

Estimating Stock Return Volatility in Indian and Chinese Stock Market

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Abstract

Investors step into the stock market with the objective of earning smart returns on their investments. The stock market can help in realising these goals of the investors, however, all investments are subject to risks. The origin of the risk is the uncertainty of realising the desired returns on the investment. This aspect is known as risk of the investment. This paper aims to search the best model to estimate and forecast volatility of Indian and Chinese stock market. The data for the paper is related to the two main indices of Indian Stock Market namely, SENSEX and NIFTY and two indices of Chinese stock market, namely, Shenzhen composite index and Shanghai composite index for the period July 2003 to June 2013. We applied symmetrical as well as asymmetrical GARCH models to the data. Among all the three models i.e. GARCH, EGARCH and TARCH, we found the GARCH (1,1) model as the best model to estimate and forecast the volatility of Chinese stock market for both the daily and weekly return series. For the Indian stock market, the recommended volatility estimation and forecasting model is EGARCH model that captures the leverage effect. We did not find volatility clustering and leverage effect for the monthly return series for both Indian and Chinese stock market. Thus, it is suggested to use the traditional time invariant volatility models for the monthly return series.

Keyword: Stock Return Volatility, EGARCH, TARCH, GARCH Family Models, Asymmetric Volatility

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1. INTRODUCTION

1.1. Stock Return Volatility: The Concept

Volatility may be computed for a single asset or a portfolio of financial assets and even for the entire stock market. The volatility measuring has been very active area in the field of finance. The main characteristics of the financial time series of stock return observed are as follows:

First, financial time series are often leptokurtic which means that the distribution of their returns is fat-tailed i.e. relative high probability for extreme values.

Second, large changes in return tend to be followed by large changes and small changes tend to be followed by small changes, which mean that volatility clustering is observed in financial returns data.

Third, changes in stock prices tend to be negatively correlated with changes in volatility (i.e. volatility is higher after negative shocks than after positive shocks of same magnitude) which is called “leverage effect”.

To capture the above characteristics, ARCH models were introduced by Engle (1982) and generalized as GARCH (Generalized ARCH) by Bollerslev (1986). These models are widely used in financial econometrics, especially in financial returns time series analysis.

Stock return volatility has been examined in detail for the developed markets such as US, UK, Germany, France etc. by Black (1976), Christie (1982), French, Schwert and Stambaugh (1987), Akgiray (1989), Cheung and Ng

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(1992), Theodossiou and Lee (1995), Mougoni and White (1996), Franses and Van Dijk (1996), Duffee (2005), Noh and Kim (2006). However, the empirical literature for the Indian and Chinese stock markets is still limited to only a few comprehensive studies such as Song, Liu and Romilly (1998), Cheng Xu (2000), Yan, Wu and Chen (2003), Harvinder kaur (2004), Pandey (2005), Kumar (2006), Karmakar (2006), Banerjee & Sarkar (2006) Hongyu pna and Zhichao Zhang (2006), etc.

Most of the studies have been conducted in developed countries stock market and not much evidence was available from emerging economy's stock market. This paper attempts to measure and forecast stock return volatility in the context of Indian and Chinese stock market. Efforts are made to search for the appropriate GARCH model to capture the volatility clustering and also to identify other asymmetric volatility models to estimate stock return volatility of Indian and Chinese stock market.

The second section provides the review of literature. The third section provides the details regarding the data and methodology. The fourth section presents the empirical results. The fifth section provides summary and conclusions of the paper.

2. REVIEW OF LITERATURE

The literature on stock return volatility is very vast and covers a huge number of research papers over a period of time. The estimation and forecasting of volatility has changed in a big way from 1980s onwards because of designing of various sophisticated models of volatility.

French, Schwert and Stambaugh (1987) studied the inter-temporal relationship between stock return and volatility for the US market. They found that the expected market risk premium is positively related to the volatility of stock returns. This paper found various evidences of the positive relationship between expected risk premium of the stock and the level of volatility.

Akgiray (1989) used the GARCH (1, 1) model to estimate daily stock return volatility. The paper concluded that the GARCH (1, 1) model is a better model of volatility as compared to the historical volatility models which are used traditionally.

Cheung and Ng (1992) used the EGARCH model to study the leverage effect and found the negative relationship

between stock returns and one day future conditional volatility. The paper also found the shift in model parameters over a period of time; it indicates that the parameter estimation depends on the time period selected for building volatility model.

Song, Liu and Romilly (1998) research work aims at measuring and forecasting volatility in the Chinese stock market by taking the daily closing prices on the Shanghai and Shenzhen stock exchange. According to the *Authors*, the GARCH (1, 1) model with mean equation of ARMA (6,6) for Shanghai and ARMA (10,10) for Shenzhen are the best specifications for measuring volatility. The empirical result shows that all the parameters in the mean and variance equation are statistically significant and the estimated values of the parameters satisfy the various restrictions on which GARCH model is based. .

Laurence and Biqiong (2003) study concluded that "There appears to be no leverage effect in any of the four Chinese markets, which is not very surprising since local investors were probably justified in disregarding debt levels and the prospect of bankruptcy as minor dangers, at least for the earlier part of our data period. How far this result is attributable to the peculiar patterns of corporate ownership and governance in China is an issue that remains to be investigated". They also added that as the Chinese stock markets are still in nascent stage, so the relationship between volume and volatility in China was not very conclusive.

Kaur (2004) conducted a research on time varying nature of volatility of Indian stock market. The results show that the EGARCH (1, 1) is better for Sensex and TARCH (1, 1) for Nifty, the same models were used for assessing the impact of day of the week effect. There is no evidence of day of the week effect and month of the year effect in Indian stock market. There is also no conclusive evidence for return and volatility spill over between Indian and US market.

Pandey (2005) compares empirical performance of various unconditional volatility estimators and conditional volatility models (GARCH and EGARCH) using time-series data of S&PCNX NIFTY. The results indicate that while conditional volatility models provide less biased estimates, extreme-value estimators are more efficient estimators of realized volatility. As far as forecasting ability of models and estimators is concerned, conditional volatility models fare extremely poorly in forecasting five-day (weekly) or monthly realized volatility. In contrast,

extreme value estimators, other than the Parkinson estimator, perform relatively well in forecasting volatility over these horizons.

Kumar (2006) attempted to evaluate the forecasting ability of ten different volatility models for Indian stock market and foreign exchange market. The results of the study on the basis of various symmetric and asymmetric error statistics methods for evaluating various models show that the EWMA is a better model for forecasting volatility of Indian stock market. Overall it is GARCH (5, 1) that had come out as the best model of forecasting volatility of Indian foreign exchange market.

Karmakar (2006) measured the volatility of daily stock return in the Indian stock market over the period from 1961 to 2005. The TARCh model is also used to test the asymmetric volatility effect and the result suggests the asymmetry in volatility.

Banerjee & Sarkar (2006) conducted their research to model volatility by daily frequency data series and high frequency intraday data series. This study found that the FIIs do not have any magnifying effect on volatility of stock return and it conveys some important information for the market regulators to design their policies.

Deo and Kulkarni (2007) conducted the study of volatility and correlation in Indian stock market using random matrix theory (RMT). This study finds volatility clustering in Indian stock market.

Goudarzi and Ramanarayan (2011) conducted a study to analyse the effect of bad and good news on the Indian stock market volatility by applying the non asymmetric ARCH models. The data is related to BSE500 index for the time period starting from July 2000 to January 2009. The study found the leveraging effect in Indian stock market using BSE500 return series. This study shows that the Indian stock market does not remain unaffected by the global events and the financial integration of Indian economy with world economy is strengthening fast.

Kumar (2012) studied the statistical properties of the volatility index (VIX) of India. The *Authors* found that “VIX returns are negatively related to stock market returns and the leverage effect is only significant around the middle of the joint distribution. The asymmetric response of VIX is also not observed in the left tail and is significant again around the centre of the distribution.”

With this we conclude the review of relevant existing literature available on the stock return volatility which reflects that there is major shift towards usage of GARCH family models to estimate stock return volatility.

3. Data and Research Methodology

3.1 Data and their Sources

Secondary data is collected for the Indian and Chinese stock market. The indices that are selected for this paper from India are SENSEX i.e. sensitivity index of Bombay stock exchange and NIFTY i.e. the market index of 50 securities compiled by National stock exchange.

The two major indices from the Chinese stock market are Shenzhen composite index and Shanghai composite index. These are selected due to their ability to reflect the share price movements in Chinese stock market. These indices are computed by taking all the A-shares and B-shares of the respective stock exchanges.

The total time period of the paper covers the time span from July 2003 to June 2013, it is divided into two parts for the purpose of analysis. The first part starts from July 2003 to June 2012 which is in-sample time period and it is used to estimate the various parameters of volatility models. The second part covers the time period from July 2012 to June 2013 and it is used for out of sample forecasting and back testing of the volatility models. The data is collected in three frequencies i.e. daily, weekly and monthly frequencies. The time span is spread over ten years and it covers not only 2008 financial crises time period but also some years before and some after the financial crisis.

The data for the paper are collected from BSE website at <http://www.bseindia.com/>, NSE website at http://www.nseindia.com/index_nse.htm and Bloomberg database.

3.2 Research Methodology

3.2.1 Computation of Return

The logarithmic return is used for the data analysis and is given in equation 1 as follows:

$$r_{t+1} = \ln\left(\frac{P_{t+1}}{P_t}\right) = \ln(P_{t+1}) - \ln(P_t) \quad 1$$

The empirical studies have found that returns of financial assets exhibit limited liability, which is contrary to

the normal distribution. Since the normal distribution stretches from $-\infty$ to ∞ and the lower bound of -1 violates this property of normality.

3.2.2 Jarque-Bera Test

Jarque-Bera statistic test is test of normality and is given by equation 2:

$$JB = N * \left[\frac{S^2}{6} + \frac{(K-3)^2}{24} \right] \quad 2$$

Where N stands for the sample size, S is the coefficient of Skewness and K is for kurtosis. When the data is normally distributed, the JB statistics asymptotically follows Chi-square distribution. For this test, the null hypothesis is the joint hypothesis of zero value for skewness and excess kurtosis.

3.2.3 GARCH Model

Volatility of return may be defined as the variability of the return around its expected value.

The GARCH model is popularly used to capture volatility clustering. The following is the specification of GARCH model.

Let the mean equation 3 be:

$$r_t = \gamma + \epsilon_t \quad 3$$

Where γ is a constant and $\epsilon_t | I_{t-1} \sim N(0, \sigma_t^2)$

Where ϵ_t is conditional on the past information set and with time varying variance term and further assumption is that it follows normal distribution. We applied Box-Jenkins methodology to estimate the mean return equation of all the GARCH family models.

The conditional variance equation 4 is

$$\sigma_t^2 = \omega + \sum_{i=1}^p \alpha_i \epsilon_{t-i}^2 + \sum_{j=1}^q \beta_j \sigma_{t-j}^2 \quad 4$$

Where, σ_t^2 is the conditional variance, ϵ_{t-i}^2 is the previous day's squared error and σ_{t-j}^2 is the previous time period volatility.

Thus, it is assumed that the error term follows the normal distribution with zero mean and conditional variance as opposed to the constant variance.

Where the conditions for stable GARCH model are, $\omega > 0$, $\alpha_1 > 0$, $\beta_1 > 0$. The stationarity condition for GARCH (1, 1) is $\alpha_1 + \beta_1 < 1$. When this sum is less than unity, the model has finite unconditional variance which is also called long run volatility. The long run average variance is computed as $\frac{\omega}{1 - \alpha_1 - \beta_1}$.

3.2.4 EGARCH Model

The plain vanilla GARCH model fails to capture the leverage effect. Nelson (1991) proposed EGARCH (Exponential GARCH) model of volatility which captures leverage effect.

The specification for the conditional variance is given in equation 5 as:

$$\ln \sigma_t^2 = \omega + \beta \ln(\sigma_{t-1}^2) + \gamma \frac{\epsilon_{t-1}}{\sqrt{\sigma_{t-1}^2}} + \alpha \left(\left| \frac{\epsilon_{t-1}}{\sqrt{\sigma_{t-1}^2}} \right| - \sqrt{\frac{2}{\pi}} \right) \quad 6$$

Where, σ_t^2 is the conditional variance, ϵ_{t-1}^2 is the previous days squared error and σ_{t-1}^2 is the previous time period volatility.

The test of the presence of the leverage effect is conducted by hypothesis that $\gamma < 0$. The impact is symmetric when $\gamma = 0$.

3.2.5 TARCH Model

TARCH (Threshold ARCH) was introduced independently by Zakoian (1990) and Glosten, Jagannathan, and Runkle (1993). The specification for the conditional variance under TARCH (1, 1) is given in equation 6 as:

$$\sigma_t^2 = \omega + \alpha_1 \epsilon_{t-1}^2 + \beta_1 \sigma_{t-1}^2 + \gamma \epsilon_{t-1}^2 d_{t-1} \quad 7$$

Where, σ_t^2 is the conditional variance, ϵ_{t-1}^2 is the previous days squared error and σ_{t-1}^2 is the previous time period volatility, $d_{t-1} = 1$, if $\epsilon_t < 0$, and $d_{t-1} = 0$ otherwise.

The impact of good news ($\epsilon_t > 0$) and bad news ($\epsilon_t < 0$) have different effect on conditional variance. The impact of good news is ∞ and the bad news has an impact of $\infty + \gamma$. If $\gamma = 0$, the volatility is symmetric $\gamma = 0$, otherwise it is asymmetric.

3.2.6 Forecasting Error Statistics

There are three types of error statistics used in this paper to measure the forecasting abilities of three different models

of volatility, namely, GARCH, EGARCH and TARCH. The three forecasting error statistics are given below:

(i) The **Root Mean Squared Error (RMSE)**

The formula to compute RMSE is given in equation 7 as:

$$RMSE = \sqrt{\frac{1}{n} \sum_{t=1}^n (\hat{h}_t - h_t)^2} = \sqrt{\frac{1}{n} \sum_{t=1}^n \varepsilon_t^2} \quad 7$$

Where, \hat{h}_t is the forecasted volatility, h_t is the actual volatility and ε_t^2 is the square of the prediction error and n is the forecast sample size.

(ii) The **Mean Absolute Error (MAE)** is another popular error measure that corrects the ‘cancelling out’ effects by averaging the absolute value of the errors. The formula to compute the MAE is given in equation 8 as:

$$MAE = \frac{1}{n} \sum_{t=1}^n |\hat{h}_t - h_t| = \frac{1}{n} \sum_{t=1}^n |\varepsilon_t| \quad 8$$

(iii) The **Mean Absolute Percent Error**

The following formula is used to compute this error statistics is given in equation 9 as:

$$MAPE = \frac{1}{n} \sum_{t=1}^n \left| \frac{(\hat{h}_t - h_t)}{h_t} \right| = \frac{1}{n} \sum_{t=1}^n \left| \frac{\varepsilon_t}{h_t} \right| \quad 9$$

All these tests are useful to test the forecasting ability of the various volatility models from different angles.

4. Empirical Analysis

This section shows the results of the daily, weekly and monthly data of stock markets indices.

4.1. Empirical Analysis: Daily Data

The following section discusses the volatility modeling and the forecasting abilities of different volatility models

4.1.1 GARCH Model Results

The results of the selected GARCH models on the basis of AIC/SIC and principal of parsimony.

The final models for all indices are as follows:

Shenzhen Composite Index: GARCH (1, 1)

Shanghai Composite Index: GARCH (1, 1)

SENSEX: GARCH (1, 1)

NIFTY: GARCH (1, 1)

The value of various parameters and the z-statistics are given in table 1 which is provided below.

Table 1 GARCH Model: Daily Data

The table 1 shows the coefficients of parameters and Z-statistics of GARCH model of volatility of log-returns of four indices i.e. SHZN_D is the Shenzhen composite index daily return, SHGH_D is the Shanghai composite index daily return series, SENSEX_D is the daily return series of sensitivity index of Bombay Stock Exchange and NIFTY_D is the daily return series of nifty of National Stock Exchange. The time period is from July 2003 to June 2012. * means significance at 5% level and ** means that it is significant at 1% level.

Table 1: GARCH MODEL

Variables	SHZN		SHGH		SENSEX		NIFTY	
	Coefficient	Z-stat	Coefficient	Z-stat	Coefficient	Z-stat	Coefficient	Z-stat
ω	0.0000033	4.290**	0.0000022	3.898**	0.0000058	6.170**	0.0000062	6.41**
α_1	0.0546670	8.454**	0.0487650	8.268**	0.1260560	12.08**	0.1303760	12.30**
β_1	0.9365940	137.2**	0.9441910	144.2**	0.8560240	76.4**	0.8528110	76.5**

Source: Estimated by Authors

We now discuss the economic interpretations of the estimated parameters as defined in methodology section.

Shenzhen Composite Index

The ARCH term coefficient is 0.0547 and the GARCH term is 0.9366. It shows high persistence and low reaction. The sign of both the coefficients is positive as required by GARCH model. The most of the information (93.66%) comes from the previous day's volatility. The sum of the above two coefficient is 0.9913, the closer the sum of parameters to the unity, the greater is the volatility persistence. The long run variance is computed by using the formula defined in methodology section and its value is 0.000381 which implies that the unconditional long run variability is 0.000381.

Shanghai Composite Index

The ARCH term coefficient is 0.0488 and the GARCH term is 0.9442. It also shows high persistence and low reaction. The sign of both the coefficients is positive as required by GARCH model. The major information (94.42%) comes from the previous day's volatility. The sum of the above two coefficient is 0.9930, the closer the sum of parameters to the unity, the greater is the volatility persistence. The long run variance is 0.000316.

SENSEX

The ARCH term coefficient is 0.1261 and the GARCH term is 0.8560. It also shows high persistence and low reaction. The sign of both the coefficients is positive as required by GARCH model. The major information (85.60%) comes from the previous day's volatility. The sum of the above two coefficient is 0.9821, the closer the sum of parameters to the unity, the greater is the volatility persistence. The long run variance is 0.000324.

NIFTY

The ARCH term coefficient is 0.1304 and the GARCH term is 0.8528. It also shows high persistence and low reaction. The sign of both the coefficients is positive as required by GARCH model. The major information (85.28%) comes from the previous day's volatility. The sum of the above two coefficient is 0.9821, the closer the sum of parameters to the unity, the greater is the volatility persistence. The long run variance is 0.000367.

4.1.2 EGARCH Model

The main difference between GARCH and EGARCH is related to the interpretation of γ . The negative sign of it denotes leveraging effect. The results are reported in table 2 which is given below.

The table 2 states that the value of leveraging variable i.e. is negative for all the stock market indices, namely SHZN, SHGH, SENSEX and NIFTY. It is further noted that leveraging variable is significant for all the indices at 5% level of significance expect for SHZN where it is significant at 10% level only. Though, in case of SENSEX and NIFTY, the leveraging variable is significant even at 1% level of significance.

Table 2 EGARCH Model: Daily Data

The table 2 shows the coefficients of parameters and Z-statistics of EGARCH model of volatility of log-returns of four indices i.e. SHZN_D is the Shenzhen composite index daily return, SHGH_D is the Shanghai composite index daily return series, SENSEX_D is the daily return series of sensitivity index of Bombay Stock Exchange and NIFTY_D is the daily return series of nifty of National Stock Exchange. The time period is from July 2003 to June 2012. * means significance at 5% level and ** means that it is significant at 1% level.

Table 2: EGARCH Model

Variables	SHZN_D		SHGH_D		SENSEX_D		NIFTY_D	
	Coefficient	Z-stat	Coefficient	Z-stat	Coefficient	Z-stat	Coefficient	Z-stat
ω	-0.2151	-7.4144**	-0.1751	-6.6659**	-0.2385	0.1053**	-0.7861	0.1660**
α	0.1331	10.0016**	0.1214	9.6401**	0.1323	0.0445**	0.3122	0.0705**
γ	-0.0125	-1.8154	-0.0117	-1.9950*	-0.0017	0.0165**	-0.0970	0.0294**
β	0.9859	324.6078**	0.9898	383.9958**	0.9795	0.0123**	0.9213	0.0207**

Source: Estimated by Authors

Thus, there is leveraging impact which states that the volatility will be higher after negative shocks.

This behaviour can be understood by taking note of some pioneering work in the field of behavioural finance where the prospect theory (Kahneman and Tversky 1979) states that investors do not perceive gains and losses equally. The disutility by a given level of loss is greater than the utility by equal amount of gain, thereby resulting in asymmetric responses to negative and positive shocks.

4.1.3 TARCH Model

The main difference between GARCH and TARCH

is related to the interpretation of γ . The zero value of it denotes no asymmetry effect. The results are reported in table 3.

Table 3 TARCH Model: Daily Data

The table 3 shows the coefficients of parameters and Z-statistics of TARCH model of volatility of log-returns of four indices i.e. SHZN_D is the Shenzhen composite index daily return, SHGH_D is the Shanghai composite index daily return series, SENSEX_D is the daily return series of sensitivity index of Bombay Stock Exchange and NIFTY_D is the daily return series of nifty of National Stock Exchange. The time period is from July 2003 to June 2012. * means significance at 5% level and ** means that it is significant at 1% level.

Table 3: TARCH MODEL

	SHZN_D		SHGH_D		SENSEX_D		NIFTY_D	
	Coefficient	Z-stat	Coefficient	Z-stat	Coefficient	Z-stat	Coefficient	Z-stat
ω	0.0000	4.3964**	0.0000	4.0481**	0.0000	7.4792**	0.0000	7.8942**
α_1	0.0499	5.9834**	0.0448	6.1064**	0.0501	5.3950**	0.0524	5.1550**
γ	0.0093	0.9735	0.0106	1.3218	0.1409	7.7929**	0.1466	7.8734**
β_1	0.9357	136.32**	0.9419	142.14**	0.8538	73.0298**	0.8475	71.0478**

Source: Estimated by Authors

The main variable for determining the leverage effect is γ . Though, it is positive for all the indices, however, it is not significant for SHZN and SHGH indices even at 10% level of significance, whereas this variable is positive and significant for both SENSEX and NIFTY. The results are almost similar to EGARCH model, as in that case also the leveraging variable is highly significant for Indian stock market index and not very highly significant for both the Chinese stock market index and even insignificant for SHZN composite index.

4.1.4 Forecasting Volatility

This section discusses the forecasting ability of different GARCH models. The results are presented in table 4.

Chinese Stock Market Indices

For Shenzhen composite index, we saw that the leveraging variable of EGARCH model and asymmetry

effect variable of TARCH models were not significant and consequently these models are not suitable for this index. The method which is best suited to the Shenzhen composite index is GARCH (1, 1) model. The forecasting ability test should not be applied blindly to this model as previously discussed the other GARCH family models are not applicable for this case.

For Shanghai composite index, we found from the previous discussion that the leveraging variable is significant but the asymmetry variable of TARCH model is not significant, so we can rule out the use of TARCH model and among the GARCH and EGARCH model, we can observe from table 4 that the value of RMSE, MAE and MAPE is least for EGARCH model. Thus, it is the model that is best suited to the Shanghai composite index as it also captures the leveraging effect which was found in Shanghai composite index.

Table 4 Forecasting Error Test: Daily Data

The table 4 shows the value of Root Mean Square Error (RMSE), Mean Absolute Error (MAE) and Mean Absolute Percentage Error (MAPE) for four indices i.e. SHZN is the Shenzhen composite index daily return, SHGH is the Shanghai composite index daily return series, SENSEX is the daily return series of sensitivity index of Bombay Stock Exchange and NIFTY is the daily return series of nifty of National Stock Exchange. The time period that is used for testing forecasting abilities is from July 2012 to June 2013.

Table 4: Forecasting Error Test

SHZN			
	GARCH	EGARCH	TARCH
RMSE	0.014550	0.014547	0.014549
MAE	0.011313	0.011325	0.011316
MAPE	100.221800	100.026700	100.171200
SHGH			
	GARCH	EGARCH	TARCH
RMSE	0.011551	0.011548	0.011548
MAE	0.008197	0.008196	0.008196
MAPE	101.206900	100.347700	100.478900
SENSEX			
	GARCH	EGARCH	TARCH
RMSE	0.008505	0.008468	0.008472
MAE	0.006360	0.006322	0.006325
MAPE	310.484300	225.804000	238.808900
NIFTY			
	GARCH	EGARCH	TARCH
RMSE	0.008716	0.008684	0.008685
MAE	0.006537	0.006499	0.006500
MAPE	180.881500	150.184700	150.762000

Source: Estimated by Authors

Indian Stock Market Indices

For the Indian stock market indices, all the GARCH family models are significant in terms of significance of

the coefficient of their parameters. Here we have a clear cut verdict on the basis of all error statistics i.e. RMSE, MEA and MAPE. All these methods found the minimum value for the EGARCH model. Thus, we can say that the most appropriate method of volatility estimation and forecasting for Indian stock market is EGARCH model. The leveraging effect which means that the volatility is higher after negative shocks than the positive shocks operates for the Indian stock market. This property is well captured by EGARCH model.

4.2. Empirical Analysis: Weekly Data

The weekly data series has 455 observations for the Chinese data and 470 observations for the Indian data. The number is different due to public holidays and other days on which stock exchanges do not open in these two markets.

4.2.1 GARCH Model

The final models for all indices are as follows:

Shenzhen Composite Index: GARCH (1, 1)

Shanghai Composite Index: GARCH (1, 1)

SENSEX: GARCH (1, 1)

NIFTY: GARCH (1, 1)

The value of various parameters and the z-statistics are given in table 5 which is provided below.

Table 5 GARCH Model: Weekly Data

The table 5 shows the coefficients of parameters and Z-statistics of GARCH model of volatility of log-returns of four indices i.e. SHZN_W is the Shenzhen composite index weekly return, SHGH_W is the Shanghai composite index weekly return series, SENSEX_W is the weekly return series of sensitivity index of Bombay Stock Exchange and NIFTY_W is the weekly return series of nifty of National Stock Exchange. The time period is from July 2003 to June 2012. * means significance at 5% level of statistics and ** means that it is significant at 1% level.

Table 5: GARCH Model

	SHZN		SHGH		SENSEX		NIFTY	
	Coefficient	Z-stat	coefficient	Z-stat	coefficient	Z-stat	coefficient	Z-stat
ω	0.000027	1.81	0.000021	1.66	0.000056	3.11**	0.000067	3.03**
α_1	0.057249	2.86**	0.050542	2.74**	0.192407	5.23**	0.187610	5.20**
β_1	0.928658	37.18**	0.934408	36.96**	0.774315	22.56**	0.770552	23.14**

Source: Estimated by Authors

We discuss the economic interpretations of the estimated parameters as defined in methodology section.

Shenzhen Composite Index

The ARCH term coefficient is 0.0572 and the GARCH term is 0.9286. It shows high persistence and low reaction. The sign of both the coefficients is positive as required by GARCH model. The most of the information (92.86%) comes from the previous week's volatility. The sum of the above two coefficient is 0.9859, the closer the sum of parameters to the unity, the greater is the volatility persistence. The long run variance is computed by using the formula defined in methodology section and its value is 0.00188.

Shanghai Composite Index

The ARCH term coefficient is 0.05054 and the GARCH term is 0.9344. It also shows high persistence and low reaction. The sign of both the coefficients is positive as required by GARCH model. The major information (93.44%) comes from the previous week's volatility. The sum of the above two coefficient is 0.9849, the closer the sum of parameters to the unity, the greater is the volatility persistence. The long run variance is 0.00139.

SENSEX

The ARCH term coefficient is 0.1924 and the GARCH term is 0.7743. It also shows high persistence and low reaction. The sign of both the coefficients is positive as required by GARCH model. The major information (77.43%) comes from the previous week's volatility. The sum of the above two coefficient is 0.9667, the closer the sum of parameters to the unity, the greater is the volatility persistence. The long run variance is 0.00169.

NIFTY

The ARCH term coefficient is 0.1876 and the GARCH term is 0.7705. It also shows high persistence and low

reaction. The sign of both the coefficients is positive as required by GARCH model. The major information (77.05%) comes from the previous week's volatility. The sum of the above two coefficient is 0.9581, the closer the sum of parameters to the unity, the greater is the volatility persistence. The long run variance is 0.00160.

We observe that the major part of Chinese stock market volatility comes from previous week's volatility. The proportion of previous week's volatility in India is also substantial that is around 77%.

4.2.2 EGARCH Model

The table 6 states that the value of leveraging variable i.e. is negative for all the stock market indices, namely SHZN, SHGH, SENSEX and NIFTY. However, this leveraging variable is not significant for both the Chinese stock market indices even at the 10% level of significance. Though, in case of SENSEX and NIFTY, the leveraging variable is significant even at 1% level of significance. Thus we can say that the Indian stock market data has the leveraging effect which is also captured in developed market as discussed in review of literature section.

Table 6 EGARCH Model: Weekly Data

The table 6 shows the coefficients of parameters and Z-statistics of EGARCH model of volatility of log-returns of four indices i.e. SHZN is the Shenzhen composite index weekly return, SHGH is the Shanghai composite index weekly return series, SENSEX is the weekly return series of sensitivity index of Bombay Stock Exchange and NIFTY is the weekly return series of nifty of National Stock Exchange. The time period is from July 2003 to June 2012. * means significance at 5% level of statistics and ** means that it is significant at 1% level.

Table 6: EGARCH Model

	SHZN		SHGH		SENSEX		NIFTY	
	Coefficient	Z-stat	Coefficient	Z-stat	coefficient	Z-stat	coefficient	Z-stat
ω	-.2742	-2.6305**	-.2385	-2.265*	-.7861	-4.736**	-.87	-4.1947**
α	.1464	3.2793**	.1323	2.9732**	.3122	4.4272**	.3117	4.3776**
γ	-.007	-.3686	-.0017	-.1002	-.097	-3.3059**	-.0987	-3.1578**
β	.9749	78.1505**	.9795	79.6225**	.9213	44.4518**	.9086	33.5707**

Source: Estimated by Authors

Thus, there is leveraging impact which states that the volatility will be higher after negative shocks. The EGARCH model is useful to apply for the Indian stock market, though it is not essential for the Chinese stock market as it does not show any leveraging effect in its volatility.

4.2.3 TARCH Model

The results are reported in table 7.

Table 7 TARCH Model: Weekly Data

The table 7 shows the coefficients of parameters and Z-statistics of TARCH model of volatility of log-returns of four indices i.e. SHZN is the Shenzhen composite index weekly return, SHGH is the Shanghai composite index weekly return series, SENSEX is the weekly return series of sensitivity index of Bombay Stock Exchange and NIFTY is the weekly return series of nifty of National Stock Exchange. The time period is from July 2003 to June 2012. * means significance at 5% level of statistics and ** means that it is significant at 1% level.

Table 7: TARCH MODEL

	SHZN		SHGH		SENSEX		NIFTY	
	Coefficient	Z-stat	Coefficient	Z-stat	coefficient	Z-stat	coefficient	Z-stat
ω	.00003	1.78193	.00002	1.7019	.00006	3.34052**	.00008	3.066**
α_1	.05727	2.49117**	.03845	2.0271*	.11319	2.08325*	.11617	2.0344*
γ	-.00005	-.00217	.02179	.89138	.14354	2.6702**	.12877	2.3850*
β_1	.92868	36.745**	.93471	37.709**	.76922	20.695**	.76418	18.719**

Source: Estimated by Authors

The main variable for determining the leverage effect is γ . Though, it is positive for all the indices, however, it is not significant for SHZN and SHGH indices even at 10% level of significance, whereas this variable is positive and significant for both SENSEX and NIFTY. The results are almost similar to EGARCH model, as in that case also the leveraging variable is highly significant for Indian stock market index and not significant for both the Chinese stock market index. It confirms the use of asymmetry volatility model for the Indian stock market, though these are not very helpful for the Chinese stock market data.

4.2.4 Forecasting Volatility

This section discusses the forecasting ability of different GARCH models. The results are given in table 8.

Chinese Stock Market Indices

For both the Chinese stock market indices, we found that the leveraging variable of EGARCH model and asymmetry variable of TARCH model are insignificant. Thus, these methods should not be considered and we can also observe from table 8, the error statistics are least for most of the time in case of GARCH model. This paper recommends the use of GARCH model for estimation and forecasting of volatility of Chinese stock market weekly data series. The leveraging effect states that the volatility is higher after negative shocks than the positive shocks and the asymmetry effect states that the good and bad news have different effects on the volatility are not significant for the Chinese stock market and we can use the traditional GARCH model for volatility modeling and forecasting.

Table 8 Forecasting Error Test: Weekly Data

The table 8 shows the value of Root Mean Square Error (RMSE), Mean Absolute Error (MAE) and Mean Absolute Percentage Error (MAPE) for four indices i.e. SHZN is the Shenzhen composite index daily return, SHGH is the Shanghai composite index daily return series, SENSEX is the daily return series of sensitivity index of Bombay Stock Exchange and NIFTY is the daily return series of nifty of National Stock Exchange. The time period that is used for testing forecasting abilities is from July 2012 to June 2013.

Table 8: Forecasting Error Test

SHZN			
	GARCH	EGARCH	TARCH
RMSE	0.032838	0.032842	0.032838
MAE	0.028454	0.028454	0.028454
MAPE	100.767	100.92	100.7709
SHGH			
	GARCH	EGARCH	TARCH
RMSE	0.025715	0.02569	0.025666
MAE	0.021399	0.0214	0.021396
MAPE	95.62938	96.23669	97.62219
SENSEX			
	GARCH	EGARCH	TARCH
RMSE	0.018984	0.018782	0.018841
MAE	0.015395	0.01521	0.015261
MAPE	154.1446	128.0894	138.2346
NIFTY			
	GARCH	EGARCH	TARCH
RMSE	0.019501	0.019339	0.019393
MAE	0.015753	0.015583	0.015643
MAPE	134.0632	114.4377	123.2122

Source: Estimated by Authors

Indian Stock Market Indices

Similar to the daily data results, in case of weekly return data series also for the Indian stock market indices, all the GARCH family models are significant in terms of significance of the coefficient of their parameters. Here also we have a clear decision on the basis of all error statistics i.e. RMSE, MAE and MAPE. All these method

found the minimum value for the EGARCH model. Thus, we can say that the most appropriate method of volatility estimation and forecasting for Indian stock market is EGARCH model. The leveraging effect which means that the volatility is higher after negative shocks than the positive shocks operates for the Indian stock market.

4.3. Empirical Analysis: Monthly Data

The following section discusses the volatility modeling of the monthly return series.

4.3.1 GARCH Models

We have not found any ARCH effect in the monthly stock return volatility for all the indices, thus it is advisable to use the traditional time invariant models such as standard deviation and variance to compute the monthly stock return volatility.

The Autoregressive Conditional Heteroskedasticity-Lagrange Multiplier (ARCH-LM) test is used to test the heteroscedasticity. Here the null hypothesis is of no ARCH effect which it means homoscedasticity. The results as shown in table 9 exhibit the absence of heteroskedasticity in the residuals of ARMA model for all indices.

Table 9 ARCH-LM Test: Monthly Data

The table 9 presents the ARCH-LM test for the mean return model of four indices i.e. SHZN_M is the Shenzhen composite index monthly return, SHGH_M is the Shanghai composite index monthly return series, SENSEX_M is the monthly return series of sensitivity index of Bombay Stock Exchange and NIFTY_M is the monthly return series of nifty of National Stock Exchange. The time period is from July 2003 to June 2012. * means significance at 5% level and ** means that it is significant at 1% level. The null hypothesis is the presence of no ARCH effect in the mean return equation.

Table 9: ARCH-LM Test

	SHZN	SHGH	SENSEX	NIFTY
F-statistic	0.1405	0.0697	0.6833	0.0109
p-value	0.7085	0.7923	0.4103	0.9170
Obs*R-squared	0.1430	0.0710	0.6919	0.0111
p-value	0.7053	0.7899	0.4055	0.9160

Source: Estimated by Authorss

As reported in the table 9, we can see that the F-statistics is insignificant for all the indices at 5% as well as 1% level of significance. It means that there is no need to use GARCH model to estimate volatility of the monthly return series due to absence of any ARCH effect in the series. Therefore, we can use the conventional unconditional volatility model to estimate monthly stock return volatility.

5. Summary and Conclusions

Risk analysis is the fundamental to any investment analysis. The appropriate question is how to estimate the level of stock return volatility and use to it forecast future expected volatility. This paper undertook the task of identifying the best volatility estimation model for India and China. The simplest model to estimate volatility is the standard deviation. However, it fails to capture various stylized facts like fat tails, volatility clustering and leverage effect. First, large changes in return tend to be followed by large changes and small changes tend to be followed by small changes, which mean that volatility clustering is observed in financial returns data. Secondly, financial time series often exhibit leptokurtosis which means that the distribution of their returns is fat-tailed i.e. relative high probability for extreme values. Third, changes in stock prices tend to be negatively correlated with changes in volatility (i.e. volatility is higher after negative shocks than after positive shocks of same magnitude), which is called "leverage effect".

We employed three types of forecasting error tests namely, Root Mean Square Error, Mean Absolute Error and Mean Absolute Percentage Error. On the basis of result, we found that the best model for estimating and forecasting volatility for Chinese stock market is GARCH (1, 1). For the Indian stock market, the leverage effect was found to be strongly significant and consequently the best model of volatility is EGARCH model.

For weekly frequency data, we used forecasting error test and found out that the GARCH (1, 1) model is the best predictor of Chinese stock market weekly return series. For Indian stock market weekly return series, we found leverage variable significant and the best volatility estimation model is EGARCH model. For the monthly frequency data, we did not find volatility clustering as per autocorrelation test of squared returns. We can use

the plain vanilla standard deviation for knowing monthly return volatility.

The findings of the paper have important implications for security analysts (including fund managers), equity investors and stock market regulators.

(1) For Security Analysts

The job of the security analysts is to manage the investment of their clients. Given the intense level of competition and limited opportunities in developed economies, securities analyst have now started exploring the emerging stock markets and they are moving beyond their domestic stock market. The best emerging economies in the world at present are India and China. The most important point of concern at the time of entering into emerging stock markets is the correct assessment of their risks. This paper provides the results that are very useful to the securities analyst in estimating the risk of these stock markets. We suggest the use of GARCH (1,1) model to estimate and forecast the stock market volatility of the Chinese stock market where the asymmetric effect is statistically insignificant. For Indian stock market, the best volatility model is EGARCH model as the asymmetry effect of volatility is clearly visible in Indian stock market.

(2) For Investors

The general investors face the main task of allocating their money in various financial and non financial instruments. While allocating money to various financial instruments, investors must be aware of their return opportunities as well as the risk associated with the investment.

The general understanding of the risk return mechanism is essential for the investors. We have elucidated various advanced volatility estimation and forecasting models.

(3) For Regulators

The regulators of the financial markets are required to curb the unknown excessive volatility in the stock market. The excessive volatility per se is not bad because it may be the reflection of market realities but the unknown excessive volatility is the main cause of concern. This task is handled by first knowing the appropriate tools to measure the volatility. This paper facilitates in knowing the appropriate volatility model to assess the level of volatility in the stock market.

References

- Akgiray, V. (1989). Conditional heteroskedasticity in time series of stock returns: Evidence and forecasts. *Journal of Business*, 55-80.
- Banerjee, A., & Sarkar, S. (2006). Modeling Daily Volatility of the Indian Stock Market using Intra-Day Data. Working paper No: 588, IIM Calcutta. Available: <http://www.iimcal.ac.in/res/upd%5CWPS%20588.pdf>.
- Black, F. (1976). Studies of Stock Price volatility changes. *American Statistical Society*. Washington DC, 177-181.
- Bollerslev, T. (1986). Generalised autoregress conditional heteroscedasticity. *Journal of Econometrics*, 301-327.
- Brook, C. (2002). *Introductory econometrics for Finance*. Cambridge: Cambridge University Press.
- Cheng, X. (2000). The microstructure of the Chinese stock market. *China Economic Review*, 79-97.
- Cheung, Y. W and Ng L K. (1997). Stock price dynamics and firm size: An empirical investigation. *The Journal of Finance*, 1992(1985).
- Christie, A. (1982). The stochastic behaviour of common stock variances: Value, leverage and Interest rate effects. *Journal of Financial Economics*, 407-432.
- Cont, R. (2001). Empirical properties of asset returns: Stylized facts and statistical issues. *Quantitative Finance*, 223-236.
- Deo, N., & Kulkarni, V. (2007). Correlation and volatility in an Indian stock market: A random matrix approach. *The European Physical Journal B*, 101-109.
- Duffee, G. (1995). Stock Return and Volatility: A Firm Level Analysis. *Journal of Financial Economics*, 399-420.
- Engle, R. F. (1982). Autoregressive Conditional Heteroskedasticity with estimates of the variance of United Kingdom inflation. *Econometrica*, 987-1008.
- Franses, P. H., & Dijk, D. V. (1996). Forecasting stock market volatility using (nonlinear) GARCH models. *Journal of Forecasting*, 229-235.
- French, K., Schwert, G., & Stambaugh, R. (1957). Expected Stock Returns and Volatility. *Journal of Financial Economics*, 3-29.
- Glosten, L. R., Jagannathan, R., & Runkle, D. E. (1993). On the Relation between the Expected Value and the Volatility of the Nominal Excess Returns on Stocks. *Journal of Finance*, 1791-1801.
- Goudarzi, H., & Ramanarayanan, C. S. (2011). Modeling Asymmetric Volatility in the Indian Stock Market. *International Journal of Business and Management*, 221-231.
- Hongyu, P., & Zhichao, Z. (2006). Forecasting Financial Volatility: Evidence from Chinese Stock Market." Working Paper Series 06/02, Durham Business School. Retrieved from <http://citeseerx.ist.psu.edu/viewdoc/download?doi=10.1.1.122.3700&rep=rep1&type=pdf>, 2006.
- Jarque, C., & Bera, A. (1987). A Test for Normality of Observations and Regression Residuals." *International Statistical Review*, 163-172.
- Karmakar, M. (2006). Stock Market Volatility in the Long Run, 1961-2005. *Economic and Political Weekly*, 41(18), 1796-1802.
- Kaur, H. (2004). Time Varying Volatility in the Indian Stock Market. *Vikalpa*, 25-42.
- Kumar, S. S. S. (2006). Comparative performance of volatility forecasting models in Indian markets. *Decision*, 26-40.
- Kumar, S. S. S. (2012). A first look at the properties of India's volatility index. *International Journal of Emerging Markets*, 160-176.
- Laurence, C., & Biqioung, Z. (2003). Volatility and volume in chinese stock markets. *Journal of Chinese Economic and Business Studies*, 287-300.
- Nelson, D. B. (1991). Conditional heteroskedasticity in asset returns: A new approach. *Econometrica*, 347-370.
- Noh, J., & Kim, T. H. (2006). Forecasting volatility of futures market: The S&P 500 and FTSE 100 futures using high frequency returns and implied volatility. *Applied Economics*, 395-413.
- Schwert, G. W. (1989). Why Does Stock Market Volatility Change Over Time? *Journal of Finance*, 1115-1153.
- Song H., Liu, X., & Romilly, P. (1998). Stock returns and volatility: An empirical study of Chinese stock markets. *International Review of Applied Economics*, 129-139.
- Theodossiou, P., & Lee, U. (1995). Relationship between volatility and expected return across international stock markets. *Journal of Business Finance Accounting*, 289-300.
- TSay, L. S. (2005). *Analysis of financial time series*. Hoboken, N.J: Wiley.
- Yan, H., Wu, C., & Chen, Y. (2003). An explanation of the volatility disparity between the domestic and foreign shares in the Chinese stock markets. *International Review of Economic and Finance*, 171-186.