolate the effect of the introduction of index options from that of the 1987 market crash, we divide a sample period of the US and Japan into three sub-periods. [18] Table 2 reports causality tests for sub-sample periods for each national market. Compared with the results of the whole sample period, the following observations are noted. First, in the US, the causal effects of trading volume on returns and volatility become stronger after the 1987 market crash. That is, US trading volume tends to Granger-cause returns so that there is a feedback relation between the two after the 1987 market crash. However, the feedback relation between volatility and volume gets stronger and begins to exist after the introduction of index options on the NYSE in 1983. Second, in Japan, causal relations between volume and returns and between volume and volatility become weaker after the 1987 market crash but stronger after the introduction of index options on the OSAKA exchange in 1989. Specifically, after the introduction of index options in 1989, trading volume Granger-causes returns so that there is a feedback relation between the two, and the causal relation from volatility to volume begins to exist. Third, in the UK, overall causal relations between volume and returns and between volume and volatility become stronger after the 1987 market crash. Specifically, returns Granger-cause volume, and the feedback relation between volatility and volume becomes significant after the 1987 market crash.

In sum, although the 1987 market crash appears to have somewhat different effects on the causal relations among volume, returns, and volatility across countries, the overall trend seems to be a stronger spillover effect. This seems consistent with the widely held view that markets are becoming more closely integrated (e.g., Arshanapalli and Doukas, 1993; Lee and Jeon, 1995). The introduction of index options tends to bring a stronger feedback relation between volume and volatility in both the US and Japan, which indicates that options bring more private information to the market and allow a quicker

[18] For the US, we consider the pre-option period, the post-option/ pre-1987 crash period, and the post-1987 crash period. For Japan, we consider the pre-1987 crash period, the post-crash/pre-option period, and the post-option period.

dissemination of information. In addition, trading volume tends to have more information about either stock market returns or volatility in recent years of all three markets, which suggests an increased importance of trading volume as an information variable.

3.2.3. Conditional volatility based on a GARCH model

We have been using a squared return series as a measure of return volatility. An alternative measure would be conditional volatility based on a GARCH model as in Eq. (4) (see Panel B of Table 1). Table 2 also presents the causality tests between trading volume and volatility measured by a GARCH (1,1) model. The results are very similar to those with squared return series: there is a feedback relation between trading volume and volatility. [19] Regarding the relation between return volatility and expected/unexpected trading volume, we observe that unexpected volume has a significant causal effect on volatility measured by a GARCH model on all three stock markets (see Bessembinder and Seguin, 1992, 1993). [20]

3.3. Cross-country causal relationship

In this section, we investigate causal relations among trading volume, stock market returns and volatility across international markets, whose results are presented in Table 3. [21] There is no overlap in trading time between Tokyo and London or New York and Tokyo, but there is a two and one-half hour overlap between the London and New York markets. [22] The overlap may cause some

[19] In an attempt to model the time-varying linkage (or integration) between US and Canadian markets, Doukas and Switzer (2000) model excess returns for Canadian and US stocks as a bivariate (ARCH-in-mean) process in which the conditional variance/covariance dynamics are modeled as an ARCH process (see also Chan et al., 1992; Bekaert and Harvey, 1995). Their bivariate model is mainly about contemporaneous relations among returns and conditional variance/covariance of returns, which is not designed for dynamic causal relations.

[20] In the US and the UK, unexpected volume has a stronger causal effect on the volatility than expected volume does.

[21] We investigate the causal relations based also on multivariate (e.g., four-variable) models. This is because the results between bivariate and four-variable models may potentially be different, as pointed out by Sims (1980) (see also Lee, 1992). However, it turns out that there is little difference between the two results. This finding implies, among other things, that after controlling for volatility effects, the dynamic relation between trading volume and returns is not significantly affected (see Hiemstra and Jones, 1994). To save space, the results of four-variable models are not reported in the paper.

[22] The NYSE opens its trading at 9:30 a.m. and continues trading until 4:00 p.m. London operates from 9:00 a.m. to 5:00 p.m. Trading on the TSE is divided into a morning session from 9:00 to 11:00 a.m., followed by an afternoon session from 1:00 to 3:00 p.m. On 29 April 1991, the start of the afternoon session was moved forward 30 minutes to 12:30 p.m. This trading structure is unique to the TSE.

Table 3
Tests of causal relationship among stock returns, volatility and trading volume across country[a]

$$\begin{bmatrix} x_t \\ y_t \end{bmatrix} = \begin{bmatrix} d_1 \\ d_2 \end{bmatrix} + \begin{bmatrix} A_{11}(L) & A_{12}(L) \\ A_{21}(L) & A_{22}(L) \end{bmatrix} \begin{bmatrix} x_{t-1} \\ y_{t-1} \end{bmatrix} + \begin{bmatrix} u_{1t} \\ u_{2t} \end{bmatrix},$$

where $A_{ij}(L) = \sum_{s=1}^{5} a_{ij}(s)L^{s-1}$ for $i, j = 1$ and 2

Hypothesis	Comments	F-statistic (significance level) V_t = detrended volumes	F-statistic (significance level) V_t = expected volumes	F-statistic (significance level) V_t = unexpected volumes
Panel A1. $[x_t y_t]' = [USR\ UKV]'$; Obs. = 3252; 10/27/86–12/01/99				
$H_0: A_{12}(L) = 0$	UKV $\overset{G.C}{\rightarrow}$ USR	0.361 (0.875)	1.321 (0.252)	0.218 (0.954)
$H_0: A_{21}(L) = 0$	USR $\overset{G.C}{\rightarrow}$ UKV	1.381 (0.228)	4.748 (0.000)*	1.761 (0.117)
Panel A2. $[x_t y_t]' = [USV\ UKR]'$				
$H_0: A_{12}(L) = 0$	UKR $\overset{G.C}{\rightarrow}$ USV	1.291 (0.264)	7.682 (0.000)*	0.874 (0.497)
$H_0: A_{21}(L) = 0$	USV $\overset{G.C}{\rightarrow}$ UKR	2.573 (0.024)**	3.102 (0.008)*	4.219 (0.000)*
Panel A3. $[x_t y_t]' = [USV\ UKR^2]'$				
$H_0: A_{12}(L) = 0$	$UKR^2 \overset{G.C}{\rightarrow}$ USV	1.383 (0.227)	40.871 (0.000)*	2.393 (0.035)**
$H_0: A_{21}(L) = 0$	USV $\overset{G.C}{\rightarrow} UKR^2$	2.025 (0.072)***	2.434 (0.032)**	1.722 (0.125)
Panel A4. $[x_t y_t]' = [USR^2\ UKV]'$				
$H_0: A_{12}(L) = 0$	UKV $\overset{G.C}{\rightarrow} USR^2$	1.934 (0.085)***	0.339 (0.888)	1.913 (0.088)***
$H_0: A_{21}(L) = 0$	$USR^2 \overset{G.C}{\rightarrow}$ UKV	6.052 (0.000)*	35.836 (0.000)*	1.852 (0.099)***
Panel A5. $[x_t y_t]' = [USDV\ UKV]'$				
$H_0: A_{12}(L) = 0$	UKV $\overset{G.C}{\rightarrow}$ USDV	1.902 (0.091)***	2.596 (0.023)**	1.131 (0.341)
$H_0: A_{21}(L) = 0$	USDV $\overset{G.C}{\rightarrow}$ UKV	16.325 (0.000)*	109.574 (0.000)*	16.363 (0.000)*
Panel A6. $[x_t y_t]' = [USEV\ UKV]'$				
$H_0: A_{12}(L) = 0$	UKV $\overset{G.C}{\rightarrow}$ USEV	79.460 (0.000)*	3.403 (0.004)*	88.075 (0.000)*
$H_0: A_{21}(L) = 0$	USEV $\overset{G.C}{\rightarrow}$ UKV	9.779 (0.000)*	23.548 (0.000)*	11.694 (0.000)*
Panel A7. $[x_t y_t]' = [USUV\ UKV]'$				
$H_0: A_{12}(L) = 0$	UKV $\overset{G.C}{\rightarrow}$ USUV	1.944 (0.083)***	3.311 (0.005)*	1.789 (0.115)
$H_0: A_{21}(L) = 0$	USUV $\overset{G.C}{\rightarrow}$ UKV	14.399 (0.000)*	96.103 (0.000)*	15.631 (0.000)*
Panel B1. $[x_t y_t]' = [USR\ JPV]'$; Obs. = 6342; 01/04/74–12/01/99				
$H_0: A_{12}(L) = 0$	JPV $\overset{G.C}{\rightarrow}$ USR	0.555 (0.734)	1.513 (0.181)	1.184 (0.313)
$H_0: A_{21}(L) = 0$	USR $\overset{G.C}{\rightarrow}$ JPV	12.971 (0.000)*	18.813 (0.000)*	9.096 (0.000)*
Panel B2. $[x_t y_t]' = [USV\ JPR]'$				
$H_0: A_{12}(L) = 0$	JPR $\overset{G.C}{\rightarrow}$ USV	1.337 (0.245)	1.528 (0.177)	1.295 (0.262)
$H_0: A_{21}(L) = 0$	USV $\overset{G.C}{\rightarrow}$ JPR	2.781 (0.016)**	4.150 (0.000)*	1.788 (0.113)
Panel B3. $[x_t y_t]' = [USV\ JPR^2]'$				
$H_0: A_{12}(L) = 0$	$JPR^2 \overset{G.C}{\rightarrow}$ USV	5.043 (0.000)*	17.492 (0.000)*	2.675 (0.020)**
$H_0: A_{21}(L) = 0$	USV $\overset{G.C}{\rightarrow} JPR^2$	10.140 (0.000)*	5.071 (0.000)*	7.943 (0.000)*
Panel B4. $[x_t y_t]' = [USR^2\ JPV]'$				
$H_0: A_{12}(L) = 0$	JPV $\overset{G.C}{\rightarrow} USR^2$	4.086 (0.001)*	8.596 (0.000)*	5.749 (0.000)*
$H_0: A_{21}(L) = 0$	$USR^2 \overset{G.C}{\rightarrow}$ JPV	4.873 (0.000)*	9.299 (0.000)*	0.531 (0.752)

(*continued on next page*)

Table 3 (*continued*)

Hypothesis	Comments	F-statistic (significance level) V_t = detrended volumes	F-statistic (significance level) V_t = expected volumes	F -statistic (significance level) V_t = unexpected volumes
Panel B5. $[x_t y_t]' = [USDV\ JPV]'$				
$H_0 : A_{12}(L) = 0$	JPV $\overset{G.C}{\rightarrow}$ USDV	8.751 (0.000)*	5.526 (0.000)*	9.192 (0.000)*
$H_0 : A_{21}(L) = 0$	USDV $\overset{G.C}{\rightarrow}$ JPV	8.108 (0.000)*	16.969 (0.000)*	8.294 (0.000)*
Panel B6. $[x_t y_t]' = [USEV\ JPV]'$				
$H_0 : A_{12}(L) = 0$	JPV $\overset{G.C}{\rightarrow}$ USEV	14.186 (0.000)*	4.806 (0.000)*	11.311 (0.000)*
$H_0 : A_{21}(L) = 0$	USEV $\overset{G.C}{\rightarrow}$ JPV	5.889 (0.000)*	8.768 (0.000)*	5.618 (0.000)*
Panel B7. $[x_t y_t]' = [USUV\ JPV]'$				
$H_0 : A_{12}(L) = 0$	JPV $\overset{G.C}{\rightarrow}$ USUV	8.203 (0.000)*	6.199 (0.000)*	9.017 (0.000)*
$H_0 : A_{21}(L) = 0$	USUV $\overset{G.C}{\rightarrow}$ JPV	5.400 (0.000)*	11.884 (0.000)*	5.826 (0.000)*
Panel C1. $[x_t y_t]' = [JPR\ UKV]'$; *Obs. = 3185; 10/27/86–12/01/99*				
$H_0 : A_{12}(L) = 0$	UKV $\overset{G.C}{\rightarrow}$ JPR	1.403 (0.219)	2.073 (0.065)***	0.446 (0.815)
$H_0 : A_{21}(L) = 0$	JPR $\overset{G.C}{\rightarrow}$ UKV	0.810 (0.542)	3.296 (0.005)*	0.977 (0.429)
Panel C2. $[x_t y_t]' = [JPV\ UKR]'$				
$H_0 : A_{12}(L) = 0$	UKR $\overset{G.C}{\rightarrow}$ JPV	3.588 (0.003)*	11.381 (0.000)*	1.919 (0.087)***
$H_0 : A_{21}(L) = 0$	JPV $\overset{G.C}{\rightarrow}$ UKR	0.775 (0.567)	0.273 (0.927)	0.985 (0.425)
Panel C3. $[x_t y_t]' = [JPV\ UKR^2]'$				
$H_0 : A_{12}(L) = 0$	UKR^2 $\overset{G.C}{\rightarrow}$ JPV	1.562 (0.167)	6.179 (0.000)*	0.224 (0.952)
$H_0 : A_{21}(L) = 0$	JPV $\overset{G.C}{\rightarrow}$ UKR^2	1.131 (0.341)	2.145 (0.057)***	1.779 (0.113)
Panel C4. $[x_t y_t]' = [JPR^2\ UKV]'$				
$H_0 : A_{12}(L) = 0$	UKV $\overset{G.C}{\rightarrow}$ JPR^2	2.948 (0.011)**	0.662 (0.652)	2.610 (0.023)**
$H_0 : A_{21}(L) = 0$	JPR^2 $\overset{G.C}{\rightarrow}$ UKV	1.533 (0.175)	14.864 (0.000)*	0.429 (0.828)
Panel C5. $[x_t y_t]' = [JPDV\ UKV]'$				
$H_0 : A_{12}(L) = 0$	UKV $\overset{G.C}{\rightarrow}$ JPDV	2.438 (0.032)**	3.298 (0.005)*	2.537 (0.026)**
$H_0 : A_{21}(L) = 0$	JPDV $\overset{G.C}{\rightarrow}$ UKV	2.656 (0.021)**	8.185 (0.000)*	2.510 (0.028)**
Panel C6. $[x_t y_t]' = [JPEV\ UKV]'$				
$H_0 : A_{12}(L) = 0$	UKV $\overset{G.C}{\rightarrow}$ JPEV	11.341 (0.000)*	3.839 (0.002)*	10.001 (0.000)*
$H_0 : A_{21}(L) = 0$	JPEV $\overset{G.C}{\rightarrow}$ UKV	4.718 (0.000)*	1.685 (0.132)	5.331 (0.000)*
Panel C7. $[x_t y_t]' = [JPUV\ UKV]'$				
$H_0 : A_{12}(L) = 0$	UKV $\overset{G.C}{\rightarrow}$ JPUV	2.376 (0.036)**	3.548 (0.003)*	2.356 (0.038)**
$H_0 : A_{21}(L) = 0$	JPUV $\overset{G.C}{\rightarrow}$ UKV	5.102 (0.000)*	6.431 (0.000)*	5.242 (0.000)*

[a] R_t = returns; V_t = detrended trading volumes; R_t^2 = volatility of returns.
* Represent the causal relationship being significant at 1%.
** Represent the causal relationship being significant at 5%.
*** Represent the causal relationship being significant at 10%.

problem for contemporaneous relations, but it should be a less serious problem for dynamic causal relations because they are primarily lead–lag relations. To capture spillover effects, intraday data would be preferable. In Table 4, we present the results of causal relations among intraday stock returns and volatility across countries. To test whether there are structural shifts in causality relationships across countries, we also conduct sub-sample analyses.

The following observations, among other things, are noted about cross-country causal relations reported in Tables 3 and 4. First, US trading volume helps to predict all other variables except US returns. Specifically, US volume helps predict US volatility, UK returns, volatility, and volume, and Japanese returns, volatility, and volume. This indicates the importance of the information contained in US volume for international financial markets. US returns help predict UK returns and Japanese returns and volume but do not help predict UK volume. US volatility helps predict not only US volume but also UK volatility and volume and Japanese volatility and volume. In short, US financial market information contained in returns, volatility, and volume has an extensive predictive power for UK and Japanese financial market variables.

Second, while US volume helps predict all the variables of the UK and Japanese markets, UK volume does not Granger-cause either US returns, volatility, and volume [23] or Japanese returns. However, Japanese volume Granger-causes US volume, volatility and UK volume, but Japanese volume does not Granger-cause either UK returns and volatility or US returns.

Third, there is a feedback relation in trading volumes between the US and UK markets, between the US and Japanese markets, and between the UK and Japanese markets regardless of whether we use expected volume or unexpected volume. Overall, we find substantial cross-country interactions and an influential role of US trading volume.

In addition, the following observations are made about the intraday returns from Table 4. First, US intraday returns except US close-to-open (USCO) rate Granger-cause all types of UK intraday returns, while none of UK intraday returns Granger-cause US intraday returns. Although the causal effects of US volume on UK volume are stronger, there are feedback relations between US intraday volatility and U.K intraday volatility except between USCO volatility and any of UK intraday volatility. Second, US intraday returns except USCO rate Granger-cause Japanese intraday returns, while none of Japanese intraday returns Granger-cause US intraday returns. US intraday volatility except USCO volatility Granger-causes Japanese intraday volatility. Third, there seems to be a feedback relation between Japanese intraday returns and UK intraday returns and between Japanese intraday volatility and UK intraday volatility except one between UK close-to-open (CO) volatility and Japanese CO volatility. In sum, except USCO rate and USCO volatility, US intraday returns and US intraday volatility have causal effects on UK and Japanese

[23] These are at a 5% significance level.

Table 4

Tests of causal relationship among intra-day stock returns and volatility across country[a]

$$\begin{bmatrix} x_t \\ y_t \end{bmatrix} = \begin{bmatrix} d_1 \\ d_2 \end{bmatrix} + \begin{bmatrix} A_{11}(L) & A_{12}(L) \\ A_{21}(L) & A_{22}(L) \end{bmatrix} \begin{bmatrix} x_{t-1} \\ y_{t-1} \end{bmatrix} + \begin{bmatrix} u_{1t} \\ u_{2t} \end{bmatrix},$$

where $A_{ij}(L) = \sum_{s=1}^{5} a_{ij}(s)L^{s-1}$ for $i, j = 1$ and 2

Hypothesis	Comments	F-statistic (significance level)	F-statistic (significance level)	F-statistic (significance level)
Panel A1. $[x_t y_t]' = [USOCR\ UKR]'$		UKR = UKOR	UKR = UKCOR	UKR = UKCCR
Obs. = 1832; 07/16/92–12/01/99				
$H_0 : A_{12}(L) = 0$	$UKR \overset{G.C}{\rightarrow} USOCR$	0.673 (0.643)	1.047 (0.388)	0.703 (0.621)
$H_0 : A_{21}(L) = 0$	$USOCR \overset{G.C}{\rightarrow} UKR$	10.055 (0.000)*	64.363 (0.000)*	32.867 (0.000)*
Panel A2. $[x_t y_t]' = [USCOR\ UKR]'$				
$H_0 : A_{12}(L) = 0$	$UKR \overset{G.C}{\rightarrow} USCOR$	0.073 (0.996)	1.403 (0.220)	0.267 (0.931)
$H_0 : A_{21}(L) = 0$	$USCOR \overset{G.C}{\rightarrow} UKR$	2.069 (0.066)***	1.089 (0.364)	1.534 (0.175)
Panel A3. $[x_t y_t]' = [USCCR\ UKR]'$				
$H_0 : A_{12}(L) = 0$	$UKR \overset{G.C}{\rightarrow} USCCR$	0.687 (0.633)	1.121 (0.346)	0.658 (0.654)
$H_0 : A_{21}(L) = 0$	$USCCR \overset{G.C}{\rightarrow} UKR$	9.388 (0.000)*	64.324 (0.000)*	31.510 (0.000)*
Panel A4. $[x_t y_t]' = [USOCR^2\ UKR^2]'$		$UKR^2 = UKOCR^2$	$UKR^2 = UKCOR^2$	$UKR^2 = UKCCR^2$
$H_0 : A_{12}(L) = 0$	$UKR^2 \overset{G.C}{\rightarrow} USOCR^2$	12.044 (0.000)*	0.385 (0.859)	9.113 (0.000)*
$H_0 : A_{21}(L) = 0$	$USOCR^2 \overset{G.C}{\rightarrow} UKR^2$	8.079 (0.000)*	2.467 (0.031)**	8.007 (0.000)*
Panel A5. $[x_t y_t]' = [USCOR^2\ UKR^2]'$				
$H_0 : A_{12}(L) = 0$	$UKR^2 \overset{G.C}{\rightarrow} USCOR^2$	0.136 (0.983)	0.228 (0.950)	0.086 (0.994)
$H_0 : A_{21}(L) = 0$	$USCOR^2 \overset{G.C}{\rightarrow} UKR^2$	0.280 (0.924)	0.186 (0.967)	0.197 (0.963)
Panel A6. $[x_t y_t]' = [USCCR^2\ UKR^2]'$				
$H_0 : A_{12}(L) = 0$	$UKR^2 \overset{G.C}{\rightarrow} USCCR^2$	12.054 (0.000)*	0.389 (0.856)	9.513 (0.000)*
$H_0 : A_{21}(L) = 0$	$USCCR^2 \overset{G.C}{\rightarrow} UKR^2$	7.823 (0.000)*	2.493 (0.029)**	7.733 (0.000)*

Panel B1. $[x_t\ y_t]' = [USOCR\ JPR]'$		JPR = JPOCR	JPR = JPCOR	JPR = JPCCR
Obs. = 1768; 07/16/92–12/01/99				
$H_0 : A_{12}(L) = 0$	$\text{JPR} \overset{\text{G.C}}{\rightarrow} \text{USOCR}$	1.301 (0.260)	0.271 (0.929)	1.314 (0.255)
$H_0 : A_{21}(L) = 0$	$\text{USOCR} \overset{\text{G.C}}{\rightarrow} \text{JPR}$	10.175 (0.000)*	125.334 (0.000)*	21.841 (0.000)*
Panel B2. $[x_t y_t]' = [USCOR\ JPR]'$				
$H_0 : A_{12}(L) = 0$	$\text{JPR} \overset{\text{G.C}}{\rightarrow} \text{USCOR}$	0.797 (0.551)	0.364 (0.873)	0.821 (0.534)
$H_0 : A_{21}(L) = 0$	$\text{USCOR} \overset{\text{G.C}}{\rightarrow} \text{JPR}$	0.557 (0.734)	2.984 (0.011)**	0.818 (0.536)
Panel B3. $[x_t y_t]' = [USCCR\ JPR]'$				
$H_0 : A_{12}(L) = 0$	$\text{JPR} \overset{\text{G.C}}{\rightarrow} \text{USCCR}$	1.344 (0.242)	0.282 (0.922)	1.362 (0.235)
$H_0 : A_{21}(L) = 0$	$\text{USCCR} \overset{\text{G.C}}{\rightarrow} \text{JPR}$	10.286 (0.000)*	125.756 (0.000)*	22.011 (0.000)*
Panel B4. $[x_t y_t]' = [USOCR^2\ JPR^2]'$		$\text{JPR}^2 = \text{JPOCR}^2$	$\text{JPR}^2 = \text{JPCOR}^2$	$\text{JPR}^2 = \text{JPCCR}^2$
$H_0 : A_{12}(L) = 0$	$\text{JPR}^2 \overset{\text{G.C}}{\rightarrow} \text{USOCR}^2$	0.414 (0.839)	15.792 (0.000)*	0.527 (0.755)
$H_0 : A_{21}(L) = 0$	$\text{USOCR}^2 \overset{\text{G.C}}{\rightarrow} \text{JPR}^2$	2.757 (0.017)**	36.043 (0.000)*	3.430 (0.004)*
Panel B5. $[x_t y_t]' = [USCOR^2\ JPR^2]'$				
$H_0 : A_{12}(L) = 0$	$\text{JPR}^2 \overset{\text{G.C}}{\rightarrow} \text{USCOR}^2$	4.639 (0.000)*	0.852 (0.514)	3.845 (0.002)**
$H_0 : A_{21}(L) = 0$	$\text{USCOR}^2 \overset{\text{G.C}}{\rightarrow} \text{JPR}^2$	1.182 (0.315)	1.371 (0.232)	0.985 (0.424)
Panel B6. $[x_t y_t]' = [USCCR^2\ JPR^2]'$				
$H_0 : A_{12}(L) = 0$	$\text{JPR}^2 \overset{\text{G.C}}{\rightarrow} \text{USCCR}^2$	0.473 (0.796)	15.447 (0.000)*	0.605 (0.695)
$H_0 : A_{21}(L) = 0$	$\text{USCCR}^2 \overset{\text{G.C}}{\rightarrow} \text{JPR}^2$	2.794 (0.016)**	35.986 (0.000)*	3.477 (0.004)*
Panel C1. $[x_t y_t]' = [JPOCR\ UKR]'$		UKR = UKOCR	UKR = UKCOR	UKR = UKCCR
Obs. = 2253; 07/25/90–12/01/99				
$H_0 : A_{12}(L) = 0$	$\text{UKR} \overset{\text{G.C}}{\rightarrow} \text{JPOCR}$	10.561 (0.000)*	0.885 (0.489)	10.061 (0.000)*
$H_0 : A_{21}(L) = 0$	$\text{JPOCR} \overset{\text{G.C}}{\rightarrow} \text{UKR}$	2.678 (0.020)**	5.415 (0.000)*	4.126 (0.001)*

(*continued on next page*)

Table 3 (*continued*)

Hypothesis	Comments	F-statistic (significance level)	F-statistic (significance level)	F-statistic (significance level)
Panel C2. $[x_t y_t]' = [JPCOR\ UKR]'$				
$H_0 : A_{12}(L) = 0$	$UKR \overset{G.C}{\rightarrow} JPCOR$	53.865 (0.000)*	1.094 (0.361)	46.551 (0.000)*
$H_0 : A_{21}(L) = 0$	$JPCOR \overset{G.C}{\rightarrow} UKR$	2.164 (0.054)***	1.116 (0.349)	3.728 (0.002)*
Panel C3. $[x_t y_t]' = [JPCCR\ UKR]'$				
$H_0 : A_{12}(L) = 0$	$UKR \overset{G.C}{\rightarrow} JPCCR$	17.077 (0.000)*	0.708 (0.617)	15.334 (0.000)*
$H_0 : A_{21}(L) = 0$	$JPCCR \overset{G.C}{\rightarrow} UKR$	2.888 (0.013)**	5.187 (0.000)*	4.782 (0.000)*
Panel C4. $[x_t y_t]' = [JPOCR^2\ UKR^2]'$		$UKR^2 = UKOCR^2$	$UKR^2 = UKCOR^2$	$UKR^2 = UKCCR^2$
$H_0 : A_{12}(L) = 0$	$UKR^2 \overset{G.C}{\rightarrow} JPOCR^2$	1.666 (0.139)	3.331 (0.005)*	1.094 (0.361)
$H_0 : A_{21}(L) = 0$	$JPOCR^2 \overset{G.C}{\rightarrow} UKR^2$	8.997 (0.000)*	46.135 (0.000)*	6.711 (0.000)*
Panel C5. $[x_t y_t]' = [JPCOR^2\ UKR^2]'$				
$H_0 : A_{12}(L) = 0$	$UKR^2 \overset{G.C}{\rightarrow} JPCOR^2$	21.804 (0.000)*	0.267 (0.930)	16.834 (0.000)*
$H_0 : A_{21}(L) = 0$	$JPCOR^2 \overset{G.C}{\rightarrow} UKR^2$	5.172 (0.000)*	1.738 (0.122)	5.967 (0.000)*
Panel C6. $[x_t y_t]' = [JPCCR^2\ UKR^2]'$				
$H_0 : A_{12}(L) = 0$	$UKR^2 \overset{G.C}{\rightarrow} JPCCR^2$	3.565 (0.003)*	3.279 (0.005)*	2.326 (0.041)***
$H_0 : A_{21}(L) = 0$	$JPCCR^2 \overset{G.C}{\rightarrow} UKR^2$	7.408 (0.000)*	37.182 (0.000)*	5.842 (0.000)*

[a] OCR_t = open to close returns; COR_t = close to open returns; CCR_t = close to close returns; DV_t = detrended trading volumes; EV_t = expected trading volumes; UV_t = unexpected trading volumes; OCR_t^2 = volatility of open to close returns; COR_t^2 = volatility of close to open returns; CCR_t^2 = volatility of close to close returns.

* Represent the causal relationship being significant at 1%.

** represent the causal relationship being significant at 5%.

*** Represent the causal relationship being significant at 10%.

intraday returns and volatility. There seems to be a feedback relation between Japanese and UK intraday variables (see Hamao et al., 1990). [24]

Since US returns help to predict UK and Japanese returns (Table 4), we examine the response of UK and Japanese returns to US return shocks. US return shock has a strong positive initial effect on UK returns, and its effect becomes negligible after two days. However, the response of Japanese returns to US return shock increases initially and then declines quickly becoming negligible after three days. Since Japanese trading volume helps to predict US volatility (Table 3), we also look at their dynamic relationship. The effect of Japanese volume shock on US volatility is initially negative but turns to positive in a few days and then becomes negligible. [25]

Since UK volatility and volume and Japanese volatility and volume help to explain US trading volume (Table 3), we examine the dynamic relationship between the variables. The initial effect of both U.K volatility and UK volume shocks on US trading volume is positive, but their effect declines gradually over time. Both Japanese volatility and volume shocks have an initial positive effect on US volume, but the effect of the volatility disappears quickly, and the subsequent effect of volume becomes mixed afterwards.

4. Concluding remarks

In this paper, we have examined empirical dynamic relations – causal relations and the sign and magnitude of dynamic effects – between stock market trading volume and returns (and volatility) for both domestic and cross-country markets by using the daily data of the three largest stock markets: New York, Tokyo, and London. A main issue has been whether information about trading volume is useful in improving forecasts of returns and return volatility in a dynamic context.

We find that, contrary to predictions of some theoretical models, trading volume does not Granger-cause stock market returns on each of the markets. However, there exists a positive feedback relationship between trading volume and return volatility in all three markets. As to the cross-country causal relationship, US financial market variables such as returns, volatility and trading volume have an extensive predictive power for UK and Japanese financial market variables. In particular, US trading volume contains information about

[24] USCO rate is not Granger-caused either by UKR (including UKOCR, UKCOR, and UKCCR) or by JPR (including JPOCR, JPCOR, and JPCCR). This confirms that US returns are hard to predict. However, USCOR Granger-causes UKOCR and JPCOR, both of which have some overlapping time periods.

[25] The detailed figures are available upon request.

Japanese and UK financial variables. These results suggest that information flows from the US to the other countries. We also find some evidence of stronger spillover effects after the 1987 market crash and an increased importance of trading volume as an information variable after the introduction of options in the US and Japan. Our findings are consistent with the argument of Gallant et al. (1992) that more can be learned about the stock market through studying the joint dynamics of stock prices and trading volume than by focusing only on the univariate dynamics of stock prices.

Acknowledgements

We thank Ramon Rabinovitch, Jia He, Ron Singer, Raul Susmel, and Joaquin Diaz-Siaz for their valuable suggestions and comments. We are indebted to two anonymous referees for many insightful comments. Any errors are entirely our own.

References

Agmon, T., 1972. The relations among equity markets: A study of share price co-movement in the United States, United Kingdom, Germany and Japan. Journal of Finance 27, 839–855.

Agmon, T., 1974. The relationship among equity market: Reply. Journal of Finance 29, 1318–1319.

Andersen, T.G., 1996. Return volatility and trading volume: An information flow interpretation of stochastic volatility. Journal of Finance 51, 169–204.

Ariel, R.A., 1990. High stock returns before holidays: Existence and evidence on possible causes. Journal of Finance 45, 1611–1626.

Arshanapalli, B., Doukas, J., 1993. International stock market linkages: Evidence from the pre- and post-October 1987 period. Journal of Banking and Finance 17, 193–208.

Arshanapalli, B., Doukas, J., Lang, L.H.P., 1995. Pre- and post-October 1987 stock market linkages between US and Asian markets. Pacific-Basin Finance Journal 3, 57–73.

Bekaert, G., Harvey, C.R., 1995. Time varying world market integration. Journal of Finance 50, 403–444.

Bessembinder, H., Seguin, P.J., 1992. Futures-trading activity and stock price volatility. Journal of Finance 47, 2015–2034.

Bessembinder, H., Seguin, P.J., 1993. Price volatility, trading volume, and market depth: Evidence from futures markets. Journal of Financial and Quantitative Analysis 28, 21–39.

Blume, L., Easley, D., O'hara, M., 1994. Market statistics and technical analysis: The role of volume. Journal of Finance 49 (1), 153–182.

Campbell, J.Y., Grossman, S.J., Wang, J., 1993. Trading volume and serial correlation in stock returns. Quarterly Journal of Economics 108, 905–939.

CBOE, 1975. Analysis of volume and price patterns in stocks underlying CBOE options from December 30, 1974 to April 30, 1975 (Chicago, 1975).

CBOE, 1976. Analysis of volume and price patterns in stocks underlying CBOE options from December 31, 1975 to January 16, 1976 (Chicago, 1976).

Chan, K.C., Karolyi, A., Stulz, R.M., 1992. Global financial markets and the risk premium on US equity. Journal of Financial Economics 32, 137–167.

Chordia, T., Swaminathan, B., 2000. Trading volume and cross-autocorrelations in stock returns. Journal of Finance 55, 913–935.

Clark, P.K., 1973. A subordinated stochastic process model with finite variance for speculative prices. Econometrica 41, 135–155.

Copeland, T.E., 1976. A model of asset trading under the assumption of sequential information arrival. Journal of Finance 31, 1149–1168.

Copeland, M., Copeland, T., 1998. Leads, lags, and trading in global markets. Financial Analysts Journal 1998 July/August, 70–80.

Crouch, R.L., 1970. The volume of transaction and price changes on the New York Stock Exchange. Financial Analysts Journal 26, 104–109.

Dickey, D.A., Fuller, W.A., 1979. Distribution of the estimators for autoregressive time series with a unit root. Journal of American Statistical Association 74, 427–431.

Doukas, J., Switzer, L., 2000. Common stock returns and international listing announcements: Conditional tests of the mild segmentation hypothesis. Journal of Banking and Finance 24, 471–502.

Epps, T.W., Epps, M.L., 1976. The stochastic dependence of security price changes and transaction volume: Implications for the mixture-of-distributions hypothesis. Econometrica 44, 305–321.

Eun, C., Shim, S., 1989. International transmission of stock market movements. Journal of Financial and Quantitative Analysis 24, 241–256.

Foster, A.J., 1995. Volume–volatility relationships for crude oil futures markets. Journal of Futures Markets 15, 929–951.

Foster, F.D., Viswanathan, S., 1995. Can speculative trading explain the volume–volatility relation? Journal of Business and Economic Statistics 13, 379–396.

French, K., 1980. Stock returns and the weekend effect. Journal of Financial Economics 8, 55–69.

Gallant, A.R., Rossi, P.E., Tauchen, G., 1992. Stock prices and volume. Review of Financial Studies 5, 199–242.

Granger, C.W.J., 1969. Investigating causal relations by econometric models and cross-spectral methods. Econometrica 37, 424–438.

Granger, C.W.J., Morgenstern, O., 1963. Spectral analysis of New York market prices. Kyklos 16, 1–27.

Hamao, Y., Masulis, R.W., Ng, V., 1990. Correlations in price changes and volatility across international stock markets. Review of Financial Studies 3, 281–307.

Harris, L., 1986. Cross-security tests of the mixture of distributions hypothesis. Journal of Financial and Quantitative Analysis 21, 39–46.

Hiemstra, C., Jones, J.D., 1994. Testing for linear and nonlinear Granger causality in the stock price–volume relation. Journal of Finance 49, 1639–1664.

Jain, P., Joh, G., 1988. The dependence between hourly prices and trading volume. Journal of Financial and Quantitative Analysis 23, 269–283.

Jaffe, J., Westerfield, R., 1985a. The weekend effect in common stock returns: The international evidence. Journal of Finance 40, 433–454.

Jaffe, J., Westerfield, R., 1985b. Patterns in Japanese common stock returns: Day of week and turn of the year effects. Journal of Financial and Quantitative Analysis 20, 261–272.

Jennings, R., Starks, L., Fellingham, J., 1981. An equilibrium model of asset of trading with sequential information arrival. Journal of Finance 36, 143–161.

Karpoff, J.M., 1987. The relation between price changes and trading volume: A survey. Journal of Financial and Quantitative Analysis 22, 109–126.

Keim, D.B., Stambaugh, R.F., 1984. A further investigation of the weekend effect in stock returns. Journal of Finance 39, 819–840.

King, M.A., Wadhwani, S., 1990. Transmission of volatility between stock markets. Review of Financial Studies 3 (1), 5–33.

Lokonishok, J., Levi, M., 1982. Weekend effects on stock return: A note. Journal of Finance 37, 883–889.

Lokonishok, J., Maberly, E., 1990. The weekend effect: Trading patterns of individual and institutional investors. Journal of Finance 13, 231–243.

Lakonishok, J., Smidt, S., 1984. Volume and turn-of-the-year behavior. Journal of Financial Economics 13, 435–455.

Lamoureux, C.G., Lastrapes, W.D., 1990. Heteroskedasticity in stock return data: Volume versus GARCH effects. Journal of Finance 45, 221–229.

Lee, B.S., 1992. Causal relations among stock returns, interest rate, real activity, and inflation. Journal of Finance 47, 1591–1604.

Lee, B.S., Jeon, B.N., 1995. Common stochastic trends and predictability of international stock prices. Journal of the Japanese and International Economies 9 (3), 245–277.

Masih, A.M.M., Masih, R., 1997. Dynamic linkages and the propagation mechanism driving major international stock markets: An analysis of the pre- and post-crash eras. Quarterly Review of Economics and Finance 37, 859–885.

Phillip, P.C.B., Perron, P., 1988. Testing for a unit root in time series regression. Biometrica 75, 335–346.

Poon, R., 1994. An empirical examination of the return volatility–volume relation in related markets: The case of stock and options. Financial Review 29, 473–496.

Rogalski, R.J., 1979. The dependence of prices and volume. Review of Economics and Statistics 60, 268–274.

Shilling, H., 1996. The international guide to securities market indices. Fitzroy Dearborn Publishers, Chicago.

Sims, C.A., 1972. Money, income, and causality. American Economic Review 62 (4), 540–552.

Sims, C.A., 1980. Comparison of interwar and postwar business cycles: Monetarism reconsidered. American Economic Review 70 (2), 250–257.

Skinner, D.J., 1989. Options markets and stock return volatility. Journal of Financial Economics 23, 61–78.

Smirlock, M., Starks, L., 1988. An empirical analysis of the stock price–volume relationship. Journal of Banking and Finance 12, 31–41.

Tauchen, G.E., Pitts, M., 1983. The price variability–volume relationship on speculative markets. Econometrica 51, 485–505.

Wang, J., 1994. A model of competitive stock trading volume. Journal of Political Economy 102, 127–168.

Wood, R.A., McInish, T.H., Ord, J.K., 1985. An investigation of transaction data for NYSE stocks. Journal of Finance 40, 723–741.