Modeling Hong Kong Stock Market Volatility

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INTRODUCTION

Volatility is a key parameter used in many financial applications, from derivatives valuation to asset management and risk management. Volatility refers to the ups and downs in the stock prices. Volatility in the stock return is an integral part of the stock market, with the alternating bull and bear phases. Without volatility, superior returns cannot be earned. However, too much volatility is considered as a symptom of an inefficient stock market. Higher the volatility, the higher the risk. Volatility of returns in financial markets can be a major stumbling block for attracting investment in small developing economies. It has an impact on business investment spending and economic growth through a number of channels. Moderate returns, high liquidity & low level of volatility are considered as symptoms of a developed markets. Low volatility is preferred as it reduces an unnecessary risk borne by investors, thus enabling market traders to liquidate their assets without large price movements.

The rise and the fall in share prices are linked to a number of reasons such as political climate, economic cycle, economic growth, international trends, budget, general business conditions, company profits, product demand, etc. Investment decisions are governed significantly by this volatility apart from other interdependent factors like price, volume traded, stock liquidity, among many others.

Volatility estimation is important for several reasons: Investment decisions, as characterized by asset pricing models, strongly dependent on the assessment of future returns and risk of various assets. The pricing of options is based on expected volatility of a security. Various linear and nonlinear methods by which volatility can be modeled have been developed in the literature and extensively applied in practice to describe the stock return volatility.

The distribution of financial time series shows certain characteristics such as:

1. Leptokurtosis: i.e. fat tails as compared to normal distribution.

2. Volatility Clustering: Statistically, volatility clustering implies a strong autocorrelation in returns. Large changes tend to be followed by large changes, and small changes tend to be followed by small changes

3. Heteroskedasticity: i.e. non- constant variance.

Economic time series have been found to exhibit periods of unusually large volatility followed by periods of relative tranquility (Engle, 1982). In such circumstances, the assumption of constant variance (homoskedasticity) is inappropriate (Nelson, 1991).

This requires models that are capable of dealing with the volatility of the market (and the series). One of the most prominent tools for capturing such changing variance was the Autoregressive Conditional Heteroskedasticity (ARCH) and Generalized ARCH (GARCH) models developed by Engle (1982), and Bollerslev (1986) respectively.

Following the introduction of models of ARCH by Engle (1982), and their generalization by Bollerslev (1986), there have been numerous refinements of the approach to modelling conditional volatility to better capture the stylized characteristics of the data. The GARCH (1, 1) is often considered by most investigators to be an excellent model for estimating conditional volatility for a wide range of financial data (Bollerslev, Ray and Kenneth, 1992).

However, there are some features of the financial time series data, which cannot be captured by symmetric ARCH and GARCH models. The most interesting feature not addressed by these models is the *"leverage effect"*, where the conditional variance tends to respond asymmetrically to positive and negative shocks in returns.

These asymmetric effects are captured by models such as the Exponential GARCH (EGARCH) of Nelson (1991), the so-called GJR model of Glosten, Jagannathan, and Runkle (1993). Asymmetric effects were discovered by Black

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(1976) and confirmed by the findings of French, Schwert, and Stambaugh (1987); Schwert (1990); and Nelson (1991), among others.

This so called Leverage Effect appears firstly in Black (1976), who noted that: *"A drop in the value of the firm will cause a negative return on its stock, and will usually increase the leverage of the stock , which will cause a rise in the debt-equity ratio , which will surely mean a rise in the volatility of the stock"*.

A very simple but plausible explanation for the leverage effect is : Negative returns imply a larger proportion of debt through a reduced market value of the firm, which leads to a higher volatility. The risk, i.e. the volatility reacts first to larger changes of the market value; nevertheless it is empirically shown that there is a high volatility after smaller changes. On the other hand, Black said nothing about the effect of positive returns on the volatility. Although the positive returns cause smaller increases, they do cause an increase in the volatility.

The characteristics of the Hang Seng return series are consistent with the above characteristics of financial time series. The aim of this article is to track and model the volatility of Hong Kong stock Market by exploring the features of its return structure.

REVIEW OF LITERATURE

Much of the literature is present on modeling the volatility of the developed markets, but no sufficient literature is available on modeling the volatility of the emerging economies. However, recently, a few studies have been made on modelling the stock market volatility of the Indian market, but most of the studies are limited to modeling the symmetries of the market.

Madhusudan Karmakar (2003), explained the heteroskedastic behavior of the Indian stock market using '*vanilla*' GARCH (1, 1) model for a period of about 24 years from January 1980 to June 2003.

Madhusudan Karmakar (2005), estimated conditional volatility models in an effort to capture the salient features of stock market volatility in India and evaluated them in terms of out-of sample forecast accuracy. The paper also investigated whether there is any leverage effect in the Indian stock market. The results reported the presence of leverage effect, but which model can best capture the leverage effect has been left for further research.

Rousan Raya, AL-Khouri, Ritab (2005), attempted to investigate the volatility of the Jordanian emerging stock market using daily observations from Amman Stock Exchange Composite Index (ASE) for the period from January 1, 1992 through December 31, 2004. The nature of the time series suggested ARCH and GARCH models as the best to capture the characteristics of ASE. Furthermore, no asymmetry was found in the returns and hence, both good and bad news of the same magnitude have the same impact on the volatility level. Moreover, the volatility persists in the market for a long period of time, which makes ASE market inefficient; therefore, returns can be easily predicted and forecasted.

Alberg et al. (2006) estimated stock market volatility of Tel Aviv Stock Exchange indices, for the period 1992-2005, using asymmetric GARCH models. They reported that the EGARCH model is the most successful in forecasting the TASE indices.

Banerjee Ashok & Sahadeb Sarkar (2006), attempted to model the volatility in the daily return in the Indian stock market. They found that the Indian stock market experience volatility clustering and hence GARCH-type models predict the market volatility better than simple volatility models, like the historical average, moving average, etc. They also observed that the asymmetric GARCH models provide better fit than the symmetric GARCH model, confirming the presence of the leverage effect. They also found that the change in volume of trade in the market directly affects the volatility of asset returns, & the presence of FII in the Indian stock market does not appear to increase the overall market volatility.

Bhaskkar Sinha(2006), in an attempt to model stock market volatility of Indian markets and to capture the asymmetric effects, found the EGARCH model best for modeling volatility clustering and persistence of shock at BSE sensex and GJR-GARCH for NSE nifty.

Caiado, Jorge (2007),modelled the volatility for daily and weekly returns of the Portuguese Stock Index PSI-20 by using simple GARCH, GARCH-M, Exponential GARCH (EGARCH) and Threshold ARCH (TARCH) models & found that there are significant asymmetric shocks to volatility in the daily stock returns, but not in the weekly stock returns. They also found that some weekly returns time series properties were substantially different from properties of daily returns, and the persistence in conditional volatility is different for some of the sub-periods referred to. Finally, they compared the forecasting performance of the various volatility models in the sample periods before and after the terrorist attack on September 11, 2001.

Jordaan, Grové, Jooste A & Z G Alemu(2007), modelled the volatility of daily spot prices of the crops traded on the South African Futures Exchange (yellow maize, white maize, wheat, sunflower seed and soybeans). The volatility in the prices of white maize, yellow maize, and sunflower seed have been found to vary over time, suggesting the use of the GARCH approach in these cases. The volatility in the prices of wheat and soybeans was found to be constant over time; hence, the standard error of the ARIMA process was used.

Karmakar Madhusudan(2007) investigated the heteroscedastic behaviour of the Indian stock market through market index S&P CNX Nifty for 14.5 years from July 1990 to December 2004, using different GARCH models. First, the standard GARCH approach has been used to investigate whether stock return volatility changes over time and if so, whether it is predictable. Then, the EGARCH models were applied to investigate whether there is asymmetric volatility. Finally, (E) GARCH in the mean extension had been used to examine the relation between market risk and expected return. The study reports an evidence of time varying volatility, which exhibits clustering, high persistence and predictability. It is found that the volatility is an asymmetric function of past innovation, rising proportionately more during the market decline. It is also evidenced that return is not significantly related to risk.

Rajni Mala & Mahendra Reddy(2007) modeled the stock market volatility of Fiji's stock market, an emerging economy using ARCH/GARCH techniques for a period of 5 years from 2001-2005.

Marta Casas & Cepeda Edilberto(2008), explained the ARCH, GARCH, and EGARCH models and the estimation of their parameters using maximum likelihood. The study concluded based on AIC & BIC criterion that GARCH (1,2) best explains the performance of stock prices and EGARCH (2,1) best explains the returns series.

Khedhiri Sami, Muhammad Naeem (2008) investigated the volatility characteristics of the UAE stock markets measured by fat tail, volatility clustering, and leverage effects, in order to explore a parsimonious model for the UAE stock market and predict its future performance. He used EGARCH, TGARCH and other class of ARCH techniques to model the volatility.

Surya Bahadur G.C. (2008) modeled the volatility of the Nepalese stock market using daily returns from July 2003 to Feb 2009 and different classes of estimators and volatility models. The empirical findings did not report any significant asymmetry in the returns and thus suggests the GARCH (1,1) model as most appropriate for modeling the heteroskedasticity and volatility clustering in the Nepalese stock market. It also reported high persistence of volatility in the Nepalese stock market.

Floros Christos (2008), employed the simple GARCH model, as well as exponential GARCH, threshold GARCH, asymmetric component GARCH, the component GARCH and the power GARCH model using daily data from Egypt (CMA General index) and Israel (TASE-100) index to model the stock market volatility and concluded that increased risk will not necessarily lead to a rise in the returns. The most volatile series is CMA index from Egypt, because of the uncertainty in prices (and economy) over the examined period.

Yalama Abdullah & Guven Sevil (2008) attempted to forecast world's stock market volatility by employing seven different GARCH class models to forecast in-sample of daily stock market volatility in 10 different countries. The results of the study emphasized that the class of asymmetric volatility models perform better in forecasting stock market volatility than the historical models.

Hakim Ali Kanasro, Chandan Lal Rohra, Mumtaz Ali Junejo (2009), examined the presence of volatility at the Karachi Stock Exchange (KSE) by analyzing two Indexes namely;'KSE-100 Index' and 'All shares index through the use of GARCH family models introduced by Engle (1982), Bollerslev (1986) and Nelson (1991). The empirical results confirmed the presence of high volatility at Karachi Stock Exchange throughout the study period.

K.N Badhani (2009) analyzed the closing values of S&P 500 index and S&P CNX Nifty from Jan 1996 to Sept. 2008 in order to find out the impact of return & volatility in US on Indian stock market using AR (1)-TGARCH (1, 1) process. Among other objectives, the study aimed at finding out whether the Indian stock market reacts differently towards positive and negative shocks from the US market. He concluded that the returns in the Indian stock market are more sensitive to negative shocks in the US market (rather than to the positive shocks).

Marius Matei (2009) evaluated the main forecasting techniques with the motive to offer support for the rationale behind the idea: GARCH is the most appropriate model to use when one has to evaluate the volatility of the returns of groups of stocks with large amounts (thousands) of observations. The appropriateness of the model was seen through a unidirectional perspective of the quality of volatility forecast provided by GARCH, when compared to any other alternative model, without considering any cost component.

Hojatallah Goudarzi & C. S. Ramanarayanan (2010), examined the volatility of the Indian stock markets and its related stylized facts using ARCH models. The BSE500 stock index was used to study the volatility in the Indian stock market over a 10-year period. Two commonly used symmetric volatility models, ARCH and GARCH were estimated, and the fitted model of the data, was selected using the model selection criterion such as SBIC and AIC. The adequacy of the selected model was tested using ARCH-LM test and LB statistics. The study concluded that GARCH (1, 1) model explains volatility of the Indian stock markets and its stylized facts, including volatility clustering, fat tails and mean reverting, satisfactorily.

Majority of the studies on modeling volatility have found non- linear models such as ARCH & GARCH as the best. The return series exhibit all the characteristics of financial time-series data appropriate for using GARCH class models. Most of the studies on modeling volatility related to having found the GARCH (1, 1) model as the best to capture the symmetric effects, effects for which EGARCH model is the most preferred model to capture the asymmetric effects. However, the choice of the best model also depends on the models included for evaluation. Volatility persistence has also been found in the emerging economies by the studies under consideration.

RESEARCH METHODOLOGY

Traditionally, volatility modeling techniques were based on the assumption of homoscedasticity and were not able to capture the changing variance i.e. heteroskedasticity found in the returns. So more sophisticated models needed to be developed to capture such effects and leave the errors white noise. Thus, non linear models such as ARCH/GARCH were developed to capture the features of the financial time series. The following GARCH techniques have been used to capture the volatility:

GARCH (1, 1)

$$\sigma^2_t = \alpha_0 + \alpha_1 \varepsilon^2_{t-1} + \beta_1 \sigma^2_{t-1}$$

The GARCH specification, firstly, proposed by Bollerslev (1986), formulates the serial dependence of volatility and incorporates the past observations into the future volatility (Bollerslev et al. (1994).

News about volatility from the previous period can be measured as the lag of the squared residual from the mean equation (ARCH term). Also, the estimate of β shows the persistence of volatility to a shock or, alternatively, the impact of old news on volatility.

EGARCH (1, 1):

Proposed by Nelson (1991) & is given by the following equation:

$$\text{In}\,(\sigma^2_t) = \alpha_0 + \alpha_1 \ln\,(\sigma^2_{t-1}) + \beta_1 \left|\frac{u_{t-1}}{\sigma_{t-1}}\right| + \gamma\ \frac{u_{t-1}}{\sigma_{t-1}}$$

The logarithmic form of the conditional variance implies that the leverage effect is exponential (so the variance is non-negative). The leverage effect is denoted by γ and is present if γ is significantly negative.

TARCH (1, 1):

The Threshold-GARCH model was introduced by Zakoian (1994) and Glosten, Jaganathan and Runkle (1993). The TGARCH specification for the conditional variance is given by:

$$\sigma^2_2 = \alpha_0 + \alpha_1 u^2_{t-1} + \beta_1 \sigma^2_{t-1} + \gamma\, u^2_{t-1} I_{t-1}$$

where:

Where leverage effect is captured by γ. For a leverage effect, we would see γ>0 i.e. γ is significantly positive.

PARCH (1, 1):

Power-GARCH model was proposed by Ding *et al.* (1993). In the Power-GARCH model, the power parameter β of the standard deviation can be estimated rather than imposed, and the optional γ parameters are added to capture asymmetry.

$$\sigma^{\beta}_t = u + \beta \sigma^{\beta}_{t-1} + \gamma\,(|e_{t-1}| - \gamma e_{t-1})^{\beta}$$

Leverage effect is present if $\gamma \neq 0$

DATA & PRELIMINARY STATISTICS

To model the volatility of Hong Kong Stock Market, the researchers have used daily closing prices of the most popular stock index i.e. Hang Seng Index (HSI) as the proxy to the Hong Kong stock market. HSI represents about 67% of the capitalization of the Hong Kong Stock Exchange. The data used ranges for a period of ten years starting from 1st

October 2000 to 30th September 2010. The data has been collected from www.yahoofinance.com and has been analyzed using Eviews 5 software.

ANALYSIS OF DATA

Table 1 provides the result of ADF test statistic. Table 2 provides the descriptive statistics of the return series. Figure 1 and Figure 2 are graphs of the non - stationary and stationary return series. Table 11 reports the consolidated results of the various GARCH family models used in the analysis. Table 12 & Table 13 are given in the appendix. Table 12 reports the results of ARCH LM Test on GARCH (1,1) residuals and Table 13 relates to the descriptive statistics of the residuals of GARCH (1, 1) model. The Graph of the closing price series is shown in Figure 1 below. The graph of the series does not show a constant mean and thus, reports non stationarity of the data.

Figure 1: Graph of Closing Price Series

To make the series stationary, daily logarithmic returns have been calculated from the closing price series as follows:
Where
$r_t = \log(p_t - p_{t-1})$

Figure 2: Graph Of The Return Series

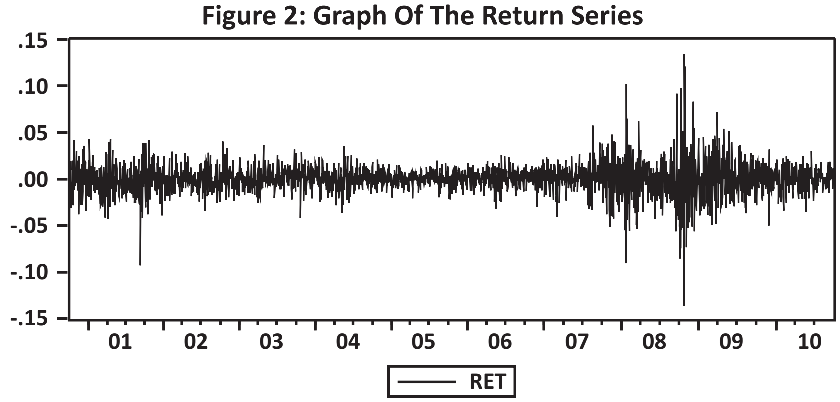


Table 1: The result of the ADF Test

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-51.34497	0.0001
Test critical values:	1% level	-3.432784	
	5% level	-2.862501	
	10% level	-2.567327	
*MacKinnon (1996) one-sided p-values.			

r_t = continuously compounded logarithmic return.

p_t =daily closing value of index at day t and,

p_{t-1} =closing value of index at day t-1.

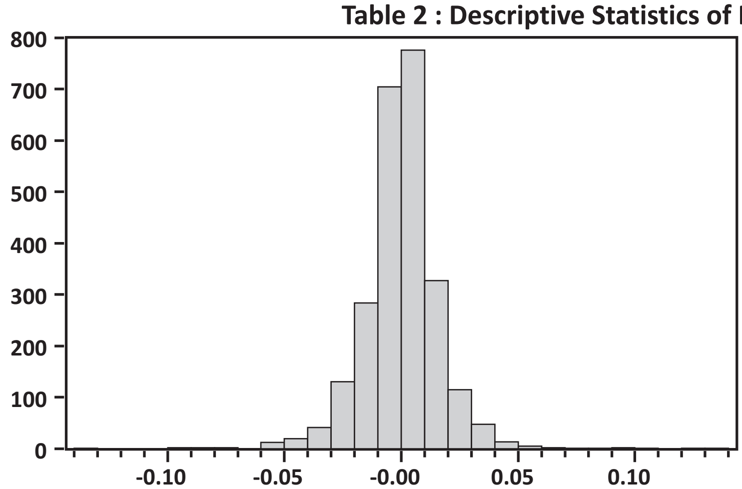
Thus, the closing value of the index is converted into continuously compounded daily logarithmic return series. Logarithmic returns are calculated since it improves the statistical properties of the data.

The stationarity of the series can also be confirmed using the Augmented Dickey Test statistic assuming H_o of non stationarity (Table 1).

The low p value of the t statistic calls for rejecting the null hypothesis of unit root and accepting the alternate of stationarity.

The graph of the return series is shown in Figure 2, with the constant mean showing the stationarity of the data. The series has a non constant variance i.e. heteroskedasticity, which is the typical feature of the financial time series data. Also, volatility clustering in the returns can also be easily seen. If we look at the Figure 2, we can easily see that the large changes tend to be followed by large changes, and small changes tend to be followed by small changes, which means that volatility is clustering, and the series vary around the constant mean, but the variance is changing with time. Thus, the return series follow the characteristics of the financial time series data i.e. heteroskedasticity, leptokurtosis & volatility clustering, which means that the linear model will not be able to capture the volatility of the series, therefore, non linear models such as ARCH/GARCH have been used for modelling the volatility of the Hong Kong stock market.

Table 2 : Descriptive Statistics of Return Series



Series:RET
Sample10/03/2000 9/29/2010
Observations2489

Mean	0.000142
Median	0.000304
Maximum	0.134068
Minimum	-0.135820
Std. Dev.	0.016444
Skewness	0.032021
Kurtosis	11.48255
Jarque-Bera	7462.622
Probability	0.000000

As evident from Table 2, the return of series is around 0.0142%, with a standard deviation of 1.63%, which indicated large variability in the mean returns. Furthermore, there are also a lot of variations between the maximum & the minimum return values.

Table 3: Correlogram: Residuals of Returns

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
| |	| |	1	-0.009	-0.009	0.2051	
| |	| |	2	0.010	0.010	0.4479	
| |	| |	3	-0.002	-0.002	0.4580	0.499
| |	| |	4	0.001	0.001	0.4597	0.795
| |	| |	5	-0.036	-0.036	3.7201	0.293
| |	| |	6	0.036	0.035	6.9624	0.138
| |	| |	7	0.023	0.024	8.2482	0.143
| |	| |	8	0.024	0.024	9.7007	0.138
| |	| |	9	-0.033	-0.033	12.369	0.089

Table 4 : Correlogram: Squared Residuals of Returns						
Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
|*** |	|*** |	1	0.374	0.374	348.50	
|*** |	|** |	2	0.369	0.267	688.45	
|*** |	|* |	3	0.352	0.189	997.53	0.000
|** |	| |	4	0.216	-0.016	1114.2	0.000
|** |	| |	5	0.213	0.028	1227.4	0.000
|* |	| |	6	0.165	0.003	1295.1	0.000
|* |	|* |	7	0.193	0.087	1388.5	0.000
|** |	|* |	8	0.247	0.141	1541.3	0.000
|* |	| |	9	0.183	0.017	1625.2	0.000
|** |	|* |	10	0.277	0.125	1816.8	0.000
|** |	| |	11	0.246	0.050	1968.6	0.000
|** |	| |	12	0.212	0.014	2081.1	0.000
|** |	|* |	13	0.255	0.067	2244.3	0.000
|** |	| |	14	0.221	0.045	2367.1	0.000
|* |	| |	15	0.167	-0.036	2436.8	0.000
|* |	| |	16	0.169	-0.006	2508.0	0.000
|* |	| |	17	0.115	-0.040	2541.1	0.000
|* |	| |	18	0.156	0.035	2602.4	0.000
|* |	| |	19	0.133	0.013	2646.8	0.000
|* |	| |	20	0.091	-0.052	2667.5	0.000
|* |	| |	21	0.115	-0.027	2700.9	0.000
|* |	| |	22	0.113	0.010	2733.1	0.000
|* |	| |	23	0.122	0.023	2770.4	0.000
|* |	| |	24	0.129	0.014	2812.3	0.000
|* |	| |	25	0.143	0.046	2863.6	0.000
|* |	| |	26	0.182	0.063	2946.5	0.000
|* |	| |	27	0.136	-0.005	2992.8	0.000
|* |	| |	28	0.145	0.018	3046.0	0.000
|* |	| |	29	0.165	0.046	3114.4	0.000
|* |	| |	30	0.139	0.034	3162.8	0.000
|* |	| |	31	0.161	0.053	3228.2	0.000
|* |	*| |	32	0.094	-0.063	3250.3	0.000
|* |	| |	33	0.140	0.038	3299.8	0.000
|* |	| |	34	0.103	-0.019	3326.3	0.000
|* |	| |	35	0.093	-0.001	3348.2	0.000
|* |	| |	36	0.096	-0.031	3371.5	0.000

The positive skewness of the series indicates that there is more probability of earning a positive return and is also indicative of the presence of asymmetries in the returns. The kurtosis of the series is greater than 3, which means that the return series is fat tailed & does not follow a normal distribution, which has been further confirmed by Jarque Bera Test statistic.

Table 5: ARCH LM test at lag 5			
F-statistic	148.4744	Prob. F(5,2477)	0.000000
Obs*R-squared	572.5681	Prob. Chi-Square(5)	0.000000

MODELLING THE MEAN

ARMA (1, 1) model has been used by using Box Jenkins methodology to model the conditional mean equation. The residuals of the equation, when tested using LJUNG BOX Q Statistic showed no correlation (Table 3) upto the 9^{th} lag, but the squared residuals showed a high degree of significant correlation (Table 4).

These residuals were further tested for ARCH effects by using ARCH LM Test. The F statistic reported by ARCH LM Test is significant at 5%, and thus rejects the null hypothesis of no heteroskedasticity, suggesting the use of non linear models for capturing the volatility.

MODELING THE CONDITIONAL VARIANCE

Since the ARCH LM test confirms the presence of ARCH effects, the researchers have used the GARCH (1, 1) model to capture the conditional variance of the series. GARCH (1, 1) is the most popular model amongst all GARCH class models. The result of the GARCH (1, 1) model using t Distribution is given in the following Table 6.

Table 6: GARCH (1, 1)				
	Coefficient	**Std. Error**	**z-Statistic**	**Prob.**
C	9.86E-07	4.17E-07	2.366263	0.0180
RESID(-1)^2	0.059497	0.008494	7.004558	0.0000
GARCH(-1)	0.936905	0.008735	107.2604	0.0000
T-DIST. DOF	8.915969	1.568274	5.685212	0.0000

The consolidated results of different models are given in the Table 11 . All the coefficients of the variance equation are highly significant. Table 12 given in the appendix gives the result of ARCH LM Test at lag 20, and does not reject the null of no heteroskedasticity. So GARCH (1, 1) model can be interpreted as the most appropriate for modeling the variance of the return series.

The sum of $\sigma + \beta = 0.996402$, which shows high persistence in volatility. i.e. a shock in the present will have a long lasting effect on the future returns, and the half life of shock would be approximately 192 days. The half life of

Table 7: Arch In Mean				
	Coefficient	**Std. Error**	**z-Statistic**	**Prob.**
@SQRT(GARCH)	-9.83E-05	0.056933	-0.001727	0.9986
C	0.000605	0.000657	0.919644	0.3578
AR(1)	-0.862865	0.103779	-8.314446	0.0000
MA(1)	0.875657	0.099466	8.803561	0.0000
	Variance Equation			
C	9.86E-07	4.17E-07	2.363413	0.0181
RESID(-1)^2	0.059495	0.008533	6.972797	0.0000
GARCH(-1)	0.936907	0.008767	106.8676	0.0000
T-DIST. DOF	8.915797	1.571806	5.672328	0.0000
R-squared	-0.000406	Mean dependent var		0.000138
Adjusted R-squared	-0.003229	S.D. dependent var		0.016446
S.E. of regression	0.016473	Akaike info criterion		-5.828063
Sum squared resid	0.672961	Schwarz criterion		-5.809352
Log likelihood	7258.111	Durbin-Watson stat		2.081678

volatility persistence has been calculated by using the following formula: ln0.5/ln ($\alpha+\beta$).

The residuals of the GARCH(1, 1) model do not show any heteroskedasticity, but the normality test of standardized residuals (as given in Table 13 in the appendix) shows that the returns are negatively skewed. This skewness could be attributed due to the presence of asymmetric effects in returns, which can be tested using a model such as EGARCH, TGARCH and PARCH. Before modelling the asymmetries, the researchers have presented another feature of the return in the Hong Kong stock market.

ARCH IN MEAN

To capture another feature of the Hong Kong stock market, i.e to know if higher risk provides for earning a higher return, the researchers included standard deviation in the mean equation. The results of the test are presented in the Table 7. The coefficient of the risk term incorporated into the mean equation (as GARCH coefficient) is negative, implying a negative relationship between risk and return, but the relationship is statistically highly insignificant, which means that increased risk does not necessarily lead to rise in mean return. i.e. it does not provide any risk premium.

Table 8 : TARCH (1, 1):

	Coefficient	Std. Error	z-Statistic	Prob.
C	1.64E-06	4.58E-07	3.589567	0.0003
RESID(-1)^2	0.020880	0.009816	2.127133	0.0334
RESID(-1)^2*(RESID(-1)<0)	0.078345	0.013771	5.689340	0.0000
GARCH(-1)	0.931244	0.009535	97.66312	0.0000
T-DIST. DOF	9.848332	1.909094	5.158643	0.0000

MODELING THE ASYMMETRIES

The limitation of symmetric models is that they variance is not affected by the sign of the past error terms. In order to capture the asymmetries, three competing models have been used: TARCH (1, 1), EGARCH (1, 1) and PARCH (1, 1) models using t distribution. The aim is to find out the best model out of the three, which can capture the asymmetries of the Hong Kong Stock Exchange. The results provided by the different asymmetric models are reported in Tables 8, 9 and 10.

Table 9 : EGARCH (1, 1)

	Coefficient	Std. Error	z-Statistic	Prob.
C(4)	-0.192615	0.031014	-6.210528	0.0000
C(5)	0.126898	0.017077	7.430751	0.0000
C(6)	-0.062342	0.010686	-5.833834	0.0000
C(7)	0.989120	0.002787	354.9666	0.0000
T-DIST. DOF	9.525150	1.794216	5.308808	0.0000

The coefficients of the variance equation are significant at the 5% level. The asymmetric factor γ is significant and is

Table 10 : PARCH(1,1)

	Coefficient	Std. Error	z-Statistic	Prob.
C(4)	8.66E-05	9.16E-05	0.944658	0.3448
C(5)	0.065865	0.010032	6.565628	0.0000
C(6)	0.508294	0.107402	4.732620	0.0000
C(7)	0.935770	0.008567	109.2276	0.0000
C(8)	1.136709	0.219836	5.170712	0.0000
T-DIST. DOF	9.785242	1.904241	5.138657	0.0000

positive suggestive of the presence of the leverage effect. The σ+β=0.952124 i.e. the sum of ARCH & GARCH terms shows a very high persistence in volatility. Here also, the coefficients of the variance equation are significant. The asymmetric factor is significantly negative, indicating the presence of the leverage effect. The ARCH & GARCH coefficients sum up to more than 1, suggestive of an integrated process and show high persistence in volatility.

Table 11: Consolidated Results Of Various Models

	GARCH(1,1)	EGARCH(1,1)	TGARCH(1,1)	PARCH(1,1)
MEAN	0.000603*	0.000455*	0.000416**	0.000428**
AR(1)	-0.862868*	0.302194**	-0.853870*	0.290446**
MA(1)	0.875658*	-0.284905**	0.868552*	-0.274202**
CONSTANT	9.86E-07*	-0.192615*	1. 64E-06*	8.66E-05**
ARCH TERM	0.059497 *	0.126898*	0.020880*	0.065865*
GARCH T[1] ERM	0.936905 *	0.989120*	0. 931244 *	0.935770*
ASSYMETRIC TERM	-	-0.062342*	0. 078345 *	0.508294*
AIC	-5.828867	-5.840603	-5.840302	-5.819767
LL	7258.111	7273.710	7273.336	7274.977

[1],*implies Significance Of Coefficients At 5% Level
**implies insignificance

The significance of the coefficients of the variance equation of the asymmetric models points towards the leverage effect in the Hong Kong stock market. In the PARCH (1, 1) model as well, we can see that the sum of alpha & beta coefficients turn up around more than 1, suggestive of an integrated volatility. The high persistence in volatility is indicative of inefficiency of the Hong Kong stock market.

The coefficient of the constant term is, however, insignificant at 5%, but the insignificance of the constant term does not affect much as the constant term has no natural interpretation. It captures the mean of the dependent variable as well as the average effects of the omitted variables. Therefore, the general rule is to ignore the insignificance of the constant term. Consolidated results of the various model are reported in the Table 11.

The results of Table 11 indicate that EGARCH (1, 1) model is the best in modeling the conditional variance of the Hong Kong Stock Market, as per Akaike Criterion & Log Likelihood Method. AIC is the least for this model, and Log Likelihood though is not the highest, but favors this model.

SUMMARY

The returns series in Hong Kong stock market exhibit characteristics such as volatility clustering, heteroskedasticity & excess peakedness, which can be best captured by using non linear models. GARCH (1, 1) model has been found to be best for modeling the symmetric volatility. The study shows that return reacts differently to different news. Bad news increases volatility more than good news. So the return series show 'leverage effect' and amongst asymmetric models, EGARCH (1, 1) model has been found as best as per AIC & LL criterion. The long persistence in volatility indicates that Hong Kong market is inefficient, and information is not reflected in stock prices quickly. Also, results of ARCH-in-mean model shows that the market does not provide for any risk premium. i.e. investors taking higher risk are not compensated by high returns in the short run.

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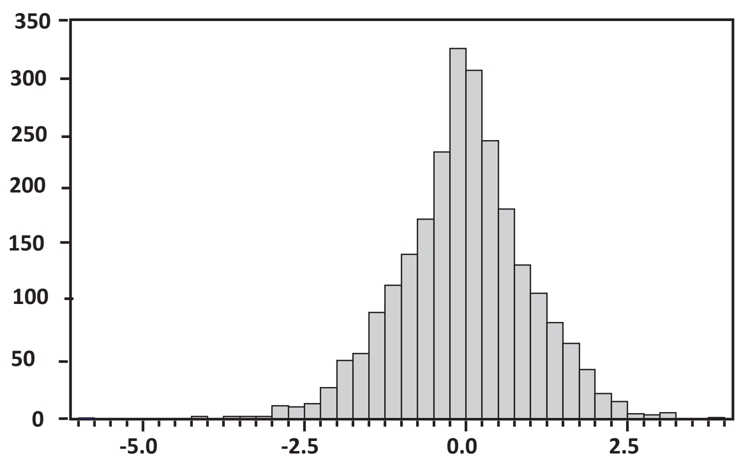
APPENDIX

Table 12: ARCH LM TEST (at lag 20)			
F-statistic	1.400765	Prob. F(20,2447)	0.110387
Obs*R-squared	27.93589	Prob. Chi-Square(20)	0.110926

Table 13: Descriptive statistics of GARCH (1, 1) Residuals:



Series: Standardized Residuals
Sample 10/05/2000 9/29/2010
Observations 2488

Mean	-0.034863
Median	-0.018669
Maximum	3.795369
Minimum	-5.750390
Std. Dev.	0.998349
Skewness	-0.194310
Kurtosis	3.957337
Jarque-Bera	110.6662
Probability	0.000000