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The Relationship between Trading Volume, Volatility and Stock Market Returns: A test of Mixed Distribution Hypothesis for A Pre- and Post Crisis on Kuala Lumpur Stock Exchange

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Abstract

The issue of stock volatility on stock return has gained a tremendous attention among academics and practitioner alike as this reflects behaviour of market microstructure. Therefore, utmost objective is to examine the volatility characteristics of Kuala Lumpur Stock Exchanges by considering mixing variable (volume) as innovation. This study presents a comprehensive analysis of the distributional and time series properties of returns to determine using GARCH model that allows for time varying variance in a process and can adequately represent return volatility. The results of our study indicate that the return volatility is best described by a GARCH (1,1) specification. Current volatility can be explained by past volatility that tends to persist over time. We add volume as an additional explanatory variable in the GARCH model to examine if volume can capture GARCH effects. Consistent with results of Najand and Yung (1991) and Foster (1995) and Huang, and Yong, C.W. (2001) contrary to those of Lamoureux and Lastrapes (1990), our results show that the persistence in volatility remains in return series even after volume is included in the model as an explanatory variable. This finding holds for contemporaneous volume when it is included in the variance equation.

Key words: volatility, mixture of distribution, GARCH, Mixture of Distribution.

Introduction

One of the contentious issue in the market microstructure literature has been the volatility and stock expected returns. Issue has received considerable attention both in developed and developing countries due to important implication for investors' portfolio positioning and liquidity of their investment portfolio. However, the issue remains illusive with regard to the question of the asymmetric impact of good news (market advances) and bad news (market retreats) or information arrival on volatility in these emerging markets. It is General phenomena that, the negative shocks raise volatility more than positive shocks in the market. This phenomenon has been attributed to the "leverage effect" (see Black (1976), Nelson (1991) and Engle and Ng (1993)). In most cases volatility is an input used for purposes of market measurement. More recently, there has been an emphasis on inter-temporal dependence models to explain the observation of volatility clustering in stock pricing.

Financial time series such as stock prices often exhibit the phenomena of volatility clustering as the arrival of diverse information from various sources such as economic events and news and other exogenous economic events such as war, and other undesirable events that have greater impact on the time series pattern of stock price. Thus in most cases, financial time series behave such a way that does not conform to the normality distribution. Hence, the volatility observed in the market is a natural application for the autoregressive conditional heteroskedasticity (ARCH). To observe this phenomena, ARCH model introduced by Engle (1982) and Bollerslev's (1986) generalized ARCH (GARCH) model is used. The GARCH specification allows the current conditional variance to be a function of past conditional variances.

Seminal works of Mandelbrot (1963) and Fama (1965) indicated that the rates of returns (percentage changes in price) implicit in the time series of stock prices are time dependent. The evidence shows that the distribution of daily stock prices is characterized by leptokurtosis, skewness and volatility clustering. Several recent studies provide evidence that the GARCH methodology is capable of capturing these characteristics. Examples of such studies include Schwert and Stambaugh (1987), Akgiray (1989), Connolly (1989), and Ballie and DeGennaro (1990) and to individual stocks by Lamoureux and Lastrapes (1990) and Kim and Kon (1994) applied the GARCH model and to both individual stocks and indexes. These studies generally found that the GARCH processes fit the data better than ARCH and normal process. GARCH imposes an autoregressive structure on the conditional variance, allowing volatility shocks to persist over time.

A number of studies have been carried out to examine the impact of volatility on stock market returns using different methodologies such as (a) simple analysis of variances, (b) linear regression analysis, (c) GARCH Models, and (d) causality analysis. These studies, however, have largely been concerned with the developed capital markets such as those of the US., UK., Japan, and Hong Kong. In recent years, some efforts have been made to examine these issues for some emerging markets such as Malaysia, Portugal and Taiwan.

In the developed capital markets such as those of the US., UK., Japan, and Hong Kong, most of the studies find little or no evidence of increased stock market volatility. While a study on the Malaysian market done by Ibrahim *et al*. (1999) using daily data for Kuala Lumpur Composite Index (KLCI) and KLCI futures contracts found no evidence of any increase in volatility of the underlying market following introduction of futures contracts in December 1995 Anwar, Ariff and Shamsher (1991), used Absolute Price Change and Trading Volume Method by running OLS regression to determine volatility in stock markets. However, in this study we divert our search by applying Lamourex and Lastrapes (1990) model which accommodates mixture of distribution in volatility clustering. Their model shows that autoregressive conditional heteroscedasticity (ARCH) phenomena tend to vanish if the volume is considered in explaining the returns volatility. In particular, trading volumes are found to be a good proxy for information arrivals in the US market (Lamourex and Lastrapes, 1990). However most of previous studies in developing markets fail to include volumes into analysis (e.g., Ibrahim, 1999 Huang & Liu, 1995). Therefore, this paper aims at examining the volatility of returns using Lamourex and Lastrapes model to the Malaysian Stock Exchange Market. More importantly this paper seeks to address three contentious issues. First, how far the returns volatility persists in Malaysian Stock Market Exchange. Such tests are instrumental in supporting or refusing the MD hypothesis and have the potential to provide intuitively clear interpretations to many ARCH related empirical finding? Second, does trading volume explain the information arrival to the market? Third, Malaysia experienced an economy crisis in 1997. Therefore, this paper also seeks to examine the nature of volatility returns of the Malaysian stock exchange market (KLSE) prior and period covering the crisis period as different results are expected, since these periods exhibit different economic characteristics. The paper is organized as follows: section 2 reviews the literature to demonstrate whether or not volatility clustering exists in the market. While section 3 of this paper highlights the methodology used to examine the stock price volatility section 4 presents and discusses the findings. The last section concludes this paper.

Literature Review

Many studies have documented the empirical evidence of a positive contemporaneous correlation between trading volume and price volatility. Schwert (1989) using monthly aggregates of daily data on Standard and Poor (S&P) composite index in NYSE evidenced a positive relationship between estimated volatility and current and lagged volume growth rates using linear distributed lag and VAR models. Similar issue was also addressed by Lamoureux and Lastrapes (1991) using individual stocks from the S&P index. They documented a positive conditional volatility-volume relationship in models with Gaussian errors and Generalized Autoregressive Conditional Heteroskedasticity (GARCH)-type volatility specifications. However, the finding was cautiously interpreted as it may be biased due to the simultaneity between stock returns and volume. Similar results were also found in Bessembinder and Seguin (1993) for a variety of futures markets. Finally, Gallant *et al*. (1992), using nonparametric methods, confirmed the positive correlation between conditional volatility and volume, when examining daily S&P data from 1928 to 1987.

Volume and volatility data are also examined in a bivariate GARCH (Generalized Autoregressive Conditional Heteroskedasticity) framework, as discussed by Engle *et al*. (1984) and Bollerslev et al. (1988), in order to determine the interrelated characteristics of these two series. A bivariate GARCH model provides insights into the interactions that are not apparent in an ordinary least squares model. Specifically, this approach provides estimates of the importance of volume and volatility conditional upon the past volatility information of each of these variables.

Empirical aspects of the volume-volatility relationship in the literature for various instruments have been examined by Bessembinder and Seguin (1993), Chang and Schachter (1992), Gallant et al. (1992), Harris and Raviv (1993), Jain and Joh (1988), Karpoff (1987), Lang et al. (1992), and Schwert (1989). These studies consistently showed that a significant relationship exists between volume and volatility, with volatility measured as the absolute price change or the squared price change

While latest phenomena in the examination of volitity of return have been the Mixture of Distributions hypothesis, Clark (1973), Epps and Epps (1976), Tauchen and Pitts (1983), and Harris (1986). Developed the hypothesis based on the assumption that the variance per transaction is monotonically related to the volume of that transaction. Further, it is assumed that a mixing variable is the cause of the joint volatility-volume relationship. Often the number (and implicitly the importance) of information arrivals are designated as the mixing variable

Each of the studies under the mixture of distribution models contains unique features. Clark's model employs volume as a proxy for the speed of information flow. He associated volume and volatility on a contemporaneous basis, with no causal relationship between them. Clark's model implies that all groups who trade on information will have a similar relationship between volume and volatility. Epps and Epps' model is based on the disagreement between traders: the greater the disagreement is, the larger the level of trading volume will be. They suggested a causal relationship from volume to volatility. Also, their model implies that groups with greater disagreement will have a more pronounced relationship between volatility and volume.

The Mixture of Distribution model has received the most attention in the literature for the volatility-volume studies. Harris (1987) and Tauchen and Pitts (1983) showed that the joint distribution of changes in price (variability) and volume are modeled as a mixture of bivariate normal distributions and they demonstrated that the variance or absolute price change is a function of volume.

The Sequential Arrival of Information model was developed and extended by Copeland (1976, 1977), Jennings and Barry (1983), Jennings, Starks, and Fellingham (1981), and Morse (1981). This model assumed that information is disseminated sequentially from one group to another. This movement of information creates numerous price changes and volume. It also implies the continuation of higher volatility after the initial information shock rather than spikes in volatility.

Admati and Pfleiderer (1988) and Kyle (1985) provided trading behavior models by associating the timing of informed trades with the size of uninformed volume. Consequently, Admati and Pfleiderer show that trading is bunched in time, which justifies the intraday U-shape volume and volatility curves prevalent in the literature. Brock and Kleidon (1992) associate the U-shape curves to market closure, the power of dealers, and portfolio rebalancing.

Harris and Raviv (1993) and Shalen (1993) developed the dispersion of beliefs/expectations as the key factor determining the additional volatility and additional expected volume associated with noisy information (as well as developing other trading behavior relationships in the futures market).

Data and Methodology

The section starts with the description of the general features of the KLSE CI returns and volume series. The investigation period starts on January 2, 1990 and ends on December 26, 2000, giving a total of 2722 return observations.

The analysis periods are divided into three sub-periods: (1) pre-crises – January 2, 1990 to June 30, 1997 (1856 daily observations); (2) during the crises – July 1, 1997 to December 31, 1998 (374 daily observations); and (3) post-crises – January 4, 1999 to December 26, 2000 (492 daily observations). This gives a total of 11 years (1990 to 2000) with 2722 daily observations.

The closing prices of (CI) were obtained from the Kuala Lumpur Daily Diary Stock Guide. In order to explore the returns volatility and the trading volume, the returns were calculated based on the following formula:

$$r_m = 100^* \ln(CI_t / CI_{t-1}), \quad t = 1,2,\ldots\ldots,2722, \tag{1}$$

where r_m is the daily market returns, CI_t is the daily closing index at the time Trading volume in day *t* is expressed as equation (2):

$$V_t = \log(Vol_t / Vol_{t-1}). \tag{2}$$

A. Model development

Since the seminal work (ARCH) of Engle (1982), various hypotheses have been tested to explain the phenomenon in asset returns. One plausible explanation is that daily returns seem to be generated by a mixture of distribution (MD). In particular, the rate of daily information arrivals can be viewed as a generating process by the stochastic mixing variable. As pointed out by Diebold (1986), a proper ARCH model can capture the time series properties of such mixing variables.

The Lamoureux and Lastrapes (1990) model is presented below to illustrate that the daily returns can be presented as a subordinated stochastic process:

$$r_t = u + \varepsilon_t \tag{3}$$

in which

$$\varepsilon_t \mid (\varepsilon_{t-1}, \varepsilon_{t-2}, \ldots\ldots) \sim N(0, h_t), \tag{4}$$

$$h_t = \alpha_0 + \alpha_1 \sum_{i=1}^{p} \varepsilon_{t-1}^2 + \alpha_2 \sum_{j=1}^{q} h_{t-1}, \tag{5}$$

where

r_t = Daily return;

u = Constant;

h_t = Conditional variance (volatility) of ε_t at day *t*;

α_0 = Constant;

α_1 = Coefficient that relates to the past values of the squared residuals ε_{t-1}^2 to current volatility;

α_2 = Coefficient that relates current volatility to the volatility of the previous periods.

Positive parameters of α_1 and α_2, that the shocks administered to returns volatility persist over time. The magnitude of persistence is dependent on the size of these parameters.

Equation (5) represents the persistence in terms of conditional variance that can be estimated by a GARCH (p, q) model.

B. Operational Model

Using price data alone excludes an important variable – quantity or trading volume, which may well lead to inadequate descriptions of the market. As Beaver (1968) put it, "An important distinction between the price and volume tests is that the former reflects change in the expectations of the market as a whole, while the latter reflects changes in the expectations of individual investors." Viewed in this perspective, it is important to examine joint distribution of both price and volume variables in order to provide more accurate statistical inferences. Well known in the literature, empirical investigations on speculative prices have revealed kurtotic properties as compared to the normal distribution[1]. The leptokurtic distribution of rate of returns is a sampling consequence, when data are pooled from a mixture of distributions (MD) with varying conditional variances. This is to say that statistical tests employing both price and volume variables tend to support the MD hypothesis. In view of this assumption, price data can be viewed as a conditional stochastic process with a changing variance parameter that can be proxied by the volume (Karpoff, 1987). Therefore, simultaneous consideration of both price and volume variables could shed new light on the understanding of the financial market.

GARCH (1,1) Model

The first step in estimation procedure of Lamoureux and Lastrapes model is to estimate equations (1) and (3) as illustrated above. Including volume variable (V_t) in equations (2) and (3) gives the following generalized variance specification:

$$r_t = r_{t-1} + \varepsilon_t, \tag{6}$$

$$\varepsilon_t \mid (V_t, \varepsilon_{t-1}, \varepsilon_{t-2}, \ldots\ldots) \sim N(0, h_t), \tag{7}$$

$$h_t = \alpha_0 + \alpha_1 \varepsilon_{t-1}^2 + \alpha_2 h_{t-1} + \alpha_3 V_t + e_t, \tag{8}$$

where

r_t = Daily returns of CI;

r_{t-1} = Conditional return on past information;

h_t = Conditional variance (volatility) of ε_t at day *t*;

V_t = Trading volume at day *t*;

e_t = White noise;

α_0 = Constant;

α_1 = Coefficient that relates the past values of the squared residuals ε_{t-1}^2 to current volatility;

α_2 = Coefficient that relates current volatility to the volatility of the previous periods.

As pointed out by Lamoureux and Lastrapes (1990), a GARCH (1,1) specification is a parsimonious representation of conditional variance, while it fits comfortably with many economic time series (e.g., Bollerslev,1987).

GARCH-in-Mean

In 1987, Engle *et al*. developed the GARCH-in-Mean to formulate the conditional mean as function of the conditional variance as well as an autoregressive function of the past values of the underlying variable.

$$r_t = r_{t-1} + \delta\sqrt{h_t} + \varepsilon_t, \tag{9}$$

$$\varepsilon_t \mid (V_t, \varepsilon_{t-1}, \varepsilon_{t-2}, \ldots\ldots) \sim N(0, h_t), \tag{10}$$

$$h_t = \alpha_0 + \alpha_1 \varepsilon_{t-1}^2 + \alpha_2 h_{t-1} + \alpha_3 V_t + e_t. \tag{11}$$

GARCH in the mean model is the natural extension due to the suggestion of the financial theory that an increase in variance (risk proxy) will result in a higher expected returns.

[1] Clark et al.

If V_t represents as reasonable proxy for information arrival and is serially correlated, estimation based on previous equations, would yield $\alpha_3 > 0$, and values of α_1 and α_2 are significantly smaller than that when V_t is not included (Lamoureux and Lastrapes, 1990). In other words, the mixing variable (V_t) is statistically significant in explaining the volatility of stock returns. According to the MD hypothesis, the inclusion of the mixing variable is expected to rid the ARCH effect in stock returns. In terms of empirical estimates, it is manifested in the size of $\alpha_1 + \alpha_2$, a measure of persistence of shocks administered to the volatility. That is, $\alpha_1 + \alpha_2$ is expected to fall far below unity, and both tend to be statistically insignificant with the presence of V_t.

The size of the sum of the coefficients α_1 and α_2 denotes the degree of persistence in the conditional variance given a shock to the market. In particular, the persistence in volatility as measured by the sum of α_1 and α_2 in GARCH (1,1) models should be less than 1 in order to have a stationary variance. As the sum tends to 1 the higher is the instability- volatility- in the variance and shocks tend to persist instead of dying out (see Engle and Bollerslev, 1986). This implies that current volatility of daily returns can be explained by past volatility that tends to persist over time.

Findings and discussions

A. Characteristics of returns

To assess the distribution properties of the daily returns series, we use descriptive statistics which are reported in Tables 1 and 2. These statistics include the following distributional parameters: mean, standard deviation, skewness, kurtosis, maximum, minimum, median, value when a normal distribution is fitted to data, Ljung-Box, and Durbin-Watson statistics (2.9643). The time series of return and volumes used for empirical analysis are shown in Fig. 1. Corresponding histograms for the returns and volume series are also shown in Fig. 2.

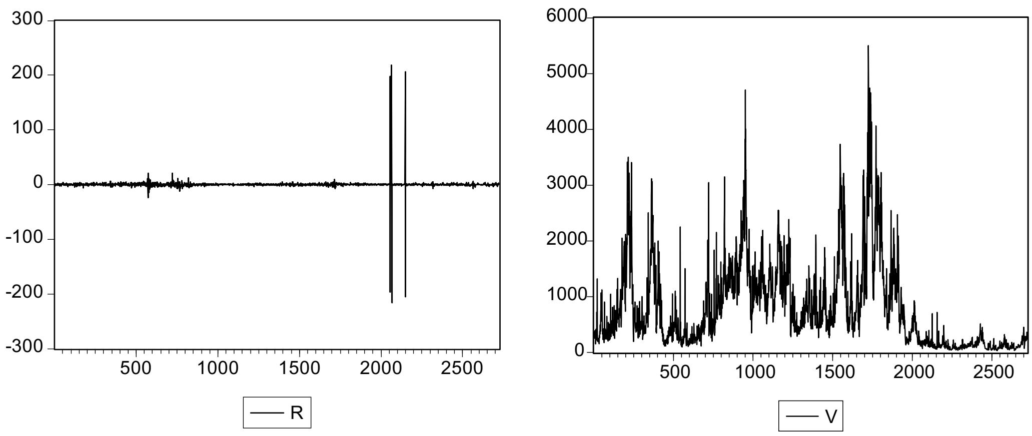
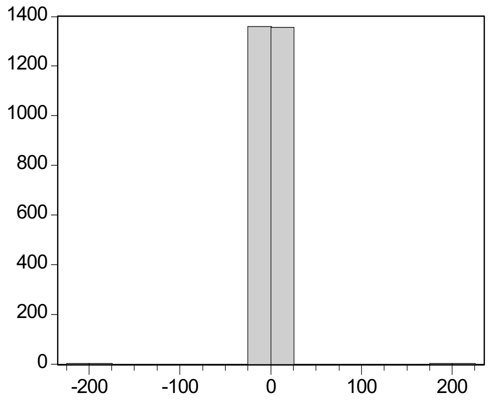


Fig.1. Time Series of Returns and Volume



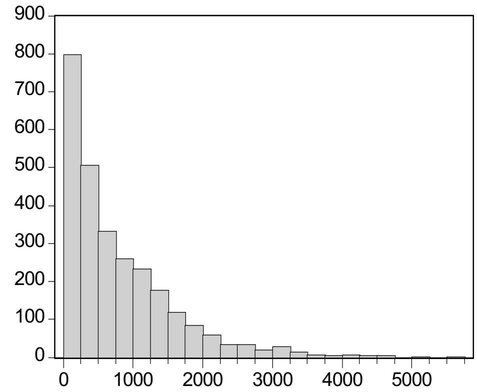


Fig. 2. Histogram of Returns and Volume Series

The sample mean of returns is very small and the corresponding variance of returns is much higher. The sample mean of the series is indistinguishable from zero at the 5% significant level. Daily returns series display high measures of skewness and kurtosis, indicating substantial departures from normality. Likewise, the Jarque-Bera test results indicate that the daily returns do not have normal distribution at the 1% significant level. Further evidence on the nature of departure from normality may be gathered from the sample skewness and excess kurtosis (larger than 3) measures. The excess kurtosis estimate for returns is large, 427.2187 clearly a sign of peaked (leptokurtic) end relative to the normal distribution (Fig. 2). The skewness estimate is positive, indicating the distribution has a right tail (Fig. 2). These wide ranges of statistics provide a conclusive rejection of the hypothesis that returns series is strict white-noise process.

Table 1

Descriptive Statistics for Volume and Return

	Volume	Return
Mean	795.5833	0.006963
Median	530.9050	-0.004950
Maximum	5504.180	217.9364
Minimum	31.20000	-216.5796
Std. Dev.	779.2832	9.871241
Skewness	1.748525	0.215394
Kurtosis	6.836953	427.2187
Jarque-Bera	3056.757	20410656
Probability	0.000000	0.000000

A common finding in time series regression is that the residuals are correlated with their own lagged values. This serial autocorrelation violates the standard assumption of regression theory that disturbance is not correlated with other disturbance. Before fitting any probability distribution model to data, the underlying assumptions of the model need to be verified empirically. Almost all of the popular models of stock returns require that returns be independent random variables, and many also require that they be identically distributed. In order to test the hypothesis of independence, a test of white noise process given by Ljung-Box-Pierce (Q-Statistic) is preferred in this study. The results of the tests are reported in Table 2, the Q-Statistics are significant at all lags, indicating the presence of serial correlation in the residuals. The ρ values for these Box-Pierce statistics are indistinguishable from zero indicating that these statistics are significant even at low level. Thus, the hypothesis that the return series is white noise process is rejected. Indeed, the presence of significant first-order correlation in returns implies the rejection of white noise too. Similarly, trading volumes exhibit a good deal of autocorrelation phenomenon as shown in **Table 2**, which is consistent with the finding of the Lamoureux and Lastrapes (1990) model or Eq. 6.

Table 2

Autocorrelation – for 12 lags

	Return				Volume			
	AR	MA	Q-Stat	Prob.	AR	MA	Q-Stat	Prob.
1	-0.482	-0.482	633.57	0.000	0.922	0.922	2316.9	0.000
2	0.003	-0.299	633.60	0.000	0.887	0.248	4463.6	0.000
3	0.001	-0.202	633.60	0.000	0.864	0.145	6501.3	0.000
4	-0.004	-0.149	633.64	0.000	0.847	0.099	8456.2	0.000
5	0.002	-0.108	633.66	0.000	0.825	0.029	10316.0	0.000
6	-0.001	-0.081	633.66	0.000	0.803	0.000	12076.0	0.000
7	0.000	-0.061	633.66	0.000	0.792	0.077	13788.0	0.000
8	-0.002	-0.049	633.67	0.000	0.777	0.020	15438.0	0.000
9	-0.159	-0.289	703.16	0.000	0.760	-0.003	17016.0	0.000
10	0.324	0.107	990.82	0.000	0.745	0.018	18535.0	0.000
11	-0.162	0.065	1063.0	0.000	0.730	-0.001	19994.0	0.000
12	0.001	0.036	1063.0	0.000	0.724	0.060	21427.0	0.000
Q (12) = Box – Pierce Statistics with lag period of 12.								

These results are evidence that the returns tend not to be independent but exhibit "volatility clustering". This is where periods of large absolute changes tend to cluster together followed by periods of relatively small absolute changes. This implies that large returns tend to be followed by large returns (of either sign); while small returns tend to be followed by small returns. This suggests that usual measures of returns volatility are temporally dependent (heteroskedastic). In other words, the data are characterized by intertemporal dependence in both mean and variance. The autocorrelation coefficients of daily returns of KLSE CI have one important implication. That is, using a conditional returns (r_{t-1}), instead of a constant represented in Eq. 6 is preferred for the time series with significant autocorrelation. In summary, the data display all the previously documented characteristics of the unconditional distribution of returns that are used to justify the various GARCH specifications that follow.

B. All Sample Analysis (1990-2000)

Table 3 presents the results of fitting GARCH (1,1) - model I - process to the return series of KLSE. The parameters are estimated jointly by using numerical techniques to maximize the log-likelihood functions. The iteration is carried out until convergence to the optimum is obtained. The parameter estimates of model I in Table 3 are statistically significant. The persistence in volatility as measured by sum of α_1 and α_2 in model I is close to unity. The fact that the sum of α_1 and α_2 is fairly close to one indicates the persistence of past volatility in explaining current volatility (see Engle and Bollerslev (1986)). Moreover, these results provide strong evidence that the daily return series can be characterized by a GARCH (1,1) specification.

Table 3

GARCH (1,1)

	α_1	α_2	α_3	$\alpha_1 + \alpha_2$
Model I*	0.106052	0.740415		0.846467
Model II**	0.151765	0.692154	11.21314	0.843919

* Equation variance does not include the volume.
** Equation variance includes the volume.
All the statistics are significant at the 5% level.

Lamoureux and Lastrapes (1990) argued that using volume, as a mixing variable in the conditional variance equation would disappear the GARCH effects. They hypothesize that the persistence of volatility as measured by $\alpha_1 + \alpha_2$ would become small and statistically insignificant if the rate of information flow, as measured by contemporaneous volume, explains the presence of GARCH in the return series. Najand and Yung (1991) examined T-bond futures with a GARCH model and used contemporaneous volume in the GARCH equation while Huang and Yang (2000) examined returns of the Taiwan Stock Index (TSI). Unlike Lamoureux and Lastrapes, they found that GARCH effects remain when current volume is included in the equation for the conditional variance.

This study also found that volume does not remove the GARCH effect. Table 3 reports theses results which are similar to those of Najand and Yung (1991), Foster (1995), Huang and Yang (2000) and differ from those of Lamoureux and Lastrapes (1990) in that the GARCH effect remains strongly significant. With respect to the impact of contemporaneous volume on volatility, statistically significant coefficients are obtained for return series. These coefficients are positive and their sum is fairly close to unity, and do not undergo noticeable change when compared to the model without the proxy variable and their impact on GARCH coefficients is negligible.

In Table 4, the GARCH-in-Mean analysis of Model I without volume and Model II including the volume are reported. Similar to results of GARCH (1,1) the ARCH effect is consistently significant across returns series. There is a positive and statistically significant relationship between volume and returns volatility. Moreover, the sums of α_1 and α_2 are close to unity (0.847871), and do not undergo noticeable change when compared to the model without the proxy variable (0.846467). There is actually no improvement over the results obtained using volume.

The results of using GARCH and GARCH-in-Mean are consistent with those of Foster (1995) and indicate that the presence of simultaneity problem is less serious than that suggested by Lamoureux and Lastrapes (1990). The failure of contemporaneous volume to capture GARCH effects in conditional volatility equation is consistent with the proposition by Blume, Easley and O'Hara (1994) that the volume provides information on the precision and dispersion of information signals, rather than serving as proxy for the information signal itself.

Table 4

GARCH-in-Mean

	α_1	α_2	α_3	$\alpha_1 + \alpha_2$
Model I*	0.133551	0.708314		0.841865***
Model II**	0.181563	0.666308	16.93544	0.847871***

* Equation variance does not include the volume.
** Equation variance includes the volume.
*** significant at 5% level

C. Sub-Period Analysis

The effect of the financial crisis on the level of the presence of volatility was investigated by classifying the data into three sub-categories. The period from January 1990 to July 1997 was designated as pre-crisis period, while July 1997 to December 1997 was classified as during-crisis period and January 1998 to December 2000 was categorized as post-crisis period.

Pre-crisis period Jan, 1990-Jun, 1997

Descriptive statistics for the three sub-periods are shown in Table 5. The mean for the period before the crisis is much better than even the mean of the overall sample (Table 1). It is worth recalling here that the significant economic growth and investment boom experienced by Malaysia and the East Asian Region from the early 1990s throughout the period from 1995 to1996 helped much in the stabilization of the economic performance and business conditions. Under such circumstances it became easier for firms to predict the future earnings.

The persistence in volatility as measured by the sum of α_1 and α_2 in model I are close to unity (0.893851). That indicates the presistence of past volatility in explaining current volatility. By including the contemporaneous value of volume into the the conditional variance equation – model II – yield a positive and statistically significant relationship between volume and returns volatility. Moreover, the sums of α_1 and α_2 are close to unity (0.891676), compared to the model without the proxy variable. It is noticeable that, when using the volume as a proxy of information content of the market returns has failed to capture GARCH effects in this period. The reason could be that the volume turns out to be important to demonstrate the economic growth and investment boom experienced by Malaysia. This period was characterized by large volatility in stock prices which rose by 145% between 1990 and the end of 1996.

During crisis period Jul, 1997-Dec, 1997

In such fragile economy and fluctuating business conditions it would not be surprising to observe large impact on returns. The high negative mean of return (–16.27%) suggests that the returns made at the end of the year 1996 and the beginning of 1997 were based on the pre-downturn of businesses. However, the assumptions upon which these statistical signals were made did not hold any more as the economy slowed-down and businesses declined.

The results are presented in Table 6. Still the coeffiecents α_1 , α_2 and α_3 are significant at the 5% level. The sum of α_1 and α_2 is fairly close to unity (0.982068). It indicates that the GARCH effect is consistent across return series. Including volume to model I do not vanish GARCH effects; they remains strongly significant. It is interesting to see that, this period has higher volatility in prices than the other periods. The possible reason is that the Malaysian economy, particularly Kuala Lumpur Stock Market Exchange experienced a sharp financial collapse.

Post-crisis period Jan, 1998-Dec, 2000

The mean for this period is 3%, which has improvement compared to its level during the crisis period**.** This improvement can be explained due to the economic recovery witnessed by the East Asian Region, particularly Malaysia. This remarkable recovery was a consequence of an increase in export of electoronic and electrical products and the fiscal expansion policy (increase in puplic consumption expenditure). This in turn, improved the business cycle and as a result firms made somewhat better returns than the returns derived during the economic downturn.

In Table 6, the results of GARCH analysis of Model I and Model II are reported. Similar results have been obtianed, GARCH effects are consistently significant. There is a positive and statistically significant relationship between volume and returns volatility. It is observable that, this period has less volatility in prices than the previous periods. The reason could be due the improvement of the Malaysian economy which experienced more stability in the period.

Table 5

Descriptive statistics of return and volume for pre, during and post crisis

Descriptive Statistics of return and volume before crisis period (Jan 1990-Jun 1997)					
	Mean	*SD*	*Max.*	*Mini.*	*N*
Return	0.035033	11.81711	217.9364	-216.5796	1856
Volume	821.7903	843.1262	5504.180	31.20000	1856
Descriptive Statistics of return and volume during crisis period (Jul 1997-Dec 1998)					
	Mean	*SD*	*Max.*	*Mini.*	*N*
Return	-0.162748	3.616334	20.81740	-24.15340	374
Volume	655.3875	510.8922	3148.180	96.43000	374
Descriptive Statistics of return and volume after crisis period (Jan 1998-Dec 2000)					
	Mean	*SD*	*Max.*	*Mini.*	*N*
Return	0.030086	1.568416	5.850494	-6.229522	492
Volume	803.2926	681.0720	3502.080	115.2500	492

Table 6

GARCH Model

Estimations for the period before crisis (Jan 1990-Jun 1997)				
	α_1	α_2	α_3	$\alpha_1 + \alpha_2$
Model I	0.177063	0.716788		0.893851
Model II	0.168026	0.72365	0.67686	0.891676
Estimations for the period during crisis (Jul 1997-Dec 1998)				
	α_1	α_2	α_3	$\alpha_1 + \alpha_2$
Model I	0.260392	0.721676		0.982068
Model II	0.319374	0.579937	4.23086	0.899311
Estimations for the period after crisis (Jan 1998-Dec 2000)				
	α_1	α_2	α_3	$\alpha_1 + \alpha_2$
Model I	0.209819	0.552769		0.762588
Model II	0.306316	0.380748	1.848193	0.687064
All the statistics are significant at the 5% level				

Conclusion

This study presents a comprehensive analysis of the distributional and time series properties of returns to determine whether a GARCH model that allows for time varying variance in a process can adequately represent return volatility. This study set out to examine the volatility of returns in the Malaysian Stock Market using 2722 daily returns from 1990 to 2000. The results of our study indicate that the return volatility is best described by a GARCH (1,1) specification. Current volatility can be explained by past volatility that tends to persist over time. We add volume as an additional explanatory variable in the GARCH model to examine if volume can capture GARCH effects. Consistent with results of Najand and Yung (1991) and Foster (1995) and Huang, B.N. & Yong, C.W. (2001) and contrary to those of Lamoureux and Lastrapes (1990), our results show that the persistence in volatility remains in return series even after volume is included in the model as an explanatory variable. This finding holds for contemporaneous volume when it is included in the variance equation.

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