AN EMPIRICAL ANALYSIS OF BANK STOCK VOLATILITY AND TRADING VOLUME: MALAYSIAN EVIDENCE

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ABSTRACT

This paper investigates whether trading volume contain information to predict daily stock returns volatility of five banks traded on the Kuala Lumpur Stock Exchange and the financial index. Two competitive models that provide theoretical explanation for the observed correlation between price variability and trading volume are tested. Using GARCH model, the findings provide strong evidence supporting for the 'mixture of distribution hypothesis' (MDH), casting doubt on predictability power of trading volume on return volatility. The finding also suggests the possibility of other variables beside trading volume which can explain current volatility for banks with thin trading volume.

INTRODUCTION

It is well documented by now that information available to a market is the main determinant of the changes in prices. Thus, the way in which information arrives at the market, and the manner in which it influences the process of price adjustment is an important issue in finance. To account for this development, several authors have developed two competing hypotheses. Among them are Copeland (1976) who introduced the 'sequential arrival information model' (SAIM) and latter extended by Jennings, Starks and Fellingham (1981) and Jennings and Barry (1983) and Smirlock and Stark (1985). The main issue in this hypothesis is the time path of price adjustment when information is disseminated gradually. While the competing hypothesis of 'mixture of distributions hypothesis' (MDH) developed by Clark (1973) argues that relationship between trading volume and volatility is function of the directing (or mixing) variable, defined as the rate of information arrival. In this context, daily price variance is considered to be random variable representing the sum of individual price changes within the day, and trading volume is positively related to the number of within-day price change. Thus, trading volume can be considered as contemporaneous in respond to the change in prices.

JEL classification: G13, G14
Keywords: Returns, volatility, trading volume, bank stock

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This paper examines the dynamic relationship between price variability and trading volume with the aims of addressing three main areas of interest. By utilizing a data set of five Malaysian based banks traded on the Kuala Lumpur Stock Exchange (KLSE) and a financial index from May 1995 to July 1999, firstly, we investigate the general relationship between price volatility and trading volume. This can be achieved by testing whether contemporaneous trading volume can explains current price volatility. If it does, then it implies that the market is efficient. Secondly, the research is intended to examine whether the results of the full period hold when we partitioned the sample data into subperiod before and during economic crisis. The third area of interest is to test whether size of daily trading volume of the selected banks affects its volatility-volume relationship.

Investigations on this relationship are very useful to the investors as well as to other market participants because they can provide information on the efficiency of the Kuala Lumpur Stock Exchange (KLSE) market with specific reference to Malaysian bank stock price. Furthermore, by analyzing both individual actively traded stocks as well as market index, we hope to uncovered not only the micro behavior of stock returns but also the macro level stock market indicator returns.

The remainder of this paper is organized as follows: Section 2 summarizes previous selected literature and presents a discussion of the theoretical issues related to volume-price variability relationship. Section 3 discusses the sample data and preliminary statistics. Section 4 describes the methodology used. This is followed in Section 5 by the discussion on the empirical results. Finally, Section 6 offers some concluding remarks.

SUMMARY OF PREVIOUS WORK

The literature on the price and trading volume relationship is large and diverse covering equity markets as well as futures markets. A study of stock returns-volume relationship is first documented by Ying (1966). He finds a positive relationship between these variables. Similar positive correlation has been reported by Harris (1986). The positive relationship between absolute price changes and trading volume has been found by Wood, McInish and Ord (1985). Perhaps the most important contribution to the subject is provided by Karpoff (1987) who reviews the previous and existing literature and suggests further research on a number of areas.

Lamoureux and Lastrapes (1990) examine actively traded stock on NYSE to see whether trading volume as a measure of the amount of daily information that flows into the market has any effects on the conditional variance equation. Using contemporaneous daily trading volume, they find ARCH effects disappear for the majority of the stock examined. The result as noted by the authors is due to the fact that trading volume can explain price variability. In futures market, Clark (1973) reports a positive relationship between the square of price change and aggregated volume using daily data from the cotton futures market. Similar finding is reported by Tauchen and Pitts (1983) on daily Treasury-bill futures return and trading volume. However, Najang and Yung (1991) who investigate contemporaneous volume and price variability in the Treasury-bond futures markets with GARCH model find significant correlation in only a few cases, a finding the authors attribute to simultaneity problems. But when lagged volume is used in the equation, the correlation becomes significant in all cases. A strong positive relationship between contemporaneous trading volume and price changes is found by Bessembinder and Seguin (1993) who analyse a cross section of contracts in agriculture products, metals, currencies and financial futures. Foster (1995) examines the volume-volatility in oil futures markets. Using the General method of moment (GMM) he finds that volume is not an adequate proxy for the rate of information flow eventhough there is positive contemporaneous relationship between them. Similar results are also reported by Grammatikos and Saunders on five currency futures prices. Other studies have also related price changes to volume, but by assuming that prices are driven by information hidden in volume. For example, Gallant, Rossi and Tauchen (1992) 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.

The relationship between return volatility and trading volume

This section aims is to reexamine the general relation between trading volume and price variability using GARCH specifications. This is achieved by exploring both the predicted contemporaneous volume- volatility relationship as well as the lagged volume volatility. In other words, whether the former holds over the latter or vice versa in explaining volume-price variability relationship. If the former is true, the notion of informational efficiency in the currency futures markets hold. This mean that traders are not able to make abnormal return using news information proxy by trading volume. As such, the findings of this study will be relevant to technical analysis if trading volume is found to play an important role of providing information in explaining price variability.

Two leading models that provide theoretical explanations for the observed correlation between price variability and trading volume. They are the sequential arrival of information model (SAIM) developed by Copeland (1976) and mixture of distribution hypothesis (MDH) by Clark (1973), Epps and Epps (1976) and Harris (1987). The different between these two competing hypotheses is centred on the speed of which the new equilibrium is attained following the arrival of information. In the framework of SAIM, new information is not transmitted to all traders in a single day while the MDH assumes that new information is received simultaneously in a single trading day by all investors who act upon it after revising their expectations. A more detail explanations of the two models follow.

The Sequential Arrival of Information Model (SAIM)

The key assumption of SAIM is that traders in a market receive new information in a sequential fashion. In other words each individual trader trades in response to the signal represents one of a series of incomplete equilibria. Once all traders have received the information signal, a final market equilibrium is established where traders observe the same information set. The main implication of SAIM model suggest that asset price volatility is potentially forecastable with the knowledge of past information and trading volume.

The Mixture of Distributions Hypothesis (MDH)

The basic idea of the mixture-of-distributions hypothesis (MDH) is that the amount of information that arrives into the market during a certain time interval changes randomly over time.

Following Lamourex and Lastrapes (1990), let $R_{i,t}$ denote the total equilibrium of asset price increment in day *t* which implies

$$R_{i,t} = \sum_{i=1}^{I_t} \varepsilon_{i,t} \qquad (1)$$

where $\varepsilon_{i,t}$ is the *i*th intradaily equilibrium price increment that flows into the market during day *t*. The random variable *I*, is the mixing or directing variable representing stochastic rate of information arrival to the market. Equation 1 implies that the daily price changes are generated by a subordinate stochastic process in which $R_{i,t}$ is subordinate to $\varepsilon_{i,t}$ and I_t is the directing process. Suppose $\varepsilon_{i,t}$ is i.i.d. with mean zero and finite variance, σ^2. If I_t is sufficiently large, applying the Central Limit Theorem to equation 1 yields

$$Rt| I_t \sim N(0, \sigma^2 I_t) \quad (2)$$

where logarithm of daily price changes conditional on the number of information arrivals to the market, I_t and is normally distributed with zero mean and variance which is proportional to I_t.It is well known that volatility shocks persists over time as being shown in GARCH. If we assume I_t is serially correlated the resulting model can give rise to this persistence. For example, suppose that the logarithm of I_t follows an $AR(1)$ process which can be expressed as follows:

$$\ln I_t = a_0 + a_1 \ln I_{t-1} + v_t \quad (3)$$

where a_0 is a constant, a_1 is coefficient of lag I_t, and v_t white noise. Innovations or shocks to the mixing variable persist according to the autoregressive structure of equation 3. By defining a variance term

$$\sigma_t^2 = E(\sigma^2 \backslash I_t) \quad (4)$$

and if the mixture model is valid, then $\sigma_t^2 = \sigma^2 | I_t$. Combining equation 3 and 4 will yield:

$$\sigma_t^2 = \sigma^2 a_0 + a_1 \sigma^2_{t-1} + \sigma^2 v_t \quad (5)$$

Equation (5) captures the type of persistence in conditional variance that can be picked up by estimating a GARCH specification. The amount of information I_t may also influence the trading volume. The reason, as noted by Watanebe (1996), is that the larger the amount of information that flows into the market, the more do the traders' expectation spread and hence the larger is the trading volume. If so, he goes on to say, then the mixture of distribution hypothesis is also consistent with a well known phenomenon of a comovement between volatility and trading volume. Our empirical investigations focus on the variance of returns conditional on knowledge of mixing variable. Since I_t is not observable, we proxy trading volume as a measure of information flow.

The implication of MDH is that price and volume have similar information values due to their common distribution. All traders response to a new piece of information simultaneously. Such a case implied that no information in volume which can be used in forecasting futures returns and, likewise, there is no information in the futures returns which can be used in forecasting volume.

DATA AND PRELIMINARY STATISTICS

Price data consists of daily closing prices for five Malaysian based banks – Maybank, RHB, Public, Pacific, Bank Islam and an index for financial sector. They were obtained from Telnet (M) Sendirian Berhad over the sample period from 4 May 1995 to 9 July 1999. In order to account for the economic downturn during 1997, we partition the sample period into two sub-periods of nearly equal number of observations. The first sub-period contains the data from 4 May 1995 to 30 June 1997 (*i.e.* before the economic crisis) while the second sub-period starts on 1 July 1997 through 9 July 1999 (*i.e.* during the economic crisis).

Returns, R_t, for all series are calculated as the percentage logarithmic difference in the daily stock price and index according to

$$R_t = \ln P_t - \ln P_{t-1}$$

where, P_t *and* P_{t-1} denote price of stocks/index on day t and day t-1, respectively.

The daily trading volumes data corresponding to each stock price/index to be analysed in this study are also obtained from Telnet (M) Sendirian Berhad. They are measured according to their turnover, in thousand of shares. Following Fabozzi, Ma and Briley (1994), this study eliminates a daily observation when there is no trading volume for the day. They argued that the inclusion of non-trading in the observation often create positive serially correlated daily price change. Similarly, Scholes and Williams (1977), and Dimson (1979) noted that nonsynchronous and infrequent trading could induce autocorrelation in computed returns even when the true returns are not autocorrelated. This happened since daily price data are reported everyday including non-trading day using previous day's price. In all, after the exclusion of non-trading day and weekend, the daily futures returns and volume series yield net days of 9[illegible] for Maybank, 946 for RHB, 990 for Public Bank, 992 for Pacific Bank, 952 for BIMB and 1000 for Financial Index. The choice of the bank is based on their size of daily trading volume.

In Table 1, Panel A, we report the descriptive statistics on returns for five stocks and the financial index in our sample for the full sample period. The mean daily returns range from a low of 0.0 for RHB, BIMB and the index to a high of 0.004 for Pacific Bank and Maybank. The standard deviation of daily returns reveals that RHB is more volatile than the other banks and the index. The unconditional variance (measured by standard deviation of price returns) is larger and thus more volatile during economic crisis than before economic crisis for all banks and the financial index as reported in Panel B and C of Table 1. Table 1, Panel B and C shows a consistent pattern where greater volume is associated with more price volatility. For instant, trading volume during economic crises is larger for all cases compared to the one before economic crisis except for the pacific bank. As a result, volatility also increases dramatically in this subperiod. This finding support the notion that as trading size become larger and more liquid, their volatility rises. This notion could form the basis of the future research.

Stock returns for banks and the index all exhibit significant positive skewness suggesting that the returns from these stocks have a heavier tail of positive values. All returns series reveal significant excess kurtosis. This indicates that the stock returns and the index departures from normality. More importantly, ARCH effect is found in all return series which implies that the series in not an independently and identically distributed (i.i.d) over time since the squared returns are highly correlated as shown from the LB statistics. In fact these statistics are extremely high for squared returns demonstrating the pervasive influence of volatility clustering. As such, it implies that one of the family of ARCH models may be an appropriate modelling procedure for the returns.

GARCH MODEL FOR VOLUME AND VOLATILITY

GARCH Modelling of Volume and Volatility

Blume, Easley, and O'Hara (1994) show that volume and price together provides more information than observing price alone. He further noted that a trader watching only prices cannot learn as much as a trader watching both prices and volume and so faces an unnecessary penalty if he ignores the trading volume statistic. As such, the study proceed with special focus on the empirical tests of the variance of returns conditional on the knowledge of the mixing variable. Specifically, we use trading volume as the mixing variable to investigate its informational role in explaining futures price movement. In particular, trading volume may be informative about the process of futures markets return. Furthermore, as argued by Lamoureux *et.al.* (1990), using trading volume as the mixing variable is consistent with the sequential information models of Copeland (1976) and the mixture of distribution hypothesis (MDH) of Epps and Epps (1976). The hypothesis states that when no information is available, trading is slow and the price process evolves slowly; and when new information violates old expectations, trading is brisk with the price process evolving much faster. This study, in particular, present an analyses of trading volume as mixing variable using both contemporaneous as well as lead and lagged relation.

Contemporaneous Volume

First, following Akgiray (1989) who suggest the AR(1)-GARCH(1,1) model is an empirically good model for stock returns, we estimate the following model using the approximate maximum likelihood algorithm of Berndt, Hall, Hall and Hausman (1974):

$$R_t = \phi_0 + \phi_1 R_{t-1} + \varepsilon_t \tag{6}$$
$$\varepsilon_t \mid \psi_{t-1} \sim N(0, h_t) \tag{7}$$
$$h_t = \alpha_0 + \alpha_1 \varepsilon_{t-1} + \beta_1 h_{t-1} + \delta_1 V_t \tag{8}$$

where R_t is the return conditional on past information which is proxies by R_{t-1}, V_t is the contemporaneous volume of trade at time t *and* α_0, α_1, β_1 and δ_1 are parameters to be estimated. ψ_{t-1} - is the information set at time t-1, ε_t is the stochastic error conditional on ψ_{t-1}, and is assumed to be normally distributed with zero mean and conditional (time varying) variance, h_t. As such, GARCH models the conditional variance of the error term as a linear function of the lagged squared residuals and the lagged residual conditional variance. The advantage of a GARCH model is that it captures the tendency in financial data for volatility clustering. Secondly, following Lamourex and Lastrapes (1990), we estimate the conditional variance given by h_t by restricting the coefficient δ_1 in equation 8 to be zero. To investigate the notion of volume as a mixing variable in the conditional variance, following Lamoureux and Lastrapes (1990) and Laux and Ng (1993), we fit the unrestricted model of equation 8, *i.e.*, where $\delta_1 \neq 0$. If cluster of information, as proxied by contemporaneous trading volume, affects price variability, then we would expect a positive and significant δ_1.

The above models will be applied in three estimation periods: the first will cover the entire period for each bank and the financial index beginning 4/5/1995 until 9/7/1999; the second will be cover the first subperiod beginning 4/5/1995 until 30/6/1997, a period before the economic crisis; the third estimation period will be for the second subperiod from 1/7/1997 until 9/7/1999, a period during the economic crisis.

EMPIRICAL RESULTS

GARCH Analysis Results Without Trading Volume

The results from the AR(1)-GARCH(1,1) model for the period, when δ_i is restricted to zero, are reported in Table 2. The parameters in the conditional variance for all banks are statistically significant at 5 percent level. The results suggest that volatility persistence as measure by the sum $\alpha_i + \beta_i$ is very high for all banks examined. This indicates the persistence of past volatility in explaining current price volatility as discussed by Engle and Bollerslev (1986).

GARCH Analysis Results With Trading Volume

Since our objective of the research is to examine the relationship between price variability and trading volume, we include raw trading volume into the conditional variance equation. In doing so, we reestimate equation 8 where δ_i is different from zero this time. The results from Table 3, Panel A, shows a highly significant volatility - contemporaneous volume relationship exist in all cases. This implies that volume has significant effect on the conditional variance. In no case does volume remove the GARCH effect, the results which support the findings of Najang and Yung (1991). However, the results suggest that volatility is better explained by contemporaneous raw volume rather than previous volatility (the GARCH effect) in all cases except for the Public bank and the BIMB. From these results it is proposed here that contemporaneous volume and previous volatility are needed to describe the conditional volatility.

The following step will be to estimate the same models using two sub-samples. The first subperiod contain the period before the start of the economic crisis and the second subperiod during the period of economic crisis.

Table 2, Panel B and C report the results for the first and second subperiods when δ_i is restricted to zero. It is interesting to note that, all banks exhibit statistically significant GARCH effect except for the BIMB in subperiod 1 where the *t*-statistic for the previous volatility is 0.5528. The results when δ_i is not restricted to zero for both subperiod 1 and subperiod 2 are presented in Table 3, Panel A and B, respectively. Significance positive contemporaneous trading volume-volatility relationship is detected in both superiods, a results which are similar to those of full period except for the RHB in subperiod 1. However, volume remove the GARCH effect in half of the cases in subperiods 1 as well as subperiod 2 but for difference banks. In subperiod 1, for examples, the GARCH effect vanished for the Maybank, the Pacific bank and the financial index. In subperiod 2, the GARCH effect vanished for the RHB, the Pacific bank and the financial index.

With regard to the size of daily trading volume, it is interesting to note that banks with a very thin daily trading volume behave differently from the larger one. For instance, when we introduce a relatively thin daily trading volume of the Public bank and thin daily trading volume of the BIMB in the conditional variance equation, it does not remove the GARCH effects both before and during economic crisis compared to bank with larger daily trading volume. These results lead to the interpretation that a relatively thin daily trading volume as well as previous volatility have similar information content and can be used to explain current volatility.

SUMMARY AND CONCLUSIONS

The aim of this paper is to empirically investigate whether trading volume contain information in predicting stock price volatility for five Malaysian banks traded on KLSE and a financial index, which have not been investigated previously. The study employs GARCH (1,1) techniques and recent work on the information content proxy by volume to properly account for the role of trading volume in explaining price variability. The findings support the results of Grammatikos and Saunders (1986). The results are consistent with the 'mixture of distribution hypothesis' (MDH) of Clark (1973) and Harris (1986), thus casting doubt on predictability power of current trading volume on futures price variability in the Malaysian bank stock price. Therefore, the results are irrelevant to technical analysis since trading volume is found not to contribute to any significant role in providing information on the quality of the information contained in the return series.

The study also finds that the volatility during economic crisis is greater than before economic crisis. This is expected since during turbulent period, the stock prices are very uncertain. This phenomena will lead to voluminous trading activities of selling and buying by the market participants such as traders as well as speculators.

It is also interesting to note here that banks with relatively thin daily trading volume behave quite differently from the larger one. Upon introducing volume in the conditional variance equation, the GARCH effect remains, either before or during economic crisis. This finding leaves the possibility that other variables besides volume which can explained current volatility for banks with a thin daily trading volume.

It should be recalled that, in the study, the positive contemporaneous correlation between price changes and trading volume is attribute to the equilibrium pricing by market participants receiving new information. However, as argue by Jennings and Barry (1983), examining the total price change and volume traded using only daily data may misspecify this contemporaneous association. Watanabe (1996) has examined intraday volume and price changes and provide statistical techniques for determining when the price adjustment process has attained a new equilibrium. In future research, a similar methodology could perhaps be used to investigate the relationship between price changes and volume in the Malaysian bank stock price.

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Table 1: Summary Statistics of Returns and Trading Volume

Panel A: Full Period: 4/5/95 to 9/7/99

	Maybank		RHB		Public		Pacific		BIMB		Financial Index	
	R	V	R	V	R	V	R	V	R	V	R	V
Maximum	0.282	227992	0.4520	24706	0.2044	1337.0	0.2763	10001	0.1999	960	0.2263	353
Minimum	-0.267	170.00	-0.2375	41.00	-0.223	1.00	-0.262	1.0	-0.206	1.0	-0.205	0.0
Mean	0.0041	13180.2	-0.0021	2287.1	0.0006	105.08	0.0043	391.3	-0.001	55.553	-0.001	43.36
Std. Dev.	0.0314	15427	0.0471	2607.4	0.0327	144.93	0.0364	749.6	0.034	100.19	0.026	37.61
Skewness	1.0217	4.7511	1.8616	3.3933	0.2030	3.8713	0.7171	6.094	0.524	5.1088	1.344	2.661
Kurtosis	18.551	46.1207	17.138	17.401	21.356	21.356	10.736	53.42	8.082	33.544	17.889	11.15
LB(6)	9.7282	1224.1	21.515	1291.7	920.11	920.11	39.213	986.0	8.824	1095.2	39.31	2087
LB(12)	17.199	1999.4	36.030	1813.1	1267.2	1267.2	48.758	1435	21.78	1371.2	55.73	3031
LB(24)	32.619	3098.7	54.828	2375.1	1480.4	1480.4	72.981	2195	46.33	1584.2	74.96	3709
$LB^2(6)$	173.01	83.702	187.61	458.37	220.35	220.35	300.80	149.5	70.60	384.47	347.7	977.7
$LB^2(12)$	200.31	118.56	237.87	552.30	282.89	282.89	306.02	159.2	167.9	413.58	381.8	1177
$LB^2(24)$	216.17	145.354	289.27	580.31	320.23	320.23	372.59	238.6	250.6	430.31	404.2	1257

Panel B: Subsample 1: 4/5/95 to 30/6/97												
	Maybank		RHB		Public		Pacific		BIMB		Financial Inde	
	R	V	R	V	R	V	R	V	R	V	R	V
Maximum	0.0604	56542	0.0876	9871	0.0566	1313	0.1740	10001	0.1798	942	0.0326	140
Minimum	-0.0513	170	-0.0760	41	-0.0538	1.0	-0.1567	13.0	-0.0701	2.0	-0.0429	0.0
Mean	0.8982	6146.6	0.0042	1087.4	0.0014	81.499	0.0015	573.14	-0.914-4	34.006	0.0032	27.39
Std. Dev.	0.0089	6097.2	0.0196	893.54	0.0155	127.27	0.0282	957.58	0.0160	55.077	0.0099	20.25
Skewness	0.0154	2.7148	0.0084	3.8267	0.3863	4.9760	1.3640	4.9211	3.2496	9.9287	-0.2480	1.872
Kurtosis	0.1201	13.730	1.5825	25.335	1.6257	35.864	9.0309	33.810	34.926	148.49	1.8134	4.46
LB(6)	9.9658	589.61	10.858	100.48	23.875	240.27	7.8010	425.61	26.249	31.757	44.538	1231
LB(12)	14.846	911.97	23.862	105.21	32.602	322.23	17.279	603.13	35.170	39.301	55.352	1812
LB(24)	21.533	1343.9	27.933	109.66	41.724	373.70	47.850	887.27	40.569	83.425	72.099	2411
$LB^2(6)$	10.186	66.231	11.9851	20.900	31.788	35.666	19.272	69.952	20.059	0.3380	41.357	839.3
$LB^2(12)$	16.489	87.164	19.283	21.630	37.659	37.812	22.001	72.424	53.831	0.3785	56.271	1062
$LB^2(24)$	36.485	106.382	25.126	23.359	60.344	43.151	49.894	105.77	54.716	3.7253	66.925	1225

Panel C: Subsample 2: 1/7/97 to 9/7/99

	Maybank		RHB		Public		Pacific		BIMB		Financial Index	
	R	V	R	V	R	V	R	V	R	V	R	V
Maximum	0.2822	227992	0.4520	24706	0.2044	1337	0.2763	4899	0.1999	960	0.2263	335
Minimum	-0.2670	1657.0	-0.2375	83.0	-0.2231	2.0	-0.2629	1.0	-0.2067	1.0	-0.2057	11.0
Mean	-0.0007	20299.1	-0.0094	3631.8	-0.0002	129.15	-0.0072	206.57	-0.0020	79.435	0.0058	59.325
Std. Dev.	0.0418	18460.0	0.0655	3179.9	0.0438	157.49	0.0433	366.67	0.0469	129.39	0.0354	43.724
Skewness	0.8979	4.4558	1.5073	2.6942	0.1584	3.2655	0.5291	7.2735	0.2931	3.7067	1.1063	2.3474
Kurtosis	10.824	0.9094	8.5410	10.783	5.1889	14.827	8.7949	74.373	3.1335	16.843	9.1889	8.0285
LB(6)	6.0600	257.977*	11.606	302.77*	26.218*	576.04*	36.415*	375.25*	5.0425	610.65*	18.983*	694.51*
LB(12)	10.506	347.340*	21.297	330.69*	36.833*	763.51*	42.125*	411.66*	11.801	734.94*	28.542*	869.59*
LB(24)	20.883	413.500*	32.523	343.51*	53.829*	849.60*	61.447*	483.54*	27.094	801.03*	39.370*	913.42*
$LB^2(6)$	69.531*	25.067*	62.842*	154.60*	79.973*	194.94*	189.38*	60.932*	10.531	247.04*	146.76*	383.49*
$LB^2(12)$	75.444*	32.785*	74.234*	171.69*	86.211*	262.25*	190.84*	60.974*	27.827*	262.01*	152.49*	424.98*
$LB^2(24)$	78.053*	35.582	79.914*	180.18*	123.31*	292.16*	219.75*	63.071*	41.537*	268.41*	155.84*	441.86*

LB(6) and $LB^2(6)$, LB(12) and $LB^2(12)$, and LB(24) and $LB^2(24)$ indicate the calculated values of the Ljung-Box statistic for which χ^2 (6)) = 12.59, χ^2 (12)= 21.02 and χ^2 (24) =36.41 at 5% significant level. * denotes the significance level at 5%. Figures in parentheses are the *t*-statistics

Table 2: GARCH(1,1) estimates of returns and volatility

Parameter	Maybank	RHB	Public	Pacific	BIMB	Financial Index
Panel A: Full Period: 4/5/95 to 9/7/99						
Conditional mean						
Constant	0.0048	0.0068	0.0022	0.291-03	0.0011	0.5475-03
	(0.8118)	(0.7565)	(0.3307)	(0.2735)	(0.2085)	(1.4283)
R_{t-1}	0.0585	0.0702	0.1688	0.0600	-0.1085	0.2141
	(1.7406)	(2.0562)*	(5.3932)*	(1.4602)	(-3.0321)*	(7.0210)*
Conditional variance						
α_0	0.7905-05	0.00007	0.5330-05	0.2613-03	0.8018-05	0.2484-05
	(5.5572)*	(3.7396)*	(3.8111)*	(13.442)*	(8.9002)*	(3.5826)*
α_1	0.1206	0.0846	0.1409	0.2866	0.2152	0.1739
	(10.071)*	(9.8685)*	(12.165)*	(9.5777)*	(11.651)*	(9.3794)*
β_1	0.8796	0.9158	0.8758	0.5272	0.8222	0.8425
	(81.930)*	(136.31)*	(103.768)*	(18.059)*	(70.405)*	(57.425)*
Panel B: Subsample 1						
Conditional mean						
Constant	0.0074	0.0013	-0.0001	0.0113	0.1902-03	0.4726-[illegible]
	(1.0966)	(0.1517)	(-0.0236)	(0.8147)	(0.3542)	(1.1539)
R_{t-1}	0.0694	0.0421	0.1610	0.0174	-0.1890	0.2541
	(1.4533)	(0.8870)	(3.1032)*	(0.2932)	(-3.4881)*	(5.0812)*
Conditional variance						
α_0	0.1631-04	0.8363-04	0.1577	0.3677-03	0.1767	0.5243-[illegible]
	(2.4351)*	(1.9252)	(3.0351)*	(4.7137)*	(6.4270)*	(2.7072)*
α_1	0.0630	0.0422	0.1335	0.1679	0.2289	0.1064
	(2.7094)*	(1.3762)	(4.1417)*	(3.3252)*	(6.0432)*	(4.2837)*
β_1	0.8700	0.7236	0.8016	0.3895	0.7153	0.8387
	(20.022)*	(5.4621)*	(19.855)*	(3.1458)*	(0.5528)	(24.866)*
Panel C: Subsample 2						
Conditional mean						
Constant	-0.0036	-0.0105	-0.994-05	-0.835-03	-0.4801-03	0.3450-[illegible]
	(-0.2572)	(-0.3557)	(-0.0531)	(0.4952)	(-0.2165)	(0.2772)
R_{t-1}	0.1193	0.1439	0.1584	0.0988	0.0293	0.1745
	(2.4696)*	(2.5733)*	(3.1898)*	(1.6972)	(0.4784)	(4.1929)*
Conditional variance						
α_0	0.0030	0.0049	0.1746-03	0.2997-03	0.9718-03	0.4123-[illegible]
	(4.9292)*	(6.4017)*	(6.1438)*	(7.6582)*	(3.4106)*	(2.98[illegible])*
α_1	0.3975	0.2592	0.1904	0.3210	0.1815	0.198[illegible]
	(7.1487)*	(4.5261)*	(5.1550)*	(6.9229)*	(3.2121)*	(5.57[illegible])*
β_1	0.4692	0.6500	0.7326	0.5299	0.3889	0.789[illegible]
	(7.0043)*	(15.345)*	(19.707)*	(14.506)*	(2.4629)*	(25.3[illegible])*

* denotes the significance level at 5%. Figures in parentheses are the *t*-statistics.

Table 3: GARCH(1,1) estimates of returns, volatility and *contemporaneous* trading volume

Parameter	Maybank	RHB	Public	Pacific	BIMB	Financial Index
Panel A: Full Period: 4/5/95 to 9/7/99						
Conditional mean						
Constant	-0.346-04 (-0.0576)	-0.0136 (-1.5532)	-0.273-03 (-0.4512)	-0.0152 (-1.9885)	0.1201-03 (0.2638)	-0.504-03 (-1.0307)
R_{t-1}	0.0562 (1.5682)	0.0264 (0.7711)	0.1939 (5.3185)*	0.0257 (0.7648)	-0.1218 (-3.3835)*	0.1878 (5.7684)*
Conditional variance						
α_0	0.6488 (5.4832)*	0.00 (0.00)	0.5432-05 (1.1694)	0.1625-03 (7.4743)*	0.00 (0.00)	0.00 (0.00)
α_1	0.1777 (4.7110)*	0.1984 (4.4668)*	0.4354 (9.5148)*	0.4087 (8.9931)*	0.2360 (12.620)*	0.3406 (6.0668)*
β_1	0.1555 (3.2667)*	0.1284 (3.7839)*	0.5680 (23.733)*	0.1757 (5.5179)*	0.8035 (77.132)*	0.3406 (3.9095)*
δ_1	0.3071-07 (10.542)*	0.447-06 (15.895)*	0.983-06 (8.6009)*	0.119-05 (12.225)*	0.249-06 (8.1554)*	0.1841 (13.992)*
Panel B: Subsample 1						
Conditional mean						
Constant	0.5283-03 (0.8043)	0.2573-04 (0.0319)	-0.3190-03 (-0.4989)	-0.0110 (-1.3585)	0.1518-03 (0.3241)	0.1413-03 (0.3410)
R_{t-1}	0.0942 (1.9197)	-0.0316 (-0.6450)	0.1679 (3.0784)*	-0.0787 (-1.5872)	-0.1957 (-3.6788)*	0.2597 (5.1835)*
Conditional variance						
α_0	0.1248-03 (8.2605)*	0.111-03 (2.8762)*	0.2219-04 (2.9006)*	0.6397-04 (3.5183)*	0.5486-05 (2.3398)*	0.3922-04 (4.7516)*
α_1	0.1177 (1.8174)	0.6252 (0.5750)	0.1804 (3.5293)*	0.0405 (1.4106)	0.2629 (6.4669)*	0.1177 (1.6673)
β_1	0.00 (0.00)	0.206-06 (5.0651)*	0.6137 (8.2857)*	0.00 (0.00)	0.6721 (20.599)*	0.00 (0.00)
δ_1	0.1345-07 (5.0547)*	0.0691 (0.1427)	0.372-06 (3.3158)*	0.1012-5 (9.6430)*	0.445-06 (5.1300)*	0.1574-05 (4.6940)*
Panel C: Subsample 2						
Conditional mean						
Constant	-0.1336-02 (-1.0418)	-0.635-02 (-2.9787)*	-0.284-02 (-2.0543)*	-0.0371 (-2.9234)*	-0.0202-02 (-0.9350)	-0.03969 (-3.3515)*
R_{t-1}	-0.0880 (-0.1677)	0.0133 (0.2899)	0.0353 (0.6685)	-0.0561 (-0.1060)	-0.08108 (-0.1375)	0.0774 (1.6869)
Conditional variance						
α_0	0.1644-04 (0.3425)	0.108-03 (0.9804)	0.6110-04 (1.4891)	0.1560-03 (3.4812)*	0.9021-03 (5.4456)	0.00 (0.00)
α_1	0.1332 (2.9457)*	0.1444* (3.0481)	0.2034 (2.8122)*	0.1784 (3.6312)*	0.1667 (2.9954)*	0.1578 (2.6392)*
β_1	0.1590* (2.2049)	0.00 (0.00)	0.2034 (2.5296)*	0.0196 (0.6281)	0.2118 (1.9342)	0.00 (0.00)
δ_1	0.4559-07 (7.6280)*	0.7877-06 (10.738)*	0.1094-04 (11.9385)*	0.6266-05 (9.1198)*	0.6751-05 (3.9455)*	0.1324-04 (13.326)*

* denotes the significance level at 5%. Figures in parentheses are the *t*-statistics