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Forecasting the Time Volatility of Emerging Asian Stock Market Index

M. Selvam*, M. Raja**, P. Yazh Mozhi***

Volatility is the measure of how far the current price of an asset deviates from its average past prices. Greater the deviation, greater the volatility. It indicates the strength or conviction behind a price movement. Stock market volatility is the function of the arrival of positive and negative market information. Pricing of securities is supposed to be dependent on the volatility of each asset. Matured / developed markets continue to provide over long period of time high returns with low volatility. Emerging markets, except India and China exhibit low returns. The exponential growth in the Asian derivatives markets necessitated the need to test whether the Asian market indices are more volatile or not. The study finds an evidence of time varying volatility, which exhibits clustering, high persistence and predictability for almost all the Asian market indices in the sample. With this background the present paper investigates the dynamic behavior of stock returns of ten market indices from Asian countries, using symmetric GARCH (1,1) model for a period of one year from January 2006 to December 2006.

Introduction

Generally the term "volatility" is simply synonymous with "risk". The estimation of market volatility is important for different people for different reasons. Merton Miller (1991), the winner of the 1990 Nobel prize for economics, defined the term Volatility thus "By volatility, public seems to mean days when large market movements, particularly down moves, occur. These precipitous market wide price drops cannot always be traced to a specific news event. The public takes a more deterministic view of stock prices; if the market crushes, there must be a specific reason".

Stock market volatility responds differently to the arrival of positive and negative news in the market. This asymmetric nature of volatility exerts an impact on stock prices. Hence its implications are important for traders in the market place to chalk out different trading strategies under different conditions.

In the literature, time varying conditional volatility is modeled through the Seminal Autoregressive Conditional Heteroskedasticity (ARCH) mode of Engle (1982) and its subsequent parsimonious representation through the Generalized ARCH (GARCH) of Bollerslev (1986). But these two models do not capture the asymmetric nature of volatility. Hence (GARCH (1, 1)) is used in this study for forecasting future volatility. This GARCH (1, 1) model incorporates the asymmetric volatility of the component exactly.

The exponential growth in the Asian derivatives markets raised the question, "Have the Asian market indices become more volatile?". In order to answer this question, one has to examine the partial volatility in the Asian markets. Hence the present study is an attempt to forecast the volatility of stock market indices with the help of GARCH (1, 1) model.

Statement of the Problem

Due to uncertainty in the share market movements, an individual investor bears the risk of heavy loss on his investment. The share prices may fall or rise in the future and this volatility of the market presents a greater risk to the investor. Hence the volatility estimation is important for several reasons and for different people in the market. The pricing of securities is supposed to be dependent on volatility of each asset. The mature markets / developed

Department of Commerce and Financial Studies, Bharathidasan University, Tiruchirappalli – 620 024
*E-mail: drmselvam@yahoo.co.in, **E-mail: rajacommerce@yahoo.co.in, ***E-mail: veena_godsrose@yahoo.co.in

markets continue to provide over long period of time high returns with low volatility.

Asian countries among the emerging markets except, India and China, exhibited high returns (sometimes negative returns with high volatility). India with long history and China with short history, provide return as high as the US and the UK market could provide but the volatility in both countries is higher. Indian markets have started becoming informationally more efficient contrary to the popular perception in the recent past. Volatility has not gone up. Intra-day volatility is also very much under control and has come down as compared to past years. Peripatetic stock prices and their volatility have now become endemic features of securities markets. The growing linkages of national market in currency, commodity and stock with world markets and existence of common players have spread volatility across the markets.

The dynamic behavior of stock index returns and its volatility have been investigated extensively. As a result, several stylized facts have emerged. First, at high frequencies, stock returns are positively correlated. The autocorrelation in index returns has been attributed to no synchronous trading. Second the unconditional distributions appear to be excessively leptokurtic when compared to the normal distribution. To deal with this problem, many researchers have used more general distributions [Mandelbort 1963, Fama 1965, Nelson 1991}. Third short term returns invariably exhibit volatility clustering where tranquil periods of small returns are interspersed with volatility periods of large returns. The technical term given to this is Autoregressive Conditional Heteroskedasticity (ARCH). This type of behavior has been modeled very successfully with ARCH and GARCH models [Engle 1982, Bollerslev 1994]. Fourth, changes in stock prices tend to be negatively related to changes in volatility [Black 1976, Christie 1982]. Hence this paper investigates the dynamic behavior of stock index returns of ten sample markets of Asia Pacific countries. More specifically, the study indicates whether volatility is time varying and predictable in these countries. For this purpose, GARCH (1, 1) model is applied.

Objectives of the Study

The study is based on the following objectives

- To test the homeoskedasticity of the sample indices.
- To measure the range and rate of volatility of the sample indices and to forecast the rate of volatility for 150 days with an interval of 30 days
- To analyse all the parameters of GARCH (1, 1) model used in the study.
- To give suggestions to increase the returns of investors through forecasting the volatility and persistence

Hypotheses of the Study

The study proposes to test the following hypotheses of the study

- There is heteroskedasticity in the closing values of the sample indices.
- The current conditional variance rates of ten indices in the sample are higher than the long range conditional variance rate.
- The forecasted volatility rates for all the indices in the sample are higher than the current volatility rate.

Review of Literature

The following are selected studies relevant for the present study.

A study "Time Varying Volatility and Leverage Effect in Financial Markets of Asian Pacific Countries Using the Symmetric GARCH and Asymmetric TARCH Models" by **Madhu Sudhan Karmakar (2006)** found evidence of time varying volatility which exhibited clustering high persistence and predictability for almost all the sample countries for a period of eleven months from July 1994 to June 2005.

Mohammed Najand (2002) in his study "Forecasting Stock Index Futures Price Volatility: Linear Vs Nonlinear Models with the Help of Three Non Linear Models. i.e. GARCH, EGARCH and ESTAR" examined whether the stock index future price is volatile or not. The researcher concluded that nonlinear GARCH models dominated linear models utilizing the rise and MAPE error statistics and EGARCH appears to be the best model for forecasting stock index futures price volatility.

A study entitled "Market Structure And Returns Volatility: Evidence From Hong Kong Stock Market" by **Wilson.S.Tong, K.S.Maurice (2002)** pointed out that there was no consensus about the cause for higher volatility at the market opening than at the market closing in the US market. However the autocorrelation of the open to open return series also indicates that the temporary price deviation at the market opening is not significant.

Janusz Brzeszcznski(2000) in his project entitled "Modeling Stock Price Using the ARCH And GARCH Models" estimates various types of ARCH process including GARCH and asymmetric ARCH / GARCH specifications. The empirical applications were based on the data set to be composed of the major international stock market indices. The obtained result from this project was useful to verify the hypothesis about the stock market efficiency. (The weak form level)

Weixian Wei (2002) in his study "The Performance of The GARCH Model and Two of Its Non Linear Modifications To Forecast China's Weekly Stock Market Volatility" found that the GARCH model was best when the estimation sample did not contain extreme observations such as the stock markets crash and that the GJR models cannot be recommended for forecasting.

Gorden.W.Crawford and Michael.C.Fratantoni (2003) in their paper "Forecasting Performance of the Regime Switching ARMA and GARCH in Real Estate Economics" found while price changes on any particular home price changes were forecastable. The regime switching models were a compelling choice for real estate markets that have historically displayed boom and bust cycles.

A study on "Information Criteria For GARCH Model Selection" by **Chris Brooks and Simon. P. Burke (2003)** forecasted both the conditional mean and the conditional variance of two high frequency exchange rate series. The analysis indicated that the use of this model did lead to significantly improved forecasting accuracies for the conditional variance. In some cases, these improvements were by no means universal.

Premalatha Shenbagaraman (2003) in her study "Futures and Options Trading Increase Stock Market Volatility in NSE" assessed the impact of introducing index Futures and Options contracts on the volatility of the underlying stock index in India. The author found that the introduction of derivatives contracts improved liquidity and reduced informational asymmetries in the market. Further, the author suggested that Futures and Options trading have not led to a change in the volatility of the underlying stock index but the nature of volatility seems to have changed past futures.

From the literature cited above, it is clear that most of the studies measured the time variance volatility of various market indices. It is understood that almost all the market indices have the volatility. Majority of the studies were undertaken with individual markets indices but only few studies were undertaken covering Asian market indices. Hence the present study makes an attempt to test the time varying volatility of top ten Asian market indices.

Methodology of the Study

Sample Selection

This study includes Top ten Asian Stock Exchanges on the basis of the market capitalization. From each selected stock exchange, one popular index was chosen for this study. The name of stock exchange and the indices selected are given in the Table below

List of Stock Market Indices for each country

Sl.No.	Country	Selected Stock Market Index
1	Japan	Nikkie 225 Index
2	Hong Kong	Hang Seng Index
3	India	BSE Sensex Index
4	South Korea	Kospi Index
5	China	Shanghai Index
6	Taiwan	Taiwan Weighted Index
7	Singapore	Strait Times Composite Index
8	Malaysia	KLSE Composite Index
9	Thailand	SET Index
10	Indonesia	Jakarta Index

Sources of Data

The information about share price and sample indices were obtained from the websites **www.yahoofinance.com** and **www.indiainfoline.com** and website of sample stock exchange index. The information regarding Indian Capital Market was obtained from the RBI publications, Bombay Stock Exchange Official Directory and BSE website **www.bseindia.com**

Period of Study

The study covers a period of one year (i.e.) from 1.1.2006 to 31.12.2006.The daily series of top ten Asian indices for a period of one year were analysed for this study.

Tools used in the Study

The following four tools were used in this study in order to examine the presence of heteroskedasticity.

GARCH (1, 1) model

GARCH stands for Generalized Autoregressive Conditional Heteroskedasticity. It takes into account excess kurtosis (i.e. fat tail behavior) and volatility clustering, two important characteristics of financial time series. It provides accurate forecasts of variances and co-variances of asset returns through its ability to model time - varying conditional variances. Bollerslev (1986) later proposed a more generalised form of the ARCH (m) model appropriately termed the GARCH (p, q) (General-ARCH) model. The GARCH (p, q) model has two equations which can be written as

$$\sigma_n^2 = w + a_1\sigma_{t-1}^2 + b_1\varepsilon_{t-1}^2$$

This model is often sufficient to describe the conditional mean in a financial returns series. In the conditional variance mode (σ_{t-1}^2), the variance forecast consists of a constant plus a weighted average of last period's forecast ($a_1\sigma_{t-1}^2$) and last period's squared disturbance ($b_1\varepsilon_{t-1}^2$).

Uses of GARCH

GARCH models can be applied to diverse fields as risk management, portfolio management and asset allocation, option pricing, foreign exchange and the term structure of interest rates. There is a high significant GARCH effects in equity markets, not only for individual stocks, but also for stock portfolios and indices and equity futures markets. These effects are important in such areas as value-at-risk (VAR) and other risk management applications that concern the efficient allocation of capital. GARCH models can also be used to examine the relationship between long- and short-term interest rates.

Autocorrelation

Autocorrelation is a reliable measure for testing the independence of random variables in return series. The serial correlation coefficient measures the relationship between the values of a random variable at time t and its value in the previous period. The autocorrelation can be quantified by the preceding qualitative checks for correlation using formal hypothesis tests, such as the Ljung-Box-Pierce Q-test, Ljung-Box-Pierce Q-squared test and Engle's ARCH test.

Ljung - box – Pierce Q – test

Ljung-Box-Pierce Q-test is implemented to test the departure from randomness based on the ACF of the data. The Q-test is most often used as a post estimation lack-of-fit test applied to the fitted innovations (i.e., residuals) and can also be used as pre-fit analysis because the default model assumes that returns are just a simple constant plus a pure innovation process.

$$LB = n(n+2)\sum_{k=1}^{m}\left(\frac{pk^2}{n-k}\right) \approx x^2 m$$

Where,

P^K – autocorrelation coefficient at k, and

N – number of observations.

Engle's ARCH Test

Engle's test is implemented to test the presence of ARCH effects. Under the null hypothesis, a time series is a random sequence of Gaussian disturbances (i.e., no ARCH effects exist). This test statistics is also asymptomatically Chi-Square distributed. We can also show significant evidence in support of GARCH effects (i.e., heteroskedasticity).

Limitation of the Study

The limitations of this study are as follows

- The study is confined to secondary data.
- All the limitations of the models (GARCH (1,1) model) used in the study are applicable to this study also.
- This study is restricted to a few indices in the Asian Pacific countries.
- This study covers only ten countries in the Asian continent.

Scope for Further Research

The present study is confined to only ten top Asian indices. This study may be further extended to other indices. There may be further scope for testing the same volatility with world top ten stock exchanges like NYSE, Nasdaq, Tokyo, London, Hong Kong etc. Further the same volatility may be tested in the regional stock exchanges also like Osaka, Milan, Johannesburg, etc.

Empirical Analysis of the study

Mean and Standard Deviation

Table - 1 shows the mean returns and standard deviation of sample indices. It is obviously understood from the table that all the sample indices except SET index (Thailand) and Hang Seng Index (Hong Kong), obtained positive mean returns. Among the sample indices, Shanghai Index (China) earned the mean returns of 0.369, followed by Jakarta Index (Indonesia) (0.191) and BSE SENSEX (India) (0.1697). It is important to note that Hang Seng Index (Hong Kong) (-0.1697) and SET index (Thailand) (-0.0002) earned negative mean returns. During the study period, it is observed that all the markets, except SET index (Thailand) and Hang Seng Index (Hong Kong) obtained the heteroskedasticity and returns of these markets is also positively skewed during the study period. This result clearly revealed the fact that all the markets function actively and yield high returns to the investors whereas in SET index (Thailand) and Hang Seng Index (Hong Kong), markets experienced the highest unconditional volatility which yield negative returns. Thus the null hypothesis - I namely there is heteroskedasticity in the closing values of the sample indices is rejected.

Autocorrelation

Table - 2 explains the autocorrelation of sample indices. It is clear from the table that all indices, except Shanghai Index (China), were not perfectly autocorrelated. It means that out of all indices, Shanghai index alone obtained homeoskedasticity. It is understood from the above analysis that all the sample indices observed the high volatility except Shanghai Index (China) during the study period. Thus GARCH (1,1) model is working well in removing the autocorrelation in most of the sample indices except Shanghai Index (China).

Parameter Estimation

Table - 3 depicts the parameter estimation of the sample indices. The calculated values of parameter *a1* and *b1* show the short run dynamics of volatility time series. A large co-efficient *b1* indicates that shocks to conditional variance take a long time to die out, so volatility is "persistent". In other words, if there is a new shock it will have the implication on the price for a longer period. The market will take some time to digest the information fully into the price. The above results show the fact that all the parameters are highly significant under GARCH (1,1) model parameter estimation. From the GARCH (1,1) model parameter estimation, it is understood that sum of parameter 1 and 2 (*a1* and *b)* was less than one except Taiwan Weighted Index (Taiwan) index. It means that GARCH (1,1) model fails to estimate the parameter of the Taiwan Weighted Index (Taiwan) index. So Taiwan Weighted Index (Taiwan) may yield better results when applying the other models like integrated GARCH model, simple Exponential Weighted Moving Average Model (EWMA).

Ljung-Box-Pierce Q-Tests

Table - 4 describes the Ljung-Box-Pierce Q-Test results of sample indices. It is understood from the above analysis that all sample indices have autocorrelation except the Taiwan Weighted Index (Taiwan) (19.97) and SET index (Thailand) (20.49) because the calculated value was higher than the statistical value (18.3) at 10 lags. When the same was tested at lag 15, all indices except BSE SENSEX (India), Taiwan Weighted Index (Taiwan) and SET index (Thailand) evidenced autocorrelation. The calculated values of these indices (27.29, 29.15 and 26.69) were higher than the statistical value (24.99) which clearly exhibited heteroskedasticity. But the test at lag 15 shows that all countries, except BSE SENSEX (India), Taiwan Weighted Index (Taiwan) and SET index (Thailand), evidenced autocorrelation. The calculated values of these indices (27.29, 29.15 and 26.69) were higher than the statistical value (24.99) which exhibited heteroskedasticity. The same was again tested at 20 lags and all indices except Jakarta Index (Indonesia) experienced autocorrelation because the calculated value (33.39) was higher than the statistical value (31.41). The overall analysis shows that indices like Taiwan Weighted Index (Taiwan) and SET index (Thailand) have high volatility among the sample indices whereas Nikkie 225 index (Japan) showed moderate level because the calculated value of Nikkie Index was more or less same to the statistical value.

Ljung-Box-Pierce Q Squared -Test

Table - 5 indicates the result of L-Jung Box squared test of the sample indices. It is understood from the table that all the sample indices, except Hang Seng Index (Hong Kong) and Shanghai Index (China), have the heteroskedasticity both at lag 10 and 15. It means the calculated value in all the sample indices. The indices like Hang Seng Index (Hong Kong) and Shanghai Index (China) obtained autocorrelation because its calculated values (6.49, 18.08) at lag 10, (14.22, 18.08) at lag 15 and (17.55, 26.19) at lag 20 were less than the statistical value (18.30, 24.99 and 31.41). From the above analysis, it is obviously clear that all the sample indices did have higher volatility except Hang Seng Index (Hong Kong) and Shanghai Index (China) during the study period.

Engle Arch Test Results

Table - 6 denotes the results of Engle Arch Test on sample indices. From the above analysis, it is understood that all the sample indices have the heteroskedasticity except Shanghai Index (China) and Hang Seng Index (Hong Kong). It is established that in these two indices, the calculated values (18.27, 12.25) at lag 10, (20.66, 18.69) at lag 15 and (26.26, 23.26) at lag 20 were lower than the statistical values (18.30, 24.99, 31.41). From the overall analysis of this table, it can be inferred that all the sample indices, except Shanghai Index (China) and Hang Seng Index (Hong Kong), have high volatility during the study period.

Conditional Volatility and Conditional Variance

Pictures (a-j) display the pictures of Conditional Variance of all the sample (ten) market indices. In majority of the countries, the current conditional variance was lower than the historical conditional variance. But the current conditional variance of Shanghai Index (China) was higher than the historical variance. But in the case of SET index (Thailand) alone, the current conditional variance was equal to the historical conditional variance. On the basis of the results reported in the pictures(a-j), the indices that are most persistent in volatility seem to be in KLSE composite Index (Malaysia). On the contrary, in Kospi (South Korea) and Strait Times Composite Index (Singapore), the volatility was less persistent and more reactive in volatility than the rest of the sample markets. Thus, the null hypothesis - II (The current conditional variance rates of ten indices in the sample are higher than the long range conditional variance rate) was rejected and the alternative hypothesis is accepted.

Current Variance

The Pictures (I – X) explain the various expanded path of variance rate of ten sample indices. The straight line in the pictures (I-X) denotes the long variance rate. The curved line in the pictures (I-X) denotes the current variance rate of the index. Out of sample indices, current variance rate almost of all the indices was below the long run variance rate. Only the current variance of Shanghai Index (China) was an exception and it was above the long run variance. The fact that the current variance is below the long term volatility, denotes an upward sloping volatility structure. So the null hypothesis - III (The forecasted volatility rates for all the indices are higher than the current volatility rated) is not accepted.

Forecasting Volatility

Table - 7 explains the forecasting volatility of sample indices for 150 days. From the above analysis, it is understood that among the sample indices, Nikkie 225 index of Japan has the high volatility for all the days (30 days, 60 days, 90 days, 120 days and 150 days), followed by KLSE composite Index of Malaysia, BSE SENSEX of India, Shanghai Index of China and Kospi of South Korea.

While analyzing the forecasted volatility periodically, it is found that in 30 days Nikkie 225 index of Japan (2.230) has the highest volatility, followed by KLSE composite Index of Malaysia (1.28), Shanghai Index of China (0.12), Strait Times Composite Index of Singapore (0.61) and BSE SENSEX of India (0.32). On the other hand, Indices like SET index of Thailand (0.02), Taiwan Weighted Index (0.11), Hang Seng Index of Hong Kong (0.25) obtained low volatility.

When the same result is forecasted for 60 days, it is found that Nikkie 225 index of Japan has obtained the high volatility (1.85), followed by KLSE composite Index of Malaysia (0.92), Strait Times Composite Index of Singapore (0.36) and Shanghai Index of China (0.34). Low volatility was obtained by SET index of Thailand (0.02), followed by Jakarta Index of Indonesia (0.05) and BSE SENSEX of India (0.08).

When the volatility was forecasted for 90 days, Nikkie 225 index of Japan indices accounted for the highest volatility (1.54), followed by KLSE composite Index of Malaysia (0.66), Strait Times Composite Index of Singapore (0.81) and Shanghai Index of China (0.17) respectively. But indices like SET index of Thailand (0.02), Jakarta Index of Indonesia (0.02), BSE SENSEX of India (0.04), Hang Seng Index of Hong Kong (0.03) and BSE SENSEX of India (0.04) earned low volatility.

While analyzing the forecasted volatility for 120 days, it is found that Nikkie 225 index of Japan has the highest volatility of (1.28), followed by KLSE composite Index of Malaysia (0.48), Shanghai Index of China (0.09), Strait Times Composite Index of Singapore (0.03) and BSE SENSEX of India (0.03). The indices like Hang Seng Index of Hong Kong (0.01) and Jakarta Index of Indonesia (0.02) obtained low volatility.

It is important to note that when the same result was forecasted 150 days, Nikkie 225 index of Japan (1.07) has obtained the high volatility, followed by KLSE composite Index of Malaysia (0.35), Strait Times Composite Index of Singapore (0.08), and Shanghai Index of China (0.05). While low volatility has been obtained by Hang Seng Index of Hong Kong (0.01), followed by Kospi of South Korea (0.02) and BSE SENSEX of India (0.03).

While forecasting the volatility for a period 150 days, it is found that Nikkie 225 index of Japan has the highest volatility rate both in the instantaneous market and in the forecasted market. The Nikkie 225 index of Japan's instantaneous market has 2.68% and forecasted volatility of 2.23%.It is significant that BSE SENSEX of India has the highest volatility, next to Nikkie 225 index of Japan with instantaneous volatility of 1.66% and forecasted volatility of 0.32%.The volatility was low in the Taiwan Weighted Index market with the instantaneous volatility of 0.28% and forecasted volatility of 0.11%. Thus it could be inferred that Nikkie 225 index of Japan market, has the highest degree of heteroskedasticity and Taiwan Weighted Index has the lowest degree of heteroskedasticity.

Findings of the Study

The following are the important findings of the study

a) The set index of Thailand (-0.000269) and Hang Seng Index of Hong Kong (- 0.165745) have earned negative returns during the study period.

b) The Shanghai Index of China earned (0.3690647) the highest return among the sample indices.

c) The Hang Seng Index of Hong Kong has the highest risk of 4.627.

d) The Shanghai Index of China has the highest autocorrelation value among the sample indices.

e) The KLSE Composite Index of Malaysia and Nikkie 225 index of Japan took more time to fully digest the shocks in the closing values.

f) The Set Index of Thailand and BSE Sensex Index of India took less time to fully digest the price changes. (i.e.) It is persistent and more reactive.

g) The Taiwan Weighted Index and BSE Sensex of India have higher spike volatility where as Hang Seng Index of Hong Kong and KLSE Composite Index (Malaysia) has lower spike volatility.

h) The Hong Seng Index of Hong Kong and Shanghai Index of China has heteroskedastic nature of volatility.

i) The current Conditional Variance of Shanghai Index of China was higher than the historical variance.

j) Shanghai Index of China and Strait Times Composite Index of Singapore were more persistent in volatility.

k) Shanghai Index of China faced downward sloping volatility while other sample indices faced upward sloping volatility.

Conclusion

This paper investigated the dynamic behavior of stock index returns of sample markets of Asia Pacific countries. The study investigated specifically whether volatility is time varying and predictable in these countries for almost all the sample countries. There is evidence of time varying volatility which exhibits clustering, high persistence and predictability. The most persistent in volatility seems to be KLSE composite Index (Malaysia) during the study period. The KLSE composite Index of Malaysian market takes more time to fully digest the "Today's Price Shocks" than that of other markets. On the contrary, SET index (Thailand) seems to be less volatile. Here the SET index (Thailand) took shorter time to digest the price shocks. The volatility was less persistent and more reactive than the rest of other sample countries during the study period.

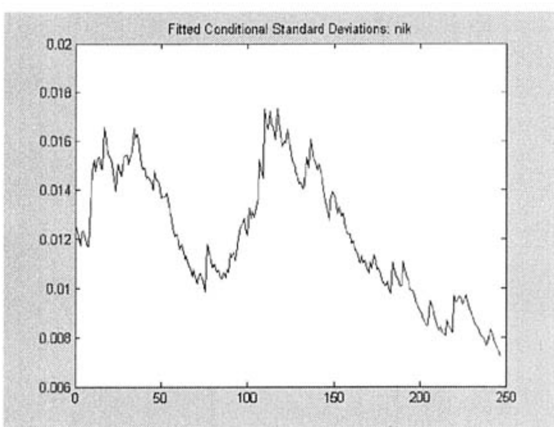
This paper forecasted the volatility of the Asian Markets. Among the Asian markets, when forecasted for 30, 60, 90, 120 and 150 days, Nikkei 225 index (Japan) index showed a high rate of volatility. On the contrary, the Hang Seng Index (Hong Kong) market index was less volatile during the study period. BSE SENSEX (India) has a moderate rate of volatility when compared to other Asian markets. This indicates the fact that in future, BSE SENSEX of Indian index could be one of the best investment zones for parking the funds.

The difference in the predictable market volatility implied by the model has important implications for option pricing also. Stock returns volatility is a major factor in determining the option price. Further since the simple GARCH model implied very different volatilities following major bad news, the dynamic hedging strategies implied by two sets of volatility estimates would be very different. Thus to predict the stock market volatility, one may use the symmetric GARCH (1,1) model.

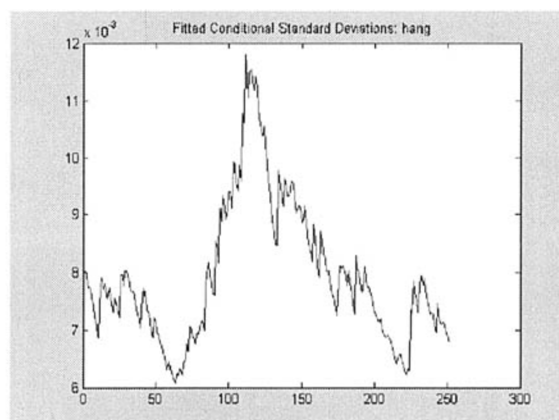
Pictures : a-j

Conditional Volatility of the Different Markets Estimated On The Conditional Variance Equation of GARCH (1, 1) Model.

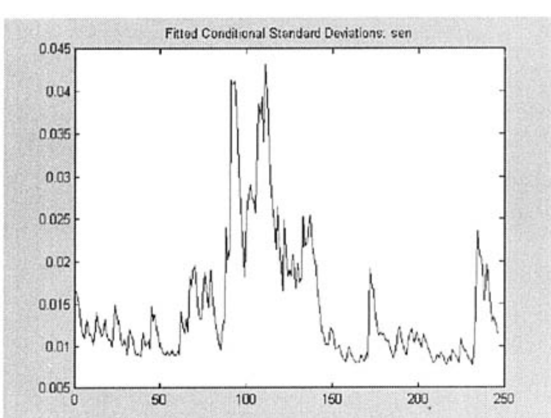
(a) Conditional Variance of Japan



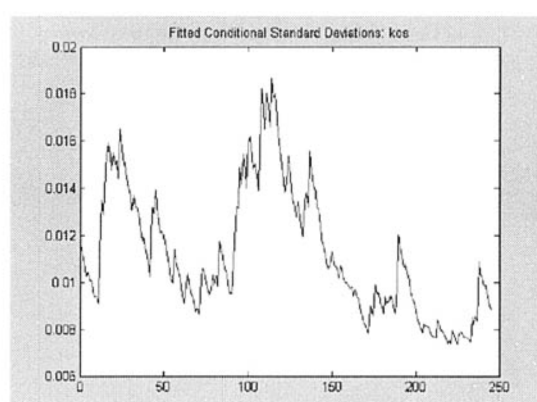
(b) Conditional Variance of Hong Kong



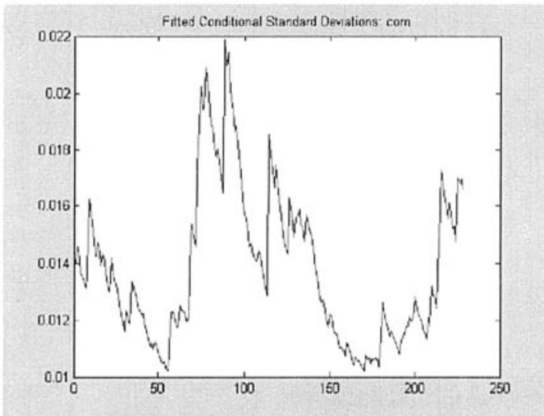
(c) Conditional Variance of India



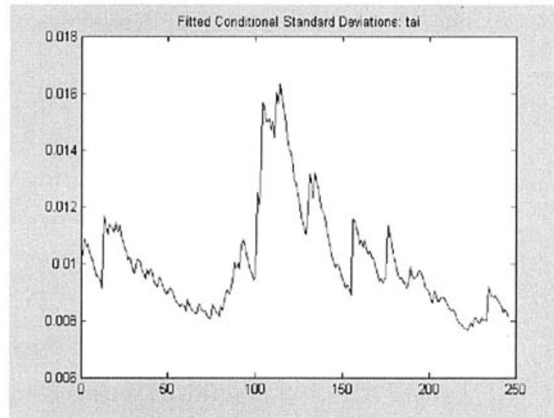
(d) Conditional Variance of South Korea



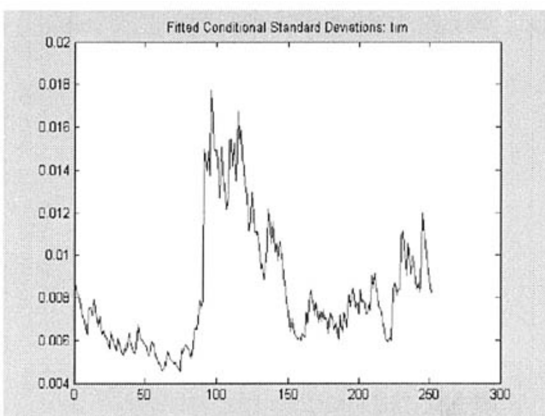
(e) **Conditional Variance of China**



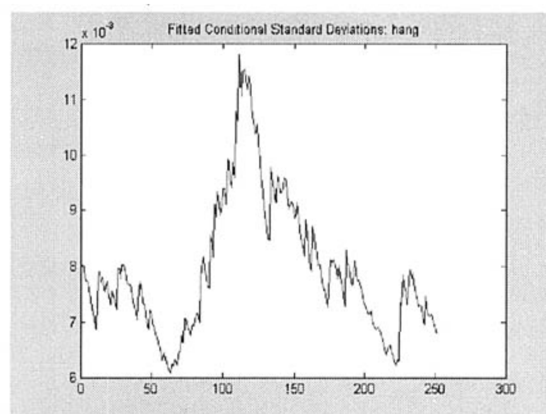
(f) **Conditional Variance of Taiwan**



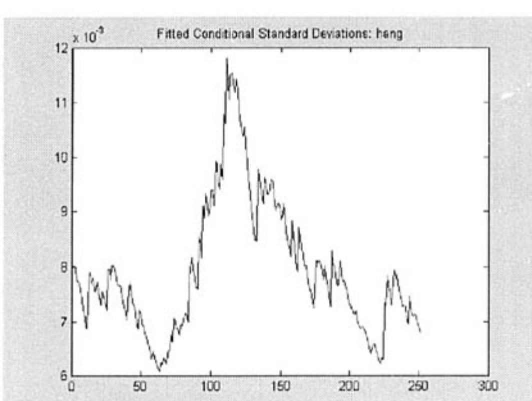
(g) **Conditional Variance of Singapore**



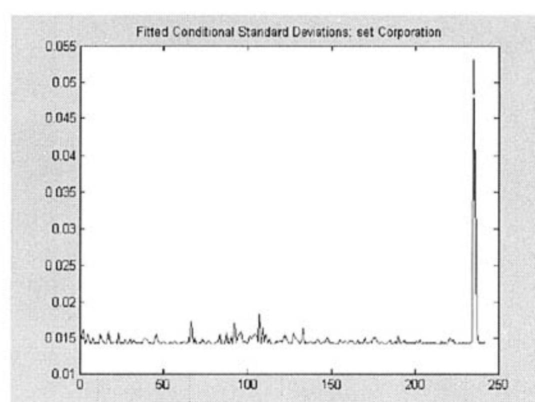
(h) **Conditional Variance of Malaysia**



(i) **Conditional Variance of Thailand**



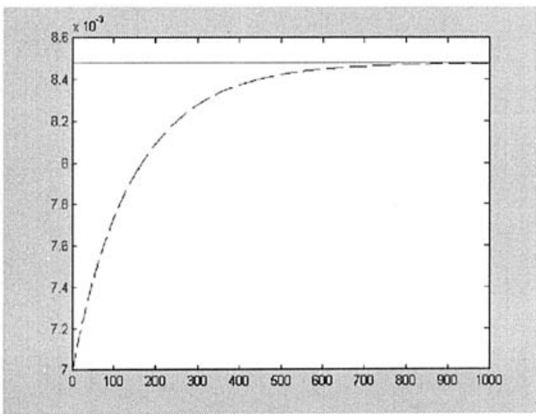
(j) **Conditional Variance of Indonesia**



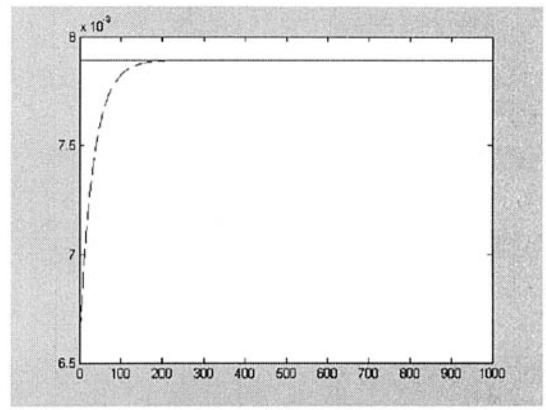
Pictures: I - X

Current Variance of the Different Markets Estimated On The Current Variance Equation of GARCH (1, 1) Model.

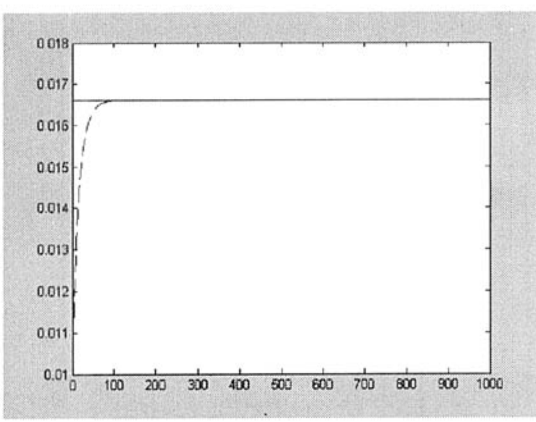
I. Current Variance of Japan



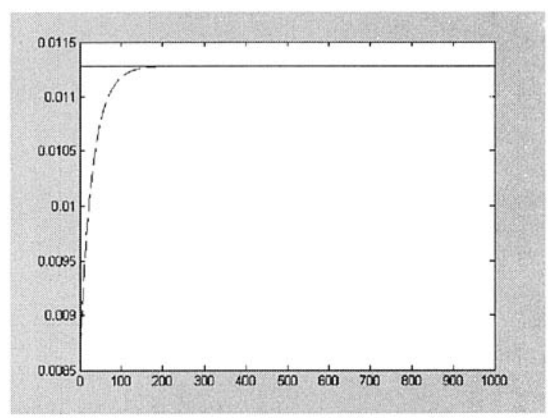
II. Current Variance of Hong Kong



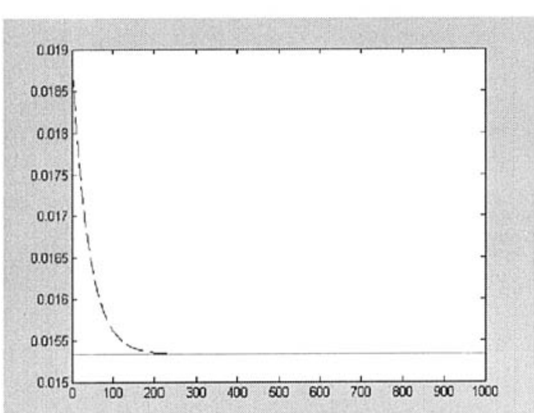
III. Current Variance of Indi



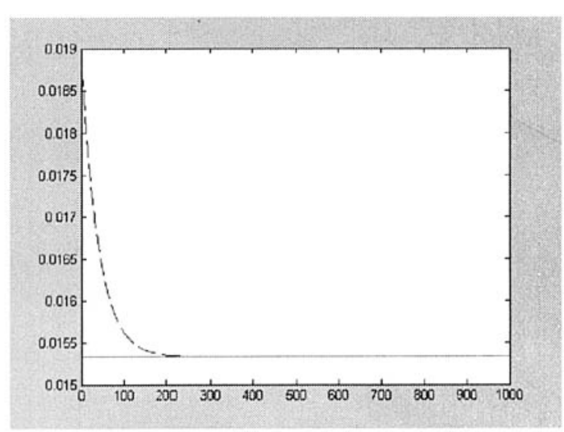
IV. Current Variance of South Korea



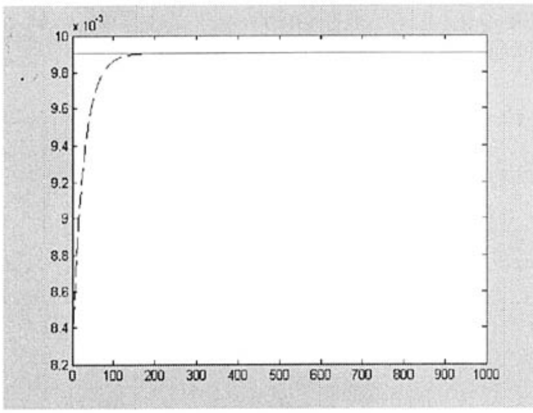
V. Current Variance of China



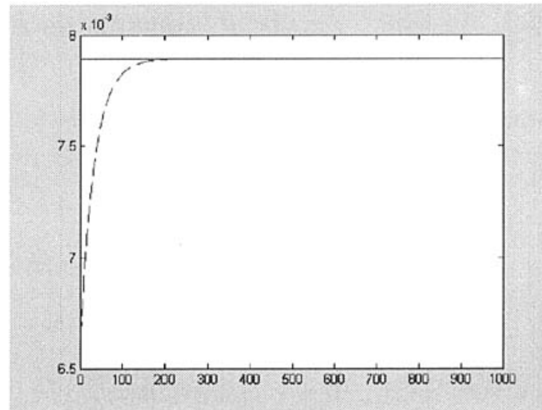
VI. Current Variance of Taiwan



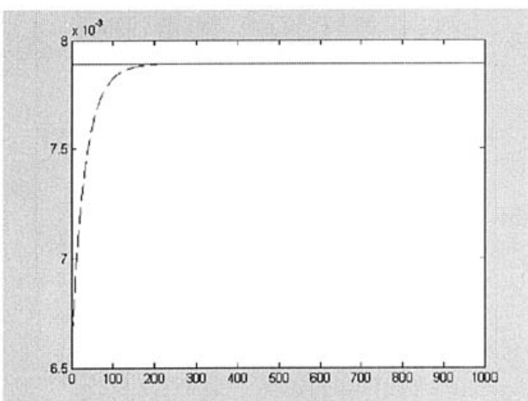
VII. Current Variance of Singapore



VIII. Current Variance of Malaysia



IX. Current Variance of Thailand



X. Current Variance of Indonesia

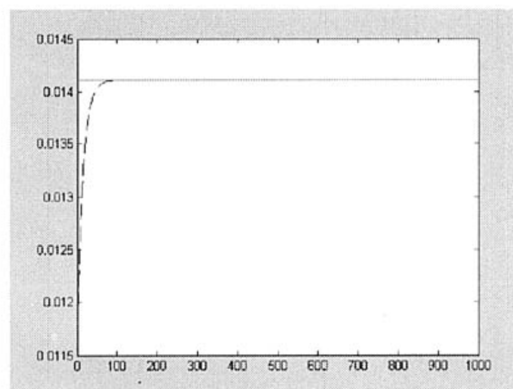


Table 1 : Return Statistics of Mean and Standard Deviation

Country	N	Mean	SD
Japan	248	0.0286493	1.2515575
Hong Kong	250	-0.165745	4.6270838
India	247	0.1697021	1.6417248
South Korea	247	0.0196192	1.1499775
China	229	0.3690647	1.3992566
Taiwan	247	0.0830419	1.0278341
Singapore	252	0.0958153	0.8537305
Malaysia	247	0.0848237	0.5233161
Thailand	243	-0.000269	0.0159306
Indonesia	240	0.1910091	1.3479715

Table 2 : Autocorrelation

Lags	Japan	Hong Kong	India	South Korea	China	Taiwan	Singapore	Malaysia	Thailand	Indonesia
1	1	1	1	1	1	1	1	1	1	1
2	-0.054	-0.002	0.058	0.013	0.966	0.004	-0.059	0.103	-0.273	-0.498
3	-0.024	-0.086	-0.085	-0.033	0.937	-0.006	-0.078	-0.039	0.051	-0.003
4	0.025	0.030	-0.093	-0.006	0.909	0.122	0.000	0.116	0.018	0.003
5	-0.051	0.024	0.074	-0.047	0.883	-0.171	0.093	0.047	0.021	-0.001
6	0.121	0.053	0.072	-0.047	0.858	0.026	0.103	0.033	-0.032	0.000
7	0.045	-0.066	0.002	-0.076	0.837	0.073	-0.005	-0.061	-0.046	0.002
8	-0.089	-0.035	-0.132	-0.067	0.816	-0.147	-0.139	0.052	0.010	-0.004
9	-0.111	-0.088	0.066	0.049	0.792	0.034	0.022	-0.107	0.013	-0.001
10	-0.005	0.016	0.114	0.133	0.770	0.075	0.001	-0.066	-0.031	0.000
11	0.045	0.000	0.035	-0.049	0.748	-0.018	0.061	0.009	-0.037	0.006
12	-0.079	0.003	-0.082	0.074	0.728	0.066	-0.018	0.045	-0.002	0.000
13	0.043	0.021	-0.107	-0.009	0.708	-0.020	-0.068	-0.051	0.037	-0.002
14	-0.009	-0.034	0.129	0.052	0.688	-0.106	0.042	-0.055	0.053	-0.003
15	0.014	0.149	0.063	-0.004	0.669	0.130	0.017	0.007	-0.116	-0.001
16	0.017	0.073	0.040	0.052	0.651	-0.048	0.068	0.127	0.079	0.005
17	-0.059	-0.054	-0.144	0.031	0.637	0.016	-0.100	0.104	-0.006	0.001
18	0.059	0.005	0.163	-0.053	0.620	0.016	0.091	0.026	0.009	-0.005
19	-0.001	-0.069	0.074	0.047	0.602	0.024	0.071	0.026	0.034	-0.002
20	0.003	-0.067	-0.085	0.034	0.584	0.033	-0.028	0.039	0.024	0.002
21	0.072	0.010	-0.131	-0.023	0.565	0.021	-0.003	0.122	0.001	-0.001

Table 3 : GARCH (1,1) Parameter Estimation

Country	W	a1	b1	a1 + b1
Japan	4.5745E-06	0.055547	0.93809	0.993637
Hong Kong	3.5906E-06	0.041443	0.91558	0.957023
India	0.000015367	0.258770	0.68556	0.944330
South Korea	0.000003877	0.089008	0.88052	0.969528
China	5.9885E-06	0.067509	0.90700	0.974509
Taiwan	3.4075E-06	0.508900	0.91437	1.423270
Singapore	1.9518E-06	0.145230	0.83679	0.982020
Malaysia	3.6002E-06	0.034227	0.95450	0.988727
Thailand	0.00020052	0.101620	0.00002	0.101640
Indonesia	0.000012817	0.094036	0.84160	0.935636

Table 4 : L - jung Box Test Results

Country	10 lag	15 lag	20 lag
Japan	18.3	24.99	31.41
Hong Kong	6.49	14.22	17.55
India	16.72	27.29	47.95
South Korea	9.8	12.69	14.75
China	12.86	21.26	27.98
Taiwan	19.97	29.15	29.84
Singapore	13.6	16.71	23.22
Malaysia	12.95	19.21	26.86
Thailand	20.49	26.69	27.17
Indonesia	7.98	17.37	33.79
Statistic Value	**18.3070**	**24.9958**	**31.4104**

Table 5 : L - jung Box squared Test Results

Country	10 lag	15 lag	20 lag
Japan	18.3	24.99	31.41
Hong Kong	6.49	14.22	17.55
India	16.72	27.29	47.95
South Korea	9.8	12.69	14.75
China	12.86	21.26	27.98
Taiwan	19.97	29.15	29.84
Singapore	13.6	16.71	23.22
Malaysia	12.95	19.21	26.86
Thailand	20.49	26.69	27.17
Indonesia	7.98	17.37	33.79
Statistic Value	**18.3070**	**24.9958**	**31.4104**

Table 6 : Engle Arch Test Results

Country	10 lag	15 lag	20 lag
Japan	29.18	32.65	36.22
Hong Kong	18.27	20.66	26.26
India	62.41	80.21	83.32
South Korea	25.47	30.79	35.69
China	12.25	18.69	23.26
Taiwan	25.16	30.8	35.2
Singapore	39.91	46.4	53.8
Malaysia	18.1	24.58	33.31
Thailand	35.81	35.9	36.54
Indonesia	31.93	34.91	42.87
Statistic Value	**18.3070**	**24.9958**	**31.4104**

Table 7 : Predicted Volatility for 150 days for the 10 sample countries

Country	per day	30 day	60 days	90 days	120 days	150 days
Japan	2.68	2.23	1.85	1.54	1.28	1.07
Hong kong	0.91	0.25	0.07	0.03	0.01	0.01
India	1.66	0.32	0.08	0.04	0.03	0.03
South Korea	1.13	0.45	0.19	0.08	0.04	0.02
China	1.53	0.72	0.34	0.17	0.09	0.05
Taiwan	0.28	0.11	445566898.8	1.7682E+13	7.01699E+17	2.78E+22
Singapore	1.04	0.61	0.36	0.21	0.13	0.08
Malaysia	1.79	1.28	0.92	0.66	0.48	0.35
Thailand	1.49	0.02	0.02	0.02	0.02	0.02
Indonasia	1.41	0.21	0.05	0.02	0.02	0.02

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