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The Dynamic Relation Between Stock Returns, Trading Volume, and Volatility

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Abstract

We examine the dynamic relation between returns, volume, and volatility of stock indexes. The data come from nine national markets and cover the period from 1973 to 2000. The results show a positive correlation between trading volume and the absolute value of the stock price change. Granger causality tests demonstrate that for some countries, returns cause volume and volume causes returns. Our results indicate that trading volume contributes some information to the returns process. The results also show persistence in volatility even after we incorporate contemporaneous and lagged volume effects. The results are robust across the nine national markets.

Keywords: stock index returns, trading volume, volatility, EGARCH

JEL Classification: G15

1. Introduction

Our purpose in this paper is to empirically examine the dynamic (causal) relation between stock market returns, trading volume, and volatility in nine major national stock markets. Most previous empirical research has used data from the United States, but relatively little work has been conducted on other national markets. Our study seeks to remedy this situation.

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Our initial analysis centers on the volume and price change relation. Clark (1973) and Lamoureux and Lastrapes (1990, 1994) link price volatility with the underlying information flow in the markets, and use volume as a measure of the information flow. These studies form the basis of our first hypothesis, which examines the reasons for the volume and stock return relation.

We test a second hypothesis in which the formation of returns is conditional on various information arrivals that all affect trading volume in the same way. The nine markets we examine are among the largest in terms of market capitalization and turnover. We use EGARCH techniques to examine the returns, trading volume, and a conditional volatility relation, and compare and contrast the results from these markets.

The paper proceeds as follows. In Section 2 we provide an overview of the previous research on the relation between trading volume, price change, and volatility. Section 3 describes our data set. In Section 4, we discuss the methodology and present the empirical results. Section 5 summarizes and concludes.

2. Literature review

Studying the relation between stock returns and trading volume has absorbed financial economists for many years. Karpoff (1986) provides three reasons for this. First, the returns/trading volume relation provides insight into the structure of financial markets. Second, the returns/trading volume relation is important for event studies that use a combination of stock returns and trading volume data to draw inferences. Third, the returns/trading volume relation is critical to the debate over the empirical distribution of speculative prices.

Beginning with Osborne (1959), researchers have studied the returns/volume relation from a variety of perspectives. For example, previous empirical investigations have included the relation between price indexes and aggregate exchange trading volume (Granger and Morgenstern, 1963), between contemporaneous absolute price change and trading volume (Crouch, 1970), between price change and trading volume (Westerfield, 1977; Tauchen and Pitts, 1983; Rogalski, 1978), between the variance of price change and trading volume (Epps and Epps, 1976), and between squared price change and trading volume (Harris, 1986; Clark, 1973). From these research studies two empirical relations emerge as stylized facts: the correlation between trading volume (V) and the absolute value of the stock price change ($|\Delta p|$) is positive, and the correlation between trading volume and the stock price change (Δp) is also positive (Karpoff, 1987).

Gallant, Rossi, and Tauchen (1992) point out that much of the previous empirical work on the return-volume relation focuses primarily on the contemporaneous relation between price changes and volume. Although some models use cross correlations to imply a dynamic relation between returns and volume, these studies do not necessarily examine causal relations. For example, Hiemstra and Jones (1994) use linear and nonlinear Granger causality tests to investigate the dynamic relation between stock returns and percentage changes in trading volume. Foster and Viswanathan (1995) derive a speculative trading model with endogenous informed trading that yields a conditionally heteroskedastic time series for volume and volatility. Andersen (1996) develops an empirical return volatility/volume model from a microstructure framework.

We believe that 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. Prior empirical research can be classified into four categories. Below, we briefly review studies in each category. The empirical studies we review use data from the United States. Comparatively few studies have been done outside of the U.S.

2.1. Trading volume and the absolute value of price changes

There is an old Wall Street adage that "It takes trading volume to make prices move." There are numerous empirical findings to support what we call a positive trading volume-absolute price change correlation.

Crouch (1970) finds positive correlations between the absolute values of daily price changes and daily trading volume for both market indexes and individual stocks. Clark (1973) finds a positive relation between the square of a measure of the price change and aggregated trading volume using daily data from the cotton futures market. Using four-day intervals and monthly data for a total of 51 stocks, Morgan (1976) finds that in all cases, the variance of price change is positively related to trading volume. Westerfield (1977) finds the same relation in a sample of daily price change and trading volume for 315 common stocks, as do Tauchen and Pitts (1983), who use daily data from the Treasury Bill futures market.

Epps and Epps (1976), using transactions data from 20 stocks, find a positive relation between the sample variances of price changes and the trading volume levels. Wood, McInish, and Ord (1985) also report a positive correlation between trading volume and the magnitude of the price change at the transactions level. Jain and Joh (1988), using data from a market index, find a similar correlation over one-hour intervals.

There are four theoretical explanations for the positive relation between the absolute price changes and trading volumes: a sequential arrival of information (SAI) model, a mixture of distributions (MD) model, a rational expectation asset pricing (REAP) model, and a differences of opinion (DO) model.

Studies by Copeland (1976), Morse (1980), Jennings, Starks, and Fellingham (1981), and Jennings and Barry (1983) develop and extend the SAI model. In their version, new information is disseminated sequentially to traders, and traders who are not yet informed cannot perfectly infer the presence of informed trading. Consequently, the sequential arrival of new information to the market generates both trading volume and price movements, both of which increase during periods characterized by numerous information shocks.

One explanation for the positive volatility/trading volume correlation comes from research into the distribution of speculative prices (Clark, 1973; Epps and Epps, 1976). According to the MD hypothesis, price volatility and trading volume should be positively correlated because they jointly depend on a common underlying variable. This variable could be interpreted as the rate of information flow to the market. In other words, both the price and trading volume change contemporaneously in response to new information.

Clark (1973) assumes the daily price change is the sum of a random number of within-day price changes. Thus the variation in the daily price change is a random variable with a mean proportional to the mean number of daily transactions. Clark argues that trading volume is related positively to the number of within-day transactions, therefore the trading volume is related positively to the variability of the price change.

Epps and Epps (1976) examine the mechanics of within-day trading. The change in the market price on each within-day transaction is the average of the changes in all of the traders' reservation prices. Epps and Epps assume there is a positive relation between the extent to which traders disagree when they revise their reservation prices and the absolute value of the change in the market price. That is, an increase in the extent to which traders disagree can indicate a larger absolute price change. Therefore, the price variability/trading volume relation arises because the volume of trading is positively related to the extent to which traders disagree when they revise their reservation prices.

Speculative trading stems from disagreements among traders over the relation between the announcement and the ultimate performance of the assets in question. Such disagreements can arise either because speculators have different private information, or because they interpret public data differently.

Rational expectations models show disagreement generated by private information. These models generally involve trading among privately informed traders, uninformed traders, and liquidity or noise traders. Wang (1994) develops an equilibrium model of stock trading in which investors are heterogeneous in their information and private investment opportunities, and trade rationally for both informational and non-informational reasons. In his model, trading is always accompanied by price changes, since investors are risk-averse. For example, when a group of investors sells their shares to rebalance their portfolios, to induce other investors to buy, the price of the stock must drop. As information asymmetry increases, the uninformed investors demand higher discounts in price when they buy the stock from the informed investors. Thus, these investors are able to cover the risk of trading against private information. Therefore, trading volume is always positively correlated with absolute price changes, and the correlation increases with information asymmetry.

Harris and Raviv (1993) assume that traders receive common information. However, traders differ in the way in which they interpret this information, and each trader believes absolutely in the validity of his interpretation. Harris and Raviv refer to this as the assumption that traders have differences of opinion, and assume that traders start with common prior beliefs about the returns to a particular asset. As information about the asset becomes available, each trader uses his own model of the relation between the news and the asset's returns to update his beliefs about returns. Harris and Raviv (1993) assume that there are two types of risk-neutral, speculative traders who they term responsive and unresponsive. The two types agree on whether a given piece of information is favorable or unfavorable, but they disagree on the extent to which the information is important. When they receive favorable (unfavorable) information, speculators in the responsive group greatly increase (decrease) their probability expectation of high returns. Speculators in the unresponsive group do not. Therefore, when the cumulative impact of the past information is favorable, the responsive speculators value the asset more highly and will own all of it. But when the cumulative impact of the past information is unfavorable, the unresponsive speculators value the asset more highly and will own all of it. Trading will occur when, and only when, cumulative information switches from favorable to unfavorable, or vice versa. Thus, the Harris and Raviv model predicts that absolute price changes and trading volume are positively correlated.

2.2. Trading volume and price change

Studies by Epps and Epps (1976), Harris (1986), Morgan (1976), Rogalski (1978), and Smirlock and Starks (1985) imply a positive correlation between trading volume and the price change per se. Jennings, Starks, and Fellingham (1981) extend Copeland's (1976) SAI model to incorporate real world margin constraints and short selling, and provide an alternate theory consistent with the correlation between and V and Δp. Their argument is that short positions are possible but are more costly than long positions. The costliness of short positions implies that the quantity demanded by an investor with a short position is less responsive to price changes than is the quantity demanded by an investor with a long position. Jennings, Starks, and Fellingham are able to show that in many cases, when a previously uninformed trader interprets the new information pessimistically, the trading volume that results is less than when the trader is an optimist. Since price decreases with a pessimist and increases with an optimist, the authors argue that trading volume is relatively high when the price increases and low when the price decreases.

Karpoff (1986) constructs a model that depends on asymmetries in the costs of going long or short. Costly short sales restrict some investors from acting on their information, so the effect is to decrease their demands. This effect decreases the variance of interperiod shifts in transaction supply relative to that for transaction demand. In turn, this shift creates a positive covariance between trading volume and price change over the period.

2.3. Causal relation between trading volume and stock price changes

Some theoretical studies explicitly investigate the dynamic relation between trading volume and stock returns, a relation that might have some causal relation implications. Campbell, Grossman, and Wang (1993) develop a model in which one implication is that price changes accompanied by high volume will tend to be reversed, and that this reversal will be less true of price changes on days with low volume.

Blume, Easley, and O'Hara (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 information about past price movements. Thus, traders who include volume measures in their technical analysis perform better in the market than those who do not.

Wang (1994) analyzes dynamic relations between volume and returns based on a model with information asymmetry. His model shows that volume may provide information about expected future returns. In their study, He and Wang (1995) develop a rational expectations model of stock trading in which investors have different information concerning the underlying value of the stock. They examine the way in which trading volume relates to the information flow in the market, and how investors' trading reveals their private information.

Chordia and Swaminathan (2000) examine the interaction between trading volume and the predictability of short-term 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 empirical result to the tendency of high volume stocks to respond promptly to market-wide information. Chordia and Swaminathan conclude that "trading volume plays a significant role in the dissemination of market-wide information".

Although these studies have some implications for causal relations between trading volume and stock returns, there has been no rigorous study of empirical causal relations between volume and returns to confirm or reject these implications. In this study, we empirically examine causal relations between stock market trading volume and stock returns.

2.4. Trading volume and conditional volatility

The Engle (1982) autoregressive conditional heteroskedasticity (ARCH) process provides a good fit for many financial return time series. The ARCH model allows the conditional variance to change over time as a function of past squared errors. The strength of the ARCH technique is that by using established and well specified models for economic variables, the conditional means and variances can be estimated jointly. The autocorrelation in the time-varying rate of information arrival leads to time-series dependencies in conditional volatility that can be modeled as GARCH processes. This research design is rooted in a class of theoretical models in which trading volume and price volatility are driven by exogenous information innovations. Lamoureux and Lastrapes (1990) use this econometric framework to test whether there are GARCH effects remaining after the conditional volatility specification expands to include the contemporaneous trading volume, which is a proxy for information arrival. They find that for individual stocks, volatility persistence falls significantly once contemporaneous trading volume is included.

3. Data

The data set comprises daily market price index and trading volume series for nine of the largest stock exchanges: New York, Tokyo, London, Paris, Toronto, Milan, Zurich, Amsterdam, and Hong Kong. We choose these markets because they are large, well established, well regulated, and have sufficient data for our statistical tests. Also, because they have many foreign investors, these markets have a global interest. Table 1 lists our specific indexes, the sample period, and the total number of observations, for each national market. Our sample does not include the dates when trading volume is not available. We value-weight all indexes. The indexes represent a large coverage (greater than 50% of total market capitalization) of stocks within each market. Data are collected from Datastream. We match all series of indexes and trading volumes.

Table 1 also presents the basic statistics relating to the returns and trading volume of each index. The statistics show that returns are negatively skewed, although the skewness statistics are not large. The negative skewness implies that the return distributions of the shares traded on these exchanges have a heavier tail of large values and hence a higher probability of earning negative returns. In all but three of the markets, the kurtosis values are very much larger than three. This result shows clearly that for most series, the distribution of returns have fat tails compared with the normal distribution. It implies that much of the non-normality is due to leptokurtosis.

Previous studies report strong evidence of both linear and nonlinear time trends in trading volume series (e.g., Gallant, Rossi, and Tauchen, 1992). We test trend stationarity in trading volume by regressing the series on a deterministic function of time. To allow for a nonlinear time trend and a linear trend, we include a quadratic time trend term:

$$v_t = \alpha + \beta_1 t + \beta_2 t^2 + \varepsilon_t \tag{1}$$

where V_t is raw trading volume in each stock market.

Panel B of Table 1 shows the coefficients (with t-statistics in parentheses) that result from regressing trading volume on linear and nonlinear time trend variables. In general, the coefficients for both the linear and the quadratic terms are statistically significant and the model fit is high. Therefore, we use trading volumes adjusted for both linear and nonlinear time trends for all nine markets. The detrended trading volumes are the residuals from equation (1).

To test for a unit root (or the difference stationary process), we use the augmented Dickey-Fuller (1979) test:

Table 1

Tests of stock returns and trading volume

Panel A shows basic information and distributional characteristics of stock returns and trading volume for nine countries. Linear and non-linear trends in trading volume are shown in panel B. The trend model is $V_t = \alpha + \beta_1 t + \beta_2 t^2 + \varepsilon_t$, where V_t is raw trading volume and t is time. t-statistics are reported in parentheses. The unit root test of stock returns and detrended trading volume is shown in panel C. We use the Augmented Dickey-Fuller regression (ADF). The model is $\Delta x_t = \rho_0 + \rho x_{t-1} + \sum_{i=1}^{n} \delta_i \Delta x_{t-1} + \varepsilon_t$, where x is stock return or detrended volume. The lag length in the ADF regression is chosen by Akaike's information criterion (AIC).

Panel A: Basic statistics of returns and raw trading volume

Country	USA	Japan	UK	France	Canada	Italy	Switzerland	Netherlands	Hong Kong
Representative Bourse	New York	Tokyo	London	Paris	Toronto	Milan	Zurich	Amsterdam	Hong Kong
Market Capitalization as of Nov. 2000 (US$billions)	11,111	3,437	2,436	1,336	841	743	733	614	582
Sample Period	4/1/73–29/12/00	5/1/74–29/12/00	28/10/86–29/12/00	3/1/92–29/12/00	2/10/93–29/12/00	17/12/96–29/12/00	2/1/97–29/12/00	4/2/86–29/12/00	23/3/89–29/12/00
Observations	7057	6794	3581	2257	1825	1019	1008	3746	2918
Index	S&P 500	TOPIX	FTSE 100	CAC 40	Toronto 100	Milan Mib 30 Index	Datastream Market Index	Datastream Market Index	All Ordinaries Index
Returns:									
Mean	0.034	0.021	0.039	0.052	0.045	0.106	0.072	0.051	0.041
Standard deviation	0.999	1.002	1.003	1.235	1.058	1.475	1.161	0.971	1.657
Skewness	−1.844	−0.377	−1.097	−0.151	−0.721	−0.240	−0.384	−0.646	−1.520
Kurtosis	43.014	16.198	15.401	1.471	7.119	1.804	2.814	10.776	23.883
Trading Volume:									
Mean	0.203	0.439	0.323	0.156	0.369	0.571	0.369	0.279	0.294
Standard deviation	0.302	0.309	0.253	0.123	0.174	0.332	0.152	0.361	0.361
Skewness	2.699	2.496	2.963	1.884	1.371	4.968	1.362	2.022	2.746
Kurtosis	8.383	8.968	16.730	4.851	3.688	46.229	2.998	4.459	10.313

(continued)

Table 1 *(continued)*

Tests of stock returns and trading volume

Panel B: Linear and nonlinear trend in trading volume

Country	USA	Japan	UK	France	Canada	Italy	Switzerland	Netherlands	Hong Kong
α	0.140	0.113	0.237	0.065	0.223	0.441	0.298	0.179	0.107
	(27.878)**	(10.849)**	(32.386)**	(15.002)**	(27.771)**	(14.378)**	(23.921)**	(25.859)**	(7.474)**
β_1	−1.66e-4	2.102e-4	−2.032e-4	−5.416e-6	−3.501e-6	2.845e-4	−7.824e-5	−3.632e-4	−1.698e-4
	(−50.585)**	(29.618)**	(−21.561)**	(−5.792)**	(−0.172)	(2.047)*	(−1.372)	(−42.555)**	(−7.477)**
β_2	3.911e-8	−2.521e-8	1.054e-7	8.793e-9	1.348e-7	−4.228e-8	3.276e-7	1.669e-7	1.532e-7
	(86.887)**	(−24.920)**	(41.377)**	(21.918)**	(12.488)**	(−0.230)	(5.985)**	(75.654)**	(20.335)**
R^2	0.851	0.715	0.874	0.868	0.571	0.758	0.892	0.904	0.693

Panel C. Unit Root Test of Return and Detrended Volume Using Augmented Dickey-Fuller Regression (ADF)

Country	USA	Japan	UK	France	Canada	Italy	Switzerland	Netherlands	Hong Kong
Return									
Lags (k)	3	16	10	6	13	14	1	19	10
$\tau(\rho)$	−43.615**	−18.157**	−16.351**	−19.754**	−10.447**	−7.071**	−29.444**	−12.373**	−14.884**
Detrended Volume									
Lags (k)	19	20	20	20	19	18	14	19	20
$\tau(\rho)$	−5.051**	−6.591**	−6.014**	−4.281**	−5.699**	−3.542**	−5.043**	−5.108**	−5.402**

** Indicates statistical significance at the 0.01 level.
* Indicates statistical significance at the 0.05 level.

$$\Delta x_t = \rho_0 + \rho x_{t-1} + \sum_{t=1}^{n} \delta_i \Delta x_{t-1} + \varepsilon_t \qquad (2)$$

where x is stock return or detrended volume.

The test results reported in Table 1, panel C, show 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. This result confirms that detrended trading volume and stock return series are both stationary.

4. Empirical results

4.1. Trading volume and stock price changes

We first examine whether the stylized facts relating to returns-volume relations fit the data for the nine markets, by testing for the contemporaneous correlation. To do so, we use two alternative forms of the stock price change (return), as shown in the following regressions:

$$V_t = a + bR_t + u_t \qquad (3)$$

$$V_t = a + b|R_t| + u_t \qquad (4)$$

where the dependent variable (V) is detrended volume, and the independent variable is the natural logarithm of the price relative or its absolute value.

Table 2 shows the results of these regressions. Equations (3) and (4) are displayed in panels A and B, respectively. In panel A, the coefficients for Japan, Switzerland, the Netherlands, and Hong Kong are significant at the 1% level, and the coefficient for France is significant at the 5% level. Therefore, there is a positive contemporaneous relation between trading volume and returns in Japan, Switzerland, the Netherlands, Hong Kong, and France. We find no significant relations for the U.S., the U.K., Canada, and Italy. The result for the U.S. market contrasts with previous studies. In panel B, the coefficients from regressing absolute returns on trading volume are statistically significant at the 1% level in all nine markets.

4.2. Causal relation between trading volume and stock price changes

Our empirical procedures test whether trading volume precedes stock returns, or vice versa. This is the notion behind causality testing 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, according to Granger (1969), 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 $\sigma^2(y_t \mid I_{t-1}) < \sigma^2(y_t \mid I_{t-1} - x_t)$, where I_t is the information set], then x Granger-causes y.

Table 2

Contemporaneous relationship between daily trading volume and stock returns

This table provides the coefficient estimates from regressions of volume against price changes (returns) and volumes. Panels A and B present the results for signed return and absolute return, respectively. In panel A, $V_t = a + bR_t + u_t$, where V_t = detrended trading volume at time t, R_t = return at time t, u_t = a random error term. In panel B, $V_t = a + b|R_t| + u_t$, where V_t = detrended trading volume at time t, R_t = return at time t, u_t = a random error term.

Panel A. Regression of daily trading volume on stock returns

Country	USA	Japan	UK	France	Canada	Italy	Switzerland	Netherlands	Hong Kong
a	0.001	−0.001	−0.001	0.001	0.0001	−0.001	0.001	0.003	−0.001
t-statistic	(0.027)	(−0.253)	(−0.043)	(0.070)	(0.034)	(−0.074)	(0.271)	(0.143)	(−0.069)
b	−0.001	0.041	0.003	−0.002	−0.002	0.071	−0.015	−0.006	0.008
t-statistic	(−0.797)	(12.021)***	(1.104)	(−1.663)*	(−0.803)	(1.037)	(−4.327)***	(−2.761)***	(2.795)***
R^2	0.001	0.021	0.0003	0.001	0.003	0.001	0.018	0.002	0.003

Panel B. Regression of daily trading volume on absolute stock returns

Country	USA	Japan	UK	France	Canada	Italy	Switzerland	Netherlands	Hong Kong
a	−0.028	−0.016	−0.021	−0.009	−0.023	−0.056	−0.048	−0.015	−0.011
t-statistic	(−12.523)***	(−3.653)***	(−6.112)***	(−4.163)***	(−6.404)***	(−3.719)***	(−8.351)***	(−5.009)***	(−1.683)*
b	0.041	0.025	0.029	0.010	0.031	0.051	0.056	0.023	−0.009
t-statistic	(17.934)***	(5.603)***	(8.453)***	(5.483)***	(9.247)***	(4.986)***	(11.324)***	(7.302)***	(2.588)***
R^2	0.044	0.005	0.019	0.013	0.045	0.032	0.113	0.014	0.003

*** Indicates statistical significance at the 0.01 level.
** Indicates statistical significance at the 0.05 level.
* Indicates statistical significance at the 0.10 level.

We use the following bivariate autoregressions to test for causality between the two variables trading volume and stock returns:

$$V_t = \alpha_0 + \sum_{i=1}^{5} \alpha_i V_{t-1} + \sum_{j=1}^{5} \beta_j R_{t-j} \quad (5)$$

$$R_t = \alpha_0 + \sum_{i=1}^{5} \gamma_i R_{t-1} + \sum_{j=1}^{5} \delta_j V_{t-j} \quad (6)$$

In equation (5), if the β_j coefficients are statistically significant, then including both past values of return and past history of volume yields a better forecast of future volume. Therefore, we say returns cause volume. If a standard F-test does not reject the hypothesis that $\beta_j = 0$ for all j, then returns do not cause volume.

In equation (6), if causality runs from volume to returns, then the δ_j coefficients will jointly be different from zero. If both β and δ are different from zero, there is a feedback relation between returns and trading volume. For the estimation of the vector autoregression (VAR), we use five lags based on both the Akaike information criterion (AIC) and the Schwarz criterion. These lags amount to allowing for week-long information in the regression.

Table 3 presents the results of causal relation tests based on a bivariate model. F-statistics and corresponding significance levels are also shown. Panel A shows the results of the test of the null hypothesis that returns do not Granger-cause volume. The F-statistic is significant at the 1% level for the the U.S., Japan, the U.K., Italy, and Hong Kong, significant at the 5% level for the Netherlands, and significant at the 10% level for France and Switzerland.

Panel B, Table 3, shows that in the test of the null hypothesis, volume does not Granger-cause return. The F-statistics are significant at the 5% level for Switzerland and the Netherlands, and significant at the 10% level for Canada and Hong Kong. This finding implies that in the presence of current and past returns, trading volume adds some significant predictive power for future returns in these countries. These results agree with some theoretical models that imply information content of volume for future returns. The results from panels A and B imply a feedback system in Switzerland, the Netherlands, and Hong Kong. In these three countries, returns are influenced by volume and volume is influenced by returns. Overall, the model fits are better for equation (5) than for equation (6). The evidence indicates stronger evidence of returns causing volume than volume causing returns.

4.3. Trading volume and conditional volatility

Table 1 shows that for most series, the distribution of returns is fat tailed compared with the normal distribution. Hence, a GARCH application is more appropriate than standard statistical models. Pagan and Schwert (1990) and Nelson (1991) develop the exponential GARCH (EGARCH) model. There are advantages of

Table 3

Granger causality test

This table provides summary results of the vector autoregression (VAR) analysis of the relation between price changes (returns) and volume. *t*-statistics in parentheses.

Panel A: summary results for $V_t = \alpha_0 + \sum_{i=1}^{5} \alpha_i V_{t-i} + \sum_{j=1}^{5} \beta_j R_{t-j}$, where V_t = *detrended trading volume at time t*, R_t = *return at time t.*

Country	USA	Japan	UK	France	Canada	Italy	Switzerland	Netherlands	Hong Kong
α_0	0.001	−0.001	0.001	0.001	−0.001	−0.005	0.001	0.001	−0.001
	(0.637)	(−0.272)	(0.042)	(0.261)	(−0.062)	(−0.624)	(0.067)	(0.234)	(−0.393)
α_1	−0.003	0.018	−0.001	−0.001	−0.001	0.008	0.002	−0.001	0.006
	(−4.191)***	(9.198)***	(−0.012)	(−1.665)*	(−0.535)	(1.426)	(0.612)	(−0.721)	(5.181)***
α_2	−0.002	−0.004	−0.002	−0.002	0.001	0.002	−0.003	−0.005	0.001
	(−3.347)***	(−1.997)**	(−1.638)	(−1.789)*	(0.193)	(0.329)	(−1.105)	(−3.051)***	(0.811)
α_3	−0.001	0.007	0.001	0.001	−0.001	0.009	0.001	0.001	0.001
	(−2.034)**	(3.874)***	(0.813)	(1.022)	(−0.266)	(1.599)	(0.477)	(0.648)	(0.612)
α_4	0.001	0.003	−0.001	−0.002	−0.003	0.016	−0.009	−0.001	0.003
	(0.834)	(1.913)*	(−0.438)	(−1.998)**	(−1.371)	(2.859)***	(−2.949)***	(−0.006)	(3.052)***
α_5	−0.001	−0.003	−0.003	−0.003	0.004	0.010	0.003	−0.002	0.001
	(−0.690)	(−1.657)*	(−1.745)*	(−0.287)	(2.144)**	(1.777)*	(0.967)	(−1.083)	(0.648)
β_1	0.515	0.541	0.390	0.328	0.345	0.320	0.422	0.425	0.577
	(43.969)***	(44.151)***	(23.713)***	(15.695)***	(15.182)***	(10.177)***	(13.326)***	(26.195)***	(30.732)***
β_2	0.098	0.035	0.120	0.087	0.011	0.034	0.059	0.101	0.144
	(7.417)***	(5.050)***	(6.797)***	(3.994)***	(0.476)	(1.060)	(1.751)*	(5.710)***	(6.691)***
β_3	0.085	0.083	0.089	0.074	0.105	0.274	0.003	0.053	0.069
	(6.469)***	(6.019)***	(4.990)***	(3.390)***	(4.256)***	(8.648)***	(0.089)	(3.013)***	(3.195)***
β_4	0.073	0.068	0.069	0.108	0.059	0.067	0.033	0.089	0.062
	(5.482)	(4.940)***	(3.901)***	(4.931)***	(2.402)**	(2.049)**	(0.968)	(5.107)***	(2.905)***
β_5	0.190	0.179	0.195	0.145	0.117	0.012	0.161	0.139	0.091
	(16.052)***	(14.788)***	(11.790)***	(6.916)***	(4.995)***	(0.416)	(5.089)***	(8.498)***	(4.873)***
F-statistic	7.286***	20.848***	12.920***	2.147*	1.315	3.306***	2.134*	2.215**	8.179***
Adjusted R-square	0.836	0.697	0.530	0.319	0.226	0.344	0.289	0.448	0.824

(continued)

Table 3 *(continued)*

Granger causality results

Panel B: summary results for $R_t = \alpha_0 + \sum_{i=1}^{5} \gamma_i R_{t-i} + \sum_{j=1}^{5} \delta_j V_{t-j}$, where V_t = *detrended trading volume at time t*, R_t = *return at time t.*

Country	USA	Japan	UK	France	Canada	Italy	Switzerland	Netherlands	Hong Kong
α_0	0.034	0.021	0.035	0.051	0.045	0.102	0.076	0.053	0.037
	(2.841)***	(1.699)*	(2.132)**	(1.961)**	(1.812)*	(2.188)**	(2.064)**	(3.368)***	(1.212)
α_1 γ_1	0.071	0.111	0.072	0.042	0.133	0.028	0.063	-0.006	0.067
	(5.959)***	(8.929)***	(4.354)***	(2.014)**	(5.689)***	(0.910)	(1.998)**	(-0.359)	(3.591)***
α_2 γ_2	-0.034	-0.065	-0.034	-0.013	-0.071	0.015	-0.023	-0.001	0.001
	(-2.816)***	(-5.258)***	(-2.030)**	(-0.645)	(-3.002)***	(0.503)	(-0.723)	(-0.018)	(0.070)
α_3 γ_3	-0.024	0.006	-0.016	-0.045	0.013	-0.045	-0.010	-0.062	0.078
	(-2.015)**	(0.508)	(-0.971)	(-2.149)**	(0.562)	(-1.542)	(-0.318)	(-3.815)***	(4.158)***
α_4 γ_4	-0.020	0.011	0.039	-0.001	-0.074	0.044	-0.006	0.009	-0.056
	(-1.679)*	(0.852)	(2.375)**	(-0.093)	(-3.173)***	(1.394)	(-0.207)	(0.557)	(-3.023)***
α_5 γ_5	-0.008	-0.026	-0.003	-0.005	-0.002	-0.019	-0.059	-0.011	0.016
	(0.699)	(-2.082)**	(-0.210)	(-0.259)	(-0.086)	(-0.606)	(-1.870)*	(-0.676)	(0.887)
β_1 δ_1	-0.160	0.094	-0.331	-0.702	0.345	0.117	-0.236	-0.167	-0.015
	(-0.774)	(1.285)	(-2.013)**	(-1.625)	(-1.424)	(0.666)	(-0.718)	(-1.081)	(-0.053)
β_2 δ_2	0.137	-0.152	0.345	0.686	0.529	0.219	-0.012	0.192	-0.047
	(0.591)	(-1.742)*	(1.949)*	(1.514)	(2.062)**	(1.192)	(-0.035)	(1.184)	(-1.431)
β_3 δ_3	0.93	0.058	0.051	0.305	0.335	-0.007	0.159	0.183	-0.371
	(0.397)	(0.668)	(0.283)	(0.674)	(1.317)	(-0.040)	(0.45)	(1.124)	(-1.112)
β_4 δ_4	0.404	-0.048	-0.208	-0.538	-0.220	-0.107	-0.482	-0.364	0.289
	(1.727)*	(-0.553)	(-1.171)	(-1.189)	(-0.857)	(-0.586)	(-1.354)	(-2.239)**	(0.878)
β_5 δ_5	-0.478	0.124	0.087	0.178	-0.246	0.119	-0.628	-0.180	0.413
	(-2.277)**	(1.622)	(0.525)	(0.411)	(-1.012)	(0.685)	(-1.909)*	(-1.195)	(1.449)
F-statistic	1.401	1.572	1.433	1.093	1.973*	0.996	2.376**	2.813**	1.882*
Adjusted R-square	0.009	0.018	0.011	0.008	0.032	0.015	0.023	0.010	0.016

*** Indicates statistical significance at the 0.01 level.
** Indicates statistical significance at the 0.05 level.
* Indicates statistical significance at the 0.10 level.

EGARCH over GARCH (see, for example, Cumby, Figlewski, and Hasbrouck, 1993). First, by using the exponential formulation, the restrictions of positive constraints on the estimated coefficients in ARCH and GARCH are no longer necessary. Second, a weakness of the GARCH model is that the conditional variance depends on the magnitude of the disturbance term, but not its sign. GARCH fails to capture the negative asymmetry apparent in many financial time series. The EGARCH model lessens this problem by modeling the standardized residual as a moving average (MA) regressor in the variance equation while preserving the estimation of the magnitude effect.

The ARCH/GARCH approach to modeling changing volatility also precludes the testing of Black's (1976) leverage effect. However, the EGARCH class of models captures the tendency for negative shocks to be associated with increased volatility. We use the following EGARCH(1,1) model to estimate stock return volatility:

$$\begin{aligned} R_t &= a + bR_{t-1} + \varepsilon_t \\ &\varepsilon \mid I_{t-1} \sim N(0,h_t), \\ ln\ h_t &= \overline{\omega} + \alpha\left(\frac{\mid \varepsilon_{t-1} \mid + \gamma\varepsilon_{t-1}}{h_{t-1}^{1/2}}\right) + \beta ln\ h_{t-1} \end{aligned} \tag{7}$$

Table 4 reports the results of the EGARCH model in equation (7). We obtain the parameter estimates by maximizing the log-likelihood using the Berndt, Hall, Hall, and Hausman (1974) algorithm.

Our results agree with those of other empirical studies on time-varying volatility. First, the log-likelihood statistics are very large. This result implies that the EGARCH model is an attractive representation of daily return behavior that successfully captures the temporal dependence of return volatility. Second, the EGARCH parameterization is statistically significant. Third, the β coefficient in each conditional variance equation is considerably larger than α, implying that large market surprises induce relatively small revisions in future volatility. Fourth, the leverage factor γ is positive. The results support the negative leverage factors suggested by Nelson (1991).

Finally, the persistence of the conditional variance process, which we measure by $\alpha+\beta$, is high and often close to unity. As the sum of the α and β coefficients approach one (1), the greater is the persistence of shocks to volatility (Lamoureux and Lastrapes, 1990; Najand and Yung, 1991). Along with the observation that $\beta > \alpha$, the fact that $(\alpha + \beta)$ is slightly less than unity suggests the processes are stationary (Bollerslev, 1987; Engle and Bollerslev, 1986). These results imply that current information is relevant in predicting future volatility over a very long horizon. As a model specification test we report the Ljung-Box statistics for 24^{th}-order serial correlation in the level and squared standardized residuals. Both Ljung-Box statistics indicate that the residuals do not show any significant serial correlation. Thus, the estimated models fit the data very well. To examine the hypothesis that the flow

Table 4

Log-likelihood estimates for models with an EGARCH parameter for the returns

$$R_t = a + bR_{t-1} + \varepsilon_t$$
$$\varepsilon \mid I_{t-1} \sim N(0,h_t),$$
$$ln\ h_t = \overline{\omega} + \alpha\left(\frac{\mid \varepsilon_{t-1} \mid + \gamma\varepsilon_{t-1}}{h_{t-1}^{1/2}}\right) + \beta ln\ h_{t-1}$$

where R_t represents the rate of return, I_{t-1} is the set of information available at the beginning of time t and V_t is the detrended trading volume. t-statistics are in parentheses. p-values for Ljung-Box statistics are in brackets.

Country	USA	Japan	UK	France	Canada	Italy	Switzerland	Netherlands	Hong Kong
a	0.017	0.024	0.028	0.039	0.033	0.095	0.059	0.051	0.050
	(1.835)*	(3.638)***	(2.021)**	(1.625)	(1.840)*	(2.384)**	(1.972)**	(4.297)***	(2.174)**
b	0.094	0.149	0.066	0.041	0.174	0.042	0.055	0.032	0.157
	(7.386)***	(12.256)***	(3.661)***	(1.932)*	(7.016)***	(1.242)	(1.612)	(1.954)*	(8.051)***
$\overline{\omega}$	0.001	0.002	−0.001	0.006	0.003	0.032	0.004	−0.001	0.057
	(1.292)	(0.973)	(−0.518)	(2.901)***	(1.061)	(2.936)***	(1.067)	(−0.688)	(14.380)***
α	0.192	0.246	0.146	0.095	0.225	0.261	0.159	0.190	0.247
	(21.263)***	(42.803)***	(13.964)***	(6.869)***	(10.710)***	(6.771)***	(5.242)***	(16.717)***	(14.609)***
β	0.782	0.752	0.749	0.902	0.771	0.732	0.763	0.791	0.742
	(22.203)***	(70.108)***	(51.859)***	(48.841)***	(68.954)***	(63.836)***	(88.513)***	(92.734)***	(39.139)***
γ	0.519	0.387	0.391	0.439	0.334	0.127	0.587	0.265	0.484
	(9.534)***	(17.064)***	(7.523)***	(4.060)***	(4.439)***	(2.002)**	(3.197)***	(7.811)***	(10.121)***
Ljung-Box (24)	24.817	30.954	21.059	30.621	33.878	30.170	26.535	31.982	33.744
for the levels	[0.359]	[0.131]	[0.577]	[0.132]	[0.067]	[0.144]	[0.276]	[0.098]	[0.089]
Ljung-Box (24)	15.963	12.793	19.680	19.616	10.067	18.118	17.477	14.323	9.085
for the squares	[0.856]	[0.753]	[0.661]	[0.664]	[0.995]	[0.684]	[0.785]	[0.917]	[0.995]
log-likelihood	−9073	−8066	−4692	−3557	−2305	−1739	−1450	−4489	−5112
$\alpha + \beta$	0.974	0.998	0.995	0.997	0.996	0.993	0.922	0.981	0.989

*** Indicates statistical significance at the 0.01 level.
** Indicates statistical significance at the 0.05 level.
* Indicates statistical significance at the 0.10 level.

of information to the market helps explain the volatility of returns, we use trading volume as a proxy for information innovations. We choose daily trading volume as a measure of the amount of daily information that flows into the market. The model is given by the following equation:

$$R_t = \alpha + bR_{t-1} + \varepsilon_t$$
$$\varepsilon \mid I_{t-1} \sim N(0,h_i), \tag{8}$$
$$ln\ h_t = \varpi + \alpha \left(\frac{| \varepsilon_{t-1} | + \gamma\varepsilon_{t-1}}{h_{t-1}^{1/2}}\right) + \beta ln\ h_{t-1} + \chi V_{t-1}$$

The mixture model predicts that $\chi > 0$. Furthermore, in the presence of volume with $\chi > 0$, if daily volume is serially correlated, α and β will be small and statistically insignificant. The persistence of variance as measured by $(\alpha + \beta)$ should become negligible if accounting for the uneven flow of information (V) explains the presence of EGARCH in the data.

Strictly speaking, we can make inferences from equation (8) only if volume is exogenous (Najand and Yung, 1991; Bessembinder and Seguin, 1993). Therefore we use lagged volume (V_{t-1}) in the model specification. Lagged volume can be interpreted as a predetermined variable. Najand and Yung (1991) find that with lagged volume the GARCH effect is consistently significant in all calendar periods. They observe a statistically meaningful positive correlation between price variability and volume for their sample. Bessembinder and Seguin (1993), using a range of different futures contracts, demonstrate that the conditional volatility exhibits strong persistence even when they include unexpected and expected volume and open interest in the specification. These results are at odds with the results of Lamoureux and Lastrapes (1990).

We find that the EGARCH coefficients α and β are statistically significant for return series in the nine stock markets, as reported in Table 5. χ is also statistically significant except for Canada and Switzerland. The sums $(\alpha + \beta)$ are close to one, indicating the persistence of past volatility in explaining current price volatility.

The EGARCH effect remains significant when lagged volume is included in the model. However, the persistence in volatility as measured by $(\alpha + \beta)$ is marginally smaller when we do so. Trading volume as a proxy for information innovations does not reduce the importance of α and β in explaining persistence in volatility of returns in the nine stock markets.

Our results suggest that volatility is better explained by previous volatility than by volume. The significant coefficients (χ) on V in Table 5 indicate that volume is an endogenous variable in the system, and that there is a positive association between return variance and lagged trading volume.

We repeat the analyses, using contemporaneous trading volume (V_t) instead of lagged volume (V_{t-1}) in equation (8). Our results are similar to those in Table 5 and therefore are not separately tabulated. One interpretation of the results is that volume

Table 5

Log-likelihood estimates for an EGARCH model used to examine the hypothesis that the flow of information to the market helps explain the volatility of returns

$$R_t = a + bR_{t-1} + \varepsilon_t$$

$$\varepsilon \mid I_{t-1} \sim N(0,h_t),$$

$$ln\ h_t = \overline{\omega} + \alpha\left(\frac{\mid \varepsilon_{t-1} \mid + \gamma\varepsilon_{t-1}}{h_{t-1}^{1/2}}\right) + \beta ln\ h_{t-1} + \chi V_{t-1}$$

where R_t represents the rate of return, I_{t-1} is the set of information available at the beginning of time t and V_t is the detrended trading volume. t-statistics are in parentheses. p-values for Ljung-Box statistics are in brackets.

Country	USA	Japan	UK	France	Canada	Italy	Switzerland	Netherlands	Hong Kong
a	0.018	0.026	0.069	0.035	0.033	0.091	0.060	0.051	0.052
	(1.967)**	(3.846)***	(2.024)**	(1.491)	(1.857)*	(2.279)**	(1.976)**	(4.219)***	(2.259)**
b	0.094	0.148	0.064	0.040	0.174	0.051	0.056	0.034	0.158
	(7.376)***	(12.223)***	(3.614)***	(1.890)*	(6.958)***	(1.504)	(1.626)	(1.981)**	(8.003)***
$\overline{\omega}$	0.001	0.001	−0.001	0.006	0.004	0.031	0.005	−0.002	0.055
	(0.054)	(0.512)	(−0.532)	(2.923)***	(1.118)	(3.109)***	(1.032)	(−0.908)	(14.261)***
α	0.181	0.231	0.149	0.094	0.228	0.217	0.154	0.193	0.242
	(20.431)***	(32.806)***	(13.903)***	(6.465)***	(10.301)***	(5.974)***	(5.061)***	(15.583)***	(14.715)***
β	0.777	0.763	0.746	0.902	0.761	0.753	0.762	0.779	0.743
	(19.286)***	(72.352)***	(48.538)***	(26.819)***	(67.819)***	(71.879)***	(80.366)***	(70.422)***	(39.346)***
χ	0.044	0.044	−0.038	−0.106	−0.049	0.088	0.033	−0.041	0.042
	(4.601)***	(10.148)***	(−2.304)**	(−2.440)**	(−0.914)	(2.954)***	(0.433)	(−2.729)***	(3.126)***
γ	0.542	0.432	0.396	0.514	0.323	0.223	0.603	0.285	0.496
	(9.474)***	(18.250)***	(7.530)***	(4.140)***	(4.301)***	(2.984)***	(3.150)***	(6.588)***	(10.304)***
Ljung-Box (24)	25.214	31.042	20.373	31.290	33.881	28.429	26.959	31.728	33.241
for the levels	[0.339]	[0.114]	[0.619]	[0.115]	[0.067]	[0.199]	[0.257]	[0.114]	[0.076]
Ljung-Box (24)	15.596	13.120	19.228	18.529	9.355	10.767	17.421	13.853	9.463
for the squares	[0.872]	[0.843]	[0.687]	[0.728]	[0.995]	[0.149]	[0.788]	[0.931]	[0.994]
log-likelihood	−9065	−8053	−4690	−3554	−2305	−1736	−1450	−4488	−5109
$\alpha + \beta$	0.958	0.994	0.995	0.996	0.989	0.970	0.926	0.972	0.985

*** Indicates statistical significance at the 0.01 level.
** Indicates statistical significance at the 0.05 level.
* Indicates statistical significance at the 0.10 level.

is not a proxy for information. This result agrees with the interpretation of Blume, Easley, and O'Hara (1994) that volume provides information about the quality of information signals, rather than representing the information signal itself. An alternative interpretation is that volume is a proxy for information. However, information does not explain the volatility that is due to noise trading in the market.

5. Summary

Our study uses Granger causality tests to examine whether returns explain volume or volume explains returns. Our data comprise index returns and trading volume from the U.S., Japan, the U.K, France, Canada, Italy, Switzerland, the Netherlands, and Hong Kong. Our results show a positive correlation between trading volume and the absolute value of the stock price change in all nine markets. These results agree with the findings from U.S. studies. Our Granger causality results show that returns cause volume and, although to a lesser extent, that volume causes returns.

Our results suggest the EGARCH models reflect an appropriate representation of the returns in stock index data. Our evidence indicates that trading volume contributes some information to the returns processes of stock indexes. However, in contrast to Lamoureux and Lastrapes (1990), we find that the persistence in volatility remains even after incorporating contemporaneous and lagged volume effects (both of which are proxies for information flow).

Our findings suggest 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. We find that our results are robust across all nine major stock markets, implying that there are similar returns, trading volume, and volatility patterns across these markets.

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