Relationship between Stock Returns and Trading Volume: Domestic and Cross-Country Evidence in Asian Stock Markets

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Abstract - **We examined the effects of trading volume on the persistence of the time-varying conditional volatility of returns and the dynamic relations between trading volume and returns (and volatility) for both domestic and cross-country markets. We considered daily prices and trading volume in four Asian stock exchanges (Korea, Japan, China, and Hong Kong). For the analysis, we used the GARCH model, which includes trading volume. To analyze whether trading volume precedes stock returns, or vice versa, we used the Granger causality test. Our major findings are as follows. First, the inclusion of trading volume in the GARCH model does not reduce the persistence of conditional variance of each of the four stock markets. Second, regarding cross-country relationships, Hong Kong financial market variables, in particular Hong Kong trading volume, have extensive predictive power for the financial markets of Japan and Korea. Third, cross-country interactions are weak, and Japan's international stock market is substantially influenced by market variables outside of the stock markets of Korea, Hong Kong, and China.**

Keywords: Causality, Persistence, Trading volume, Volatility

I. INTRODUCION

There is much interest in the relationship between stock returns and trading volume. The importance of trading volume and its impact on the volatility of financial assets is well known in finance literature. A number of studies on the relationships between trading volume and returns (and volatility) in domestic markets have been conducted. However, cross-country markets remain less explored. Most previous empirical research has used data from international markets, but relatively few studies have been conducted on Asian stock exchanges. In the present study, we examined the causal relationships among stock market returns, trading volume, and volatility in four Asian stock markets: those of Korea, Japan, Hong Kong, and China. We considered each domestic stock market individually as well as cross-country effects. In particular, we investigated whether trading volume as a proxy for information is useful for improving predictions of returns and return volatility.

The remainder of this paper is organized as follows. A literature review is presented in Section 2. Section 3 presents our sample data. A description of our methodology and empirical results are presented in Sections 4 and 5, respectively. Section 6 concludes the paper.

II. LITERATURE REVIEW

Economists have long been interested in studying the relationships between stock return volatility and trading volume. The mixing of distribution hypothesis (MDH) links changes in price, volume, and rate of information flow (Clack 1973, Epps and Epps 1976, Harris 1986, Morgan 1976, Tauchen and Pitts 1984) and implies a positive relationship between trading volume and stock returns. This relationship is a function of a mixing variable defined as the rate of information. Lamoureux and Lastrapes (1990), testing the relationship between volume and volatility for a number of actively traded stocks in the United States, used contemporaneous trading volume as an explanatory variable in the variance equation and found that the inclusion of volume eliminated the persistence of volatility. Gallo and Pacini (2000), using data on 10 actively traded U.S. stocks from 1985 to 1995, found that persistence decreased when trading volume was used in the conditional variance equation. Foster (1995) tested the predictions of MDH for the oil futures market from 1990 to 1994 and found that volume and volatility were largely contemporaneously related and that both were driven by the same factor, which is assumed to be information arrival. Alsubie and Najand (2009) tested the effect of trading volume on the persistence of the conditional volatility of returns in the Saudi stock market. They identified good proxies for information flow and contemporaneous volume.

However, not all studies have supported the contemporaneous relationship between stock return volatility and trading volume. Copeland (1976), Mores (1981), and Jennings, Starks and Fellingham (1981) derived the sequential information arrival hypothesis (SIAH), which suggests a lead-lag relationship between volume and volatility only in the presence of information. Sharma et al. (1996) investigated the relationship between trading volume and GARCH for the New York Stock Exchange (NYSE) index from 1986 to 1989. They found that trading volume did not completely explain the GARCH effect, and concluded that while trading volume might be a good proxy for information arrival about individual firms, it is not true for the market as a whole. Lee (2009) investigated the relationship between trading volume and volatility on Korean markets using the threshold GARCH (TGARCH) model and found that there was asymmetric volatility in the Korea Composite Stock Price Index (KOSPI) and on the Korean Securities Dealers Automated Quotations (KOSDAQ) market, but concluded that inclusion of trading volume did not reduce volatility persistence in the conditional variance equation. Kim and Kim (2008) investigated the relationship between return volatility and volume of the KOSPI 200 futures index using the GJR–GARCH model. They identified volatility persistence, asymmetric responses to information arrival, and a relationship between return volatility and volume.

Some studies have investigated the dynamic relationship between trading volume and returns and/or volatility. For example, Wang (1994) analyzed volume and returns and found that volume may provide information about expected future returns. Chordia and Swaminathan (2000) examined trading volume and the predictability of short-term stock returns, and found that daily returns of stocks with high trading volume lead the daily returns of stocks with low trading volume. Chen, Firth and Rui (2001) examined all three factors and found that trading volume contributes some information to the returns process; they also reported persistence in volatility even after they incorporated the effects of contemporaneous and lagged volumes. Lee and Rui (2002) examined the dynamic relationships between stock market returns/volatility and trading volume using the data for the three largest stock markets in the world: New York, Tokyo, and London. They considered each domestic market individually as well as cross-country effects, and found that trading volume does not lead to Granger cause returns in each market, but there is a positive feedback relationship between volume and volatility in all three markets. Regarding cross-country effects, they found that US financial variables have extensive predictive power for the other markets.

III. METHODOLOGY

A. GARCH model

In general, the ARCH model of Engle (1982) and the GARCH model of Bollerslev (1986) are the most popular tools for capturing the volatility dynamics of financial time series. In the present study, we used GARCH, which is particularly useful because it makes current conditional variance dependent on lags in its previous conditional variance. To test the effects of trading volume on stock return volatility, the following GARCH (1,1) model was employed:

$$r_t = \mu + \lambda V_t + \varepsilon_t \tag{1}$$

$$\varepsilon_t = z_t \sqrt{h_t}, \qquad z_t \sim N(0,1) \tag{2}$$

$$h_t = \omega + \alpha \varepsilon_{t-1}^2 + \beta h_{t-1} + \theta V_t \tag{3}$$

where r_t is the daily stock returns, μ denotes the mean of the returns, and V_t is volume change, which is used as a proxy for information arrival to the market. Equation (3) specifies conditional variance as a function of mean volatility ω, where ε_{t-1}^2 is the lag in the squared residual of the mean (the ARCH term) and provides information about volatility clustering, and h_{t-1} is the previously forecasted variance (the GARCH term). The sum $(\alpha + \beta)$ is a measure of the persistence of a shock to the variance. The degree of persistence is determined by the magnitude of the sum. The effect of a shock on volatility is said to be persistent over time as this sum approaches 1. If trading volume is considered a proxy for information arrival, then it is expected that $\theta > 0$. If trading volume is serially correlated, α and β will be small and statistically insignificant. The sum $(\alpha + \beta)$ is smaller when trading volume is included than when it is excluded. All parameters of variance in equation (4) can be estimated using the Brendt, Hall, Hall, and Husman (BHHH) algorithm, assuming general error distribution (GED).

B. Granger causality

The Granger causality test (Granger, 1969) uses a bivariate equation to test relationships between two variables, x and y. The basic idea is that if changes in x precede changes in y, then x could be a cause of y, or vice versa.

We used the following bivariate autoregressive model to test for causality among trading volume, stock returns, and volatility of stock returns:

$$x_t = a + \sum_{i=1}^{m} a_i x_{t-i} + \sum_{j=1}^{n} b_j y_{t-j} + \varepsilon_t^x \quad (4)$$

$$y_t = c + \sum_{i=1}^{m} c_i y_{t-i} + \sum_{j=1}^{n} d_j x_{t-j} + \varepsilon_t^y \quad (5)$$

Suppose that x and y are returns and trading volume, respectively. In equation (4), returns are related to past values of returns as well as past trading volume. In equation (5), trading volume is related to past values of returns as well as past trading volume.

In equation (4), if b_j coefficients are statistically significant, then including both past history of trading volume (y) and past values of returns (x) yields a better forecast of returns. Thus, we say that volume causes returns. If the F-test does not reject the null hypothesis that $b_j = 0$ for all j, then the volume does not cause returns.

In equation (5), if returns cause volume, the d_j coefficient will be non-zero. If both b_j and d_j are not zero, there is a feedback relationship between trading volume and returns. To estimate vector autoregressive (VAR) model, the optimal lag length was obtained using Akaike's information criterion (AIC) and Schwarz's Bayesian information criterion (SBIC) with two lag lengths.

IV. SAMPLE DATA

In the present study, we used daily market price index and trading volume data from four Asian stock exchanges: Japan (NIKKEI 225), Hong Kong (Hang Seng Index, HSI), Korea (Korea Composite Stock Price Index, KOSPI), and China (Shanghai Stock Exchange Index, SSEI). We used data from 2 January 2004–28 September 2012 for all indexes except for SSEI, for which we used data from 23 September 2005 to 31 December 2012; these were obtained from the Yunhap Informax Data Center.

Daily index returns and trading volume were calculated in terms of percentage logarithmic change, based on the following formulae:

$$r_t = \ln(P_t / P_{t-1}) \times 100 \quad (6)$$

$$V_t = \ln(T_t / T_{t-1}) \times 100 \quad (7)$$

where P_t is the daily closing index and T_t is the trading volume.

A. Descriptive statistics

Tables 1 and 2 list the descriptive statistics for stock market returns and trading volume. Mean returns were positive for all markets except that of Japan. The measures for skewness indicated that the returns were negatively skewed, except for Hong Kong stock returns. The kurtosis was positive for daily stock returns and trading volume, and greater than 3. This implies that the distribution of returns and trading volume was not normally distributed. Applying the Jarque-Bera (J-B) test for normality rejected the null hypothesis of normality for returns and trading volume.

TABLE I. Summary statistics for daily returns of stock markets

	Japan	**Hong Kong**	**Korea**	**China**
Mean	-0.0092	0.0225	0.0407	0.0383
Median	0.0201	0.0629	0.1108	0.1179
Maximum	13.2345	13.4068	11.2843	9.0342
Minimum	-12.1110	-13.5820	-11.1720	-9.2561
Std. Dev.	1.5642	1.6803	1.5016	1.8110
Skewness	-0.5592	0.0450	-0.5563	-0.3950
Kurtosis	12.4002	11.6385	9.1292	6.0965
Jarque-Bera	8009.3 [0.000]***	6723.2 [0.000]***	3520.0 [0.000]***	751.9 [0.000]***

Notes: Jarque-Bera (J-B) is the test statistic for the null hypothesis of normality in sample returns distributions. Numbers in brackets are p-values. Significance levels: ***1%, **5%, *10%

TABLE II. Summary statistics for daily trading volume of stock markets (unit: million)

	Japan	**Hong Kong**	**Korea**	**China**
Mean	12675.17	901.237	39.283	8559.185
Median	12425.47	541.465	37.322	7945.950
Maximum	41518.40	9527.772	120.979	27580.10
Minimum	2989.000	2.1474	13.6320	201.500
Std. Dev.	3958.742	773.109	12.967	4348.556
Skewness	0.9085	2.0900	1.1162	0.6868
Kurtosis	5.8417	14.4261	5.2260	3.3567
Jarque-Bera	1017.3 [0.000]***	13341.2 [0.000]***	902.0 [0.000]***	148.4 [0.000]***

Note: See table 1.

B. Unit root tests

We tested the stationarity of returns and trading volume, for which the most common test is the unit test. To test for a unit root, we employed both the augmented Dickey-Fuller (ADF) test and the Phillips-Perron (PP) test. Table 3 provides the results. The null hypothesis that returns and trading volume are nonstationary was rejected at the 1% significance level, indicating that both trading volume and returns are stationary.

TALBE III. Unit root test for returns and trading volume change data

	ADF		PP	
	Returns	*Trading volume change*	*Returns*	*Trading volume change*
Japan	-47.99***	-18.89***	-48.11***	-147.19***
Hong Kong	-47.85***	-18.08***	-47.94***	-322.77***
Korea	-45.60***	-21.93***	-45.60***	-128.72***
China	-41.95***	-33.04***	41.98***	-97.43***

Notes: The critical values for the ADF and PP tests are -3.9611 and -3.4323 at the 1% significance level, respectively. ADF indicates augmented Dickey-Fuller test, and PP indicates Phillips-Perron test. Significance levels: ***1%, **5%, *10%.

V. EMPIRICAL RESULTS

A. 5.1. Contemporaneous relationships

Table 4 presents the model of persistence of stock returns when trading volume is included in both the mean equation and conditional variance for all stock returns.

The coefficients of regressing returns on trading volume were both positive and significant for the Korean and Chinese markets, negative and significant for Hong Kong, and nonsignificant for Japan. When we incorporated trading volume in the volatility equation, the coefficient θ was

statistically significant for all stock markets. These results suggest that contemporaneous volume significantly explains volatility. We also found that the GARCH effect still remained for all market returns. This implies that the volatility of returns is not totally explained by trading volume. This appears to be inconsistent with the findings of Lamoureux and Lastrapes (1990), but linking volatility to trading volume does not extract all information. We evaluated the accuracy of model specification using Ljung-Box Q_s (24) and ARCH (24) tests. Neither test was

significant at the 1% level, but the estimated model fit the data very well.

TABLE IV. Contemporaneous relationship between daily trading volume and stock returns

	Japan	Hong Kong	Korea	China
μ	-0.0215 (0.0289)	0.0350 (0.0249)	0.1252 (0.0236)***	0.1597 (0.0295)***
λ	-0.0016 (0.0014)	-0.0010 (0.0003)***	0.0066 (0.0014)***	0.0138 (0.0014)***
ω	0.1564 (0.0296)***	0.0283 (0.0070)***	0.0382 (0.0115)***	0.0202 (0.0097)**
α	0.1780 (0.0171)***	0.1140 (0.0091)***	0.0943 (0.0140)***	0.0497 (0.0101)***
β	0.7657 (0.0240)***	0.8782 (0.0077)***	0.8869 (0.0158)***	0.9441 (0.0108)***
θ	0.0140 (0.0015)***	0.0057 (0.0057)***	0.0089 (0.0027)***	0.0018 (0.0006)***
$\alpha + \beta$	0.9437	0.9922	0.9812	0.9938
Q_s (24)	21.104 [0.633]	30.798 [0.160]	29.351 [0.207]	15.457 [0.907]
ARCH (24)	0.8447 [0.680]	1.3017 [0.148]	1.2463 [0.189]	0.6617 [0.891]
LR	-3591	-3610	-3594	-3259

Notes: Standard errors are in parentheses and p-values are in brackets. The Ljung-Box Q_s(24) statistic tests serial correlations up to a 24th order lag length in the squared standardized returns. The ARCH(24) statistic tests the ARCH effects at 24th order-lagged, squared residuals. LR indicates log-likelihood. Significance levels: ***1%, **5%, *10%

B. Domestic causal relationships among trading volume, returns and volatility

Table 5 presents the results of tests for domestic causal relationships based on a bivariate model. First, the returns data show that Granger causality affects all of the markets. This implies that returns add significant predictive power for future trading volume in the presence of current and past trading volume. Second, at a 1% significance level, trading volume did not prompt Granger-causality returns in the Japan, Korea, or China markets. This confirms the difficulty of improving the predictability of returns by adding information flow about trading volume, and is consistent with the MDH (Clack, 1973), which predicts no causal relationship between trading volume and returns. However, trading volume did lead to Granger-causality returns in the Hong Kong market, in which returns were influenced by trading volume and trading volume was influenced by returns. This finding contradicts the MDH and is consistent with the SIAH (Copeland, 1976; Jennings et al., 1981). Trading volume has predictive power for future returns.

TALBE V. Causality relationships among markets

	Japan	Hong Kong	Korea	China
Null hypothesis	*F-statistic*	*F-statistic*	*F-statistic*	*F-statistic*
$R \xrightarrow{G.C} V$	2.7023 (0.0673)*	3.8420 (0.0216)**	3.2131 (0.0404)**	80.764 (0.0000)***
$V \xrightarrow{G.C} R$	0.1205 (0.8864)	7.7076 (0.0005)***	0.0864 (0.9171)	1.2874 (0.2762)
$h \xrightarrow{G.C} V$	3.3906 (0.0339)**	3.1849 (0.0416)**	0.1418 (0.8678)	7.9932 (0.0004)***
$V \xrightarrow{G.C} h$	0.8818 (0.4142)	114.04 (0.0000)***	11.405 (0.0000)***	58.402 (0.0000)***

Notes: R=returns; V=trading volume change; h=conditional volatility filtered by the GARCH model. Standard errors are in parentheses. Significance levels: ***1%, **5%, *10%

Third, between trading volume and returns volatility, the F-statistics were highly significant, rejecting the null hypothesis of no causality between return volatility (trading volume) and trading volume (returns volatility) in the Hong Kong and China stock markets. That is, trading volume helps predict returns volatility and vice versa. Trading volume contains information about returns indirectly through the predictability of returns volatility, but not directly via returns itself. These results are in agreement with the findings of Clark (1973), Tauchen and Pitts (1983), and Lee and Rui (2002). Returns volatility did not prompt Granger-causality trading volume and the null hypothesis was rejected, but the hypothesis that trading volume does not lead to Granger-causality returns volatility was not rejected in the Japan and Korea markets. For trading volume, at a 1% significance level, Granger-causality returns volatility was rejected for the Korea stock market. This implies that trading volume helps predict returns volatility. Thus, in the Korea stock market, there is unidirectional Granger causality from trading volume to return volatility. However, the Japan stock market shows the opposite causality: from return volatility to trading volume.

C. *Cross-country causal relationships among trading volume, returns and volatility*

The results of Granger causality analyses among trading volume, returns, and returns volatility for all markets studied are presented in Tables 6–8. As can be derived from Table 6, Korea's trading volume helps predict the trading volume and volatility in Japan as well as the volatility in Hong Kong. Korea returns do not lead to Granger causality of all other variables except the volume in Hong Kong and China. In addition, Japan volume leads to Granger causality of trading volume in Korea as well as volatility in Hong Kong and China. This implies that Japan's volume influences the other markets. However, Japan returns do not lead to Granger causality of trading volume. China returns do not have causal effects on any other markets.

TABLE VI. Cross-country causal relationship between returns and trading volume

Null hypothesis	**F-statistic (significance level)**	**Null hypothesis**	**F-statistic (significance level)**
Panel A: Korea↔Japan		*period: 2/1/2004 – 28/9/2012*	
JPR $\xrightarrow{G.C}$ KOV	0.5450 (0.5799)	KOV $\xrightarrow{G.C}$ JPR	0.8944 (0.4090)
KOR $\xrightarrow{G.C}$ JPV	0.1829 (0.8328)	JPV $\xrightarrow{G.C}$ KOR	0.7912 (0.4534)
Panel B: Korea, Hong Kong		*period: 2/1/2004 – 28/9/2012*	
HKR $\xrightarrow{G.C}$ KOV	0.8653 (0.4211)	KOV $\xrightarrow{G.C}$ HKR	0.9717 (0.3786)
KOR $\xrightarrow{G.C}$ HKV	3.3529 (0.0352)**	HKV $\xrightarrow{G.C}$ KOR	8.1553 (0.0003)***
Panel C: Korea↔China		*period: 23/9/2005 – 28/9/2012*	
KOR $\xrightarrow{G.C}$ CIV	8.1089 (0.0003)***	CIV $\xrightarrow{G.C}$ KOR	0.9358 (0.3925)
CIR $\xrightarrow{G.C}$ KOV	0.0901 (0.9138)	KOV $\xrightarrow{G.C}$ CIR	0.2068 (0.8132)
Panel D: Hong Kong↔Japan		*period: 2/1/2004 – 28/9/2012*	
JPR $\xrightarrow{G.C}$ HKV	0.6818 (0.5058)	HKV $\xrightarrow{G.C}$ JPR	7.0924 (0.0009)***
HKR $\xrightarrow{G.C}$ JPV	2.3886 (0.0920)*	JPV $\xrightarrow{G.C}$ HKR	1.0834 (0.3386)
Panel E: Hong Kong↔China		*period: 23/9/2005 – 28/9/2012*	
HKR $\xrightarrow{G.C}$ CIV	22.2092 (0.0000)***	CIV $\xrightarrow{G.C}$ HKR	0.8028 (0.4482)
CIR $\xrightarrow{G.C}$ HKV	0.3515 (0.7036)	HKV $\xrightarrow{G.C}$ CIR	3.7478 (0.0238)
Panel F: China↔Japan		*period: 23/9/2005 – 28/9/2012*	
JPR $\xrightarrow{G.C}$ CIV	1.3791 (0.2521)	CIV $\xrightarrow{G.C}$ JPR	1.4990 (0.2237)
CIR $\xrightarrow{G.C}$ JPV	0.1259 (0.8817)	JPV $\xrightarrow{G.C}$ CIR	1.2358 (0.2909)

Notes: JPR=Japan returns; JPV=Japan volume changer; KOR=Korea returns; KOV=Korea volume change; HKR=Hong Kong returns, HKV=Hong Kong volume change; CIR=China returns; CIV=China volume change. Significance levels : ***1%, **5%, *10%

TABLE VII. Cross-country causal relationship between trading volume and volatility

Null hypothesis	**F-statistic (significance level)**	**Null hypothesis**	**F-statistic (significance level)**
Panel A: Korea↔Japan		*period: 2/1/2004 – 28/9/2012*	
JP$\hat{h}$ $\xrightarrow{G.C}$ KOV	0.0723 (0.9320)	KOV $\xrightarrow{G.C}$ JP$\hat{h}$	4.5779 (0.0087)***
KO$\hat{h}$ $\xrightarrow{G.C}$ JPV	1.7362 (0.1764)	JPV $\xrightarrow{G.C}$ KO$\hat{h}$	7.3356 (0.0007)***
Panel B: Korea↔Hong Kong		*period: 2/1/2004 – 28/9/2012*	
HK$\hat{h}$ $\xrightarrow{G.C}$ KOV	0.1963 (0.8217)	KOV $\xrightarrow{G.C}$ HK$\hat{h}$	2.3501 (0.0956)*
KO$\hat{h}$ $\xrightarrow{G.C}$ HKV	0.6892 (0.5021)	HKV $\xrightarrow{G.C}$ KO$\hat{h}$	0.0174 (0.9827)
Panel C: Korea↔China		*period: 23/9/2005 – 28/9/2012*	
KO$\hat{h}$ $\xrightarrow{G.C}$ CIV	0.5824 (0.5587)	CIV $\xrightarrow{G.C}$ KO$\hat{h}$	3.3586 (0.0350)**
CI$\hat{h}$ $\xrightarrow{G.C}$ KOV	0.0721 (0.9304)	KOV $\xrightarrow{G.C}$ CI$\hat{h}$	1.6258 (0.1971)
Panel D: Hong Kong↔Japan		*period: 2/1/2004 – 28/9/2012*	
JP$\hat{h}$ $\xrightarrow{G.C}$ HKV	2.4763 (0.0843)*	HKV $\xrightarrow{G.C}$ JP$\hat{h}$	3.3861 (0.0340)**
HK$\hat{h}$ $\xrightarrow{G.C}$ JPV	0.8358 (0.4337)	JPV $\xrightarrow{G.C}$ HK$\hat{h}$	3.4758 (0.0311)**
Panel E: Hong Kong↔China		*period: 23/9/2005 – 28/9/2012*	
CI$\hat{h}$ $\xrightarrow{G.C}$ HKV	0.0877 (0.9160)	HKV $\xrightarrow{G.C}$ CI$\hat{h}$	1.1359 (0.3214)
HK$\hat{h}$ $\xrightarrow{G.C}$ CIV	2.0416 (0.1301)	CIV $\xrightarrow{G.C}$ HK$\hat{h}$	0.4811 (0.6181)
Panel F: China↔Japan		*period: 23/9/2005 – 28/9/2012*	
CI$\hat{h}$ $\xrightarrow{G.C}$ JPV	0.2070 (0.8130)	JPV $\xrightarrow{G.C}$ CI$\hat{h}$	2.4058 (0.0905)*
JP$\hat{h}$ $\xrightarrow{G.C}$ CIV	0.3161 (0.7290)	CIV $\xrightarrow{G.C}$ JP$\hat{h}$	3.6137 (0.0272)**

Notes: JPV=Japan volume change; KOV=Korea volume change; HKV=Hong Kong volume change; CIV= China volume change; $\hat{h}$=conditional volatility filtered by the GARCH model. Significance levels : ***1%, **5%, *10%

Furthermore, as can be seen in Table 7, volatility has virtually no effect on any variable in any market. The one exception is that volatility in the Japan market leads to Granger causality of trading volume in Hong Kong.

As shown in Table 8, the only effects of trading volume on the trading volume of another country were between Korea and Japan, where the volume of each led to Granger causality of the other.

In sum, there are feedback relationships between Korea and Japan volume, between Korea returns and Hong Kong volume, and between Hong Kong volume and Japan volatility (Tables 6–8). Overall, however, there were few cross-country interactions.

TABLE VIII. Cross-country causal relationship between trading volume of each country

Null hypothesis	**F-statistic (significance level)**	**Null hypothesis**	**F-statistic (significance level)**
Panel A: Korea↔Japan		period: 2/1/2004 – 28/9/2012	
KOV $\xrightarrow{G.C}$ JPV	4.8617 (0.0078)***	JPV $\xrightarrow{G.C}$ KOV	5.3179 (0.0050)***
Panel B: Korea↔Hong Kong		period: 2/1/2004 – 28/9/2012	
HKV $\xrightarrow{G.C}$ KOV	1.8012 (0.1654)	KOV $\xrightarrow{G.C}$ HKV	0.1983 (0.8201)
Panel C: Korea↔China		period: 23/9/2005 – 28/9/2012	
KOV $\xrightarrow{G.C}$ CIV	0.1033 (0.9018)	CIV $\xrightarrow{G.C}$ KOV	0.2007 (0.8181)
Panel D: Hong Kong↔Japan		period: 2/1/2004 – 28/9/2012	
JPV $\xrightarrow{G.C}$ HKV	0.8583 (0.4240)	HKV $\xrightarrow{G.C}$ JPV	0.2815 (0.7547)
Panel E: Hong Kong↔China		period: 23/9/2005 – 28/9/2012	
CIV $\xrightarrow{G.C}$ HKV	0.4367 (0.6462)	HKV $\xrightarrow{G.C}$ CIV	0.3725 (0.6890)
Panel F: China↔Japan		period: 23/9/2005 – 28/9/2012	
CIV $\xrightarrow{G.C}$ HKV	0.5529 (0.5754)	HKV $\xrightarrow{G.C}$ CIV	1.0375 (0.3546)

Notes: JPV=Japan volume change; KOV=Korea volume change; HKV=Hong Kong volume change; CIV=China volume change. Significance levels : ***1%, **5%, *10%

VI. CONCLUSION

We examined the dynamic relationships between returns, trading volume, and volatility for both domestic and cross-country markets. Our main goal was to determine whether trading volume as a proxy for information flow can be useful to improve the prediction of future returns and return volatility.

GARCH analyses indicated that trading volume contributes some information to the returns in Asian stock markets. However, GARCH effects still remained for all market returns. This implies that the volatility of returns is not totally explained by trading volume. This evidence appears inconsistent with the findings of Lamoureux and Lastrapes (1990). Our domestic Granger-causality results showed that returns led to Granger causality of the stock market in all markets. In addition, trading volume leads to Granger causality of the Hong Kong market, and helps predict returns volatility in the Hong Kong and China markets (and vice versa). As to cross-country effects, the market variables for Hong Kong have substantial predictive power for financial market variables in Korea and Japan. Korea volume helps predict Japan's trading volume and volatility and Hong Kong volatility. Japanese volume leads to Granger causality of Korea's volume and volatility and Hong Kong and China volatility. However, Chinese financial variables have a strong influence on other market variables. There are feedback relationships between Korea and Japan volume, between Korea returns and Hong Kong volume, and between Hong Kong volume and Japan volatility.

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