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Risk and Volatility of Indian and Chinese stock markets

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Abstract

The volatility of a return does not necessarily have to equate with its risk, also an investment which is more volatile does not always mean it is riskier in the long term. The study aimed at measuring risk and volatility of Indian and Chinese stock market indices for the period 01/01/1992 to 1/12/2015. Among Chinese indices, Shenzhen composite is found to be a risky one with the highest coefficient and significant p-value. The GARCH (1, 1) reveals that all the variables in the GARCH (1, 1) reported high significance which articulates the influence of current volatility by the past volatility of all the Indian and Chinese stock market.

Keywords: Risk, volatility, GARCH models, ARCH LM.

1. Introduction

The world's largest growing economies and key significance of India and China is huge populations with large economies with even larger potential size. By contemporary "success stories" of globalisation these two economies have outwardly benefited. Success of the countries was defined by the high and continuous growth rates in aggregate Income and per capita and also a large reduction in income poverty. These economies are frequently conserved as broadly comparable in relation to growth latent and other investment features, which made the researcher to analyse the stock markets of these two economies.

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Though China and India are different in many view point, like India being mixed or democratic country whereas china is a communist country still there are similarities to compare as China being a communist country China is not following communist economy. By 1978 china started the process of liberalisation which took its economy growing much faster than India and there are no race/ competition against each other butrace of same phase. The average annual rate of growth for Chinese economy was at 9.8 per cent for two and a half decades, showing volatility around the high trend. At the same time growth of Indian economy was reported about 5-6 per cent per year. As far as the investment rate is concerned, China has reported fluctuation between 35 - 44 per cent over the past 25 years, compared to 20 - 26 per cent in India. However, the two countries are different in the speed, time and pattern in their growth. Chinese market growth trend was faster in the initial period than Indian and likely to diminish in recent months. (Fig: 1)

Fig 1 : The trend line of Indian and Chinese market

Volatility can be defined as the daily price movement of the securities as an outcome of the stochastic character of the financial markets. The main characteristics of any financial time series are the volatility clustering meaning that 'combination of continuous low swing and continuous high swing periods for a long time.

Higher volatility in general means higher risk. Major stock market research proved that if there is a high price fluctuation it would up surge the future uncertainty and increases the risk. However, the volatility of any financial time series returns not always necessarily to equate with its risk. In other words, an investment is more volatile does not necessarily mean it is riskier in the long term. Therefore an investment's volatility and risk should be a concern to investors if the money is required in the instant future. Thus the present study tries to see the volatility of financial time series along with the frame work of risk which is helpful for an investment decision.

Volatility clustering and risk of a financial time series can be captured by ARCH model introduced by Engle (1982) and GARCH by Bollerslev (1986). These models include various extensions, which are helpful in volatility forecasting and to assess the risk of the stock return series. The present paper aimed to apply models such as GARCH (1, 1) and GARCH-Mmodels of the daily index of Indian and Chinese Stock Markets. GARCH (1,1) is applied to capture the internal shocks of the markets and in addition to that risk premium can be identified using GARCH – M model. BDS test is applied to test the linearity dependence of return series so that there will not be any misjudgment in selecting the linear and non-linear models.

2. Review of literature

Across the globe, there were numerous studies conducted on the stock market volatility of developed markets. The major studies on European stock markets had been contributed by Christie (1982), French et al (1987), Akgiray (1989), Lamoureux et al (1990), Nelson (1991) Engle and Ng (1991), The odossiou and Lee (1995), Christie (1982) studied the relation between the variance of equity returns and various explanatory variables. The study found that the equity variances have a strong positive association with both financial leverage, which in turn were contrary to the forecast of the options literature and interest rates. **French et al (1987)** discovered the relation between stock returns and stock market volatility and found that expected market risk premium is having apositive correlation with the predictable volatility of stock returns. However, the unexpected stock market returns are negatively related to the unexpected change in the volatility of stock returns.

Akgiray (1989) presented new evidence about the time series behavior of stock prices. The study found that daily return series were exhibited significant levels of second-order dependence, and found not to be modeled as linear white-noise processes, concluded that the forecasts based on the GARCH model were found to be superior. **Lamoureux et al (1990)** argued that ARCH effect in daily stock return reflects time dependence in the process generating information flow to the market. Daily trading volume is taken as a proxy for information arrival time. The study found that the daily returns are subordinated to intraday equilibrium returns also ARCH effects tend to disappear when the volume is included in the variance equation.

Nelson (1991) analysed the conditional heteroskedasticity in asset returns. The study applied GARCH models for modeling the relation between conditional variance and asset risk premium. **Engle and Ng (1991),** examined the relationship between the yield curve and the time-varying conditional volatility of the Treasury bill market by giving the demonstration of differently shaped yield curves can result given different combinations of volatility and expectations about future spot rates. The result says that adjusting the forward rate for the volatility related liquidity premium can improve the performance as a predictor of future spotrates.

Theodossiou and Lee (1995) studied the stochastic behavior of weekly stock market returns and the relationship between stock market volatility and expected returns for ten industrialized countries using the GARCH-M model. The study found no relationship between expected return and conditional volatility. There are many other studies on stock market behaviour, volatility which was conducted on European stock markets. [Mougoni and White (1996), Franses and Van Dijk (1996), Jorge Caiado (2004), Duffee (2005), Noh and Kim (2006)].

However, the empirical literature for the Indian and Chinese stock markets is still limited to rare comprehensive studies conducted by authors which include, **Song, Liu, and Romilly (1998),** investigated the causal relationship between openness and economic growth in China. The study analysed integration and co-integration properties and applying the models of Granger, Sims, Geweke and Hsiao and found thebi-directional relationship among the variables.

Cheng Xu (2000), described the auction principles, clearance, settlement, and depository (CSD) facilities of the Chinese stock market. The study used the autoregressive model to characterize the time series properties and volatility in the Shanghai market. The study used VAR model and found endogenous trading volumes and volatility for the Shanghai Composite Index (SHCI). The study also found in several respects that foreign shares behave differently from domestic shares. **Robert brooks & Vanitha (2003),** analysed the transfer of information in Chinese A and B stock market. The autocorrelation and cross-correlation were conducted for the four stock indices found spill over in both directions from 'A' and 'B' shares. The study also found that there is no volatility spillover from 'B' share prices to 'A' share prices or vice-versa.

Harvinder Kaur (2004) investigated the stock market volatility of Indian stock market and found similar findings like earlier in many of the major developed and emerging stock markets. The study found volatility clustering in the returnand asymmetrical response to the arrival of news. Similar kind of studies have been conducted in Indian and Chinese markets and found the clustering volatility, asymmetric and leverage effect in these markets. [Seddighi and Nian (2004), Hongyu and Zhichao Zhang (2006), Niu, H., & Wang, J. (2013), Tsai, I. C. (2013), Ning, and Xu, and Wirjanto (2015).] However, only very few studies brought out the detailed evidence on the symmetric effect of Indian and Chinese stock exchange market; hence the present study aimed at measuring the persistence of risk, and volatility of the Indian and Chinese stock market indices.

3. Data, Methodology, and empirical discussion

The data under this study consists of daily stock indices of two emerging countries, India and China. The Indian indices considered for the study are S & P BSE Sensex and CNX Nifty where most of the trading takes place. And from china, Shanghai and Shenzhen composite included in the study which are the two stock exchanges operating independently in the People's Republic of China. The period covers 24 years, from 01/01/1992 to 31/12/2015.

The log of the first difference of daily closing price is calculated by converting the stock prices into returns, which is as follows:

$$rt = \log \frac{P_t}{P_{t-1}} \text{ ---------------------------------- } (1)$$

where r_t is the natural log return for time t, P_t is the closing price for time t, and P_{t-1} is the corresponding price of the time $_{t-1}$.

4. Descriptive Statistics

Common descriptive statistics was applied to understand the features of time series return considers in the study and the results are shown in Table 1. It reveals that Shenzhen Composite Index was detected to be the highest mean return during the study period shadowed by CNX Nifty, S & P BSE Sensex, and Shanghai composite index. Low return and variance indicate the possibilities for low expected return and low risk. As per Table 1, Chinese stock markets have high volatility than Indian counter parts. Among Chinese stock markets, Shanghai composite return is more volatile. High volatility indicates the possibility of high returns as well but carries more risk. S & P BSE seems to have the lowest volatility compared to other markets.

The negative skewness of Indian markets signifies that the distribution has long lefttail (lower values), that means the prevalence of the negative returns are more compared to the positive stock returns. In other words, there is a more chance of large down turn than the increase in returns. But both Chinese indices show positive skewness signifies an asymmetrical distribution with a long tail to the right (higher values). This indicates that prevalence of positive returns than negative return and also there is a possibility of a large increase in return. The kurtosis value expected in any Gaussian distribution is 3.0, if the values are more than standard, i.e., >3 which reveals the fat tails characteristics of the asset returns distribution. The Jarque-Bera (JB) test of normality clearly rejects the null hypothesis of normality in all cases. In general, the results suggest that the distributions of the return series are non-normal.

Table 1: Descriptive statistics of the returns

	S & P BSE	**CNX Nifty**	**Shanghai Composite**	**Shenzhen Composite**
Mean	0.00046	0.000462	0.000646	0.000432
Median	0.000819	0.000818	0.001013	0.000507
Maximum	0.1599	0.163343	0.27221	0.775565
Minimum	-0.136607	-0.130539	-0.205651	-0.179051
Std. Dev.	0.01671	0.0166	0.021809	0.024744
Skewness	-0.12361	-0.13753	0.065955	6.093389
Kurtosis	9.701042	10.28848	13.93703	180.6581
Jarque-Bera	10904.03*	12900.4*	29011.71*	7689896*
Observation	5820	5820	5820	5820

***Significance at 1% leve**

5. Unit Root Test

The stationarity of the series was checked by applying the popular unit root tests such as augmented Dickey–Fuller and Phillips-Perron test (H_0:data has a unit root) and Kwiatkowski–Phillips–Schmidt–Shin test (KPSS) (H_o: Data is stationary). The result shows that the data is without unit root with stationarity (presented in Table 2). Thus it confirms the application of time series stochastic models to study the dynamic analysis of symmetric effect.

Table 2: ADF, PP and KPSS unit root test for the stock return series

Indices	ADF	PP	KPSS
S&P BSE Sensex	0.0010	0.001	0.05801
CNX Nifty	0.0001	0.0001	0.16534
SHSE	0.0000	0.0001	0.182072
SZSE	0.0000	0.0001	0.149513

ADF: Augmented Dickey–Fuller, PP: Phillips-Perron, KPSS: Kwiatkowski–Phillips–Schmidt–Shin test.

6. Linear dependence of the return series

The series were stationary only after calculating the first difference (or return). This paved a way for the application of BDS test and clarify whether the return series could be estimated by non-linear model. It also guides against model misspecification of using linear and non-linear models and there by helps to avoid model judgment error.

BDS independence test was developed by W.A. Brock, W. Dechert and J. Scheinkman in 1987. The test will identify the nonlinearity of time series. It is a two-tailed test in which the critical area of a distribution is two sided. It tests whether the test statistics greater than or less than the critical values. The null hypothesis would get rejected if the test statistic falls into either of the critical areas. (e.g. if $\propto$ = 0.05, the critical value = ± 1.96).

The BDS test statistic can be stated as:

$$BDS_{\varepsilon,m} = \frac{\sqrt{N}[C_{\varepsilon,m} - (C_{\varepsilon,1})^m]}{\sqrt{V_{\varepsilon,m}}} \qquad \text{........................ (2)}$$

It is evident from Table3 that test statistics is more than the critical values significantly, and hence the null hypothesis is rejected (H_o: the series are linearly dependent), with the strong recommendation that the stock market return of S & P BSE, CNX Nifty, Shanghai and Shenzhen composite Index are non-linearly dependent. It highlights that financial time series data are having chaotic behavior and not independently and identically distributed. Thus it gives affirmation to study the nature of nonlinearity of the time series.

Table 3: BDS Test Results

	BDS				z-Statistic			
Dimension	S&P BSE	CNX Nifty	SHGH CI	SHZN CI	S&P BSE	CNX Nifty	SHGH CI	SHZN CI
2σ	0.018	0.016	0.027	0.024	19.591*	17.904*	19.871*	21.988*
3σ	0.025	0.022	0.044	0.034	26.048*	23.738*	25.811*	28.954*
4σ	0.023	0.021	0.050	0.034	31.158*	28.441*	30.787*	35.903*
5σ	0.018	0.016	0.047	0.029	36.647*	33.353*	35.298*	42.901*
6σ	0.013	0.012	0.042	0.023	43.205*	38.836*	40.707*	51.210*

*significance at 1% level

7. Volatility and Risk in Indian and Chinese Stock market.

The preliminary check before modeling a financial time series is to sketch out the presence of volatility clustering (i.e. low volatility periods followed by low volatility periods for a long time and high volatility periods followed by high volatility periods for a long time.).The India and Chinese indices exhibit clustering volatility of the residuals for 5820 days. (See graph given in annexure). This recommends that residual or error term is conditionally heteroskedastic and it can be constituted by GARCH model.

7.1 The Generalized arch Model- GARCH (1, 1)

A generalized arch (GARCH 1, 1) model developed by Bollerslev (1986) is a widely accepted model for stochastic volatility estimation. The description of GARCH (1, 1) model is as follows;

$$\sigma^2_t = \omega + \alpha_1\varepsilon^2_{t-1} + \beta_1\propto^2_{t-1} \qquad \text{.. (3)}$$

Where σ^2_t is conditional variance, whereas ω is constant, $\alpha_1\varepsilon^2_{t-1}$ is Arch term and$\beta_1\sigma^2_{t-1}$ is thesum of squared residual/ Garch term.

GARCH models are generally of three distributions, GARCH (1, 1) - Normal Distribution, GARCH (1, 1) - Student's t distribution andGARCH (1, 1) - Generalized error distribution. Under all the three distribution we have found no serial correlation (see Table in Annexure) and no ARCH (Table 4) effect in the residuals**.** Thus there is a positive sign for modeling series with GARCH models. However, residuals were not normally distributed in all the three cases. But non-normality of the residuals is not a serious problem as estimators are still consistent also we can use the models by taking the values of Akaike Information Criterion (AIC) and Schwarz Information Criterion (SIC). From the result of AIC and SIC of all the three distribution (Table 5), are found that GARCH (1,1) (student-t distribution) to be the best-fitted model to catch the risk and volatility of time series return.

Table 4: Results of Heteroskedasticity Test: ARCH

	S&P BSE	CNX Nifty	Shanghai Composite	Shenzhen Composite
F-statistic	1.3481	3.8138	0.0117	0.3172
Obs*R-squared	1.3482	3.8127	0.0117	0.3173
Prob. F	0.2457	0.0510	0.9139	0.5733
Prob. Chi-Square(1)	0.2456	0.0510	0.9139	0.5732

The GARCH (1, 1) results are presented in Table 6. It reveals that all the parameters in the GARCH (1, 1) i.e., a (ARCH term) and ß (GARCH term) were highly significant and explains that the current volatility of all series was greatly influenced by the past volatility of the time series return of the study. The sum values of coefficient of (α + β)the series of both Indian and Chinese indices shows a value close to the value of unity which suggests that the volatility of all the return series was highly constant with 1% significance level of acceptance. It's evident from the table that for S & P BSE Sensex the ARCH term coefficient is 0.106831, and the GARCH term is 0.881095. It shows high persistence and low reaction. The sign of both the coefficients is positive as required by GARCH model. It can be inferred from the major information (88.11%) of S & P BSE Sensex comes from the previous day's volatility. The sum of the above two coefficients is 0.9879, the closer the sum of parameters to the unity, the greater is the volatility.

For the CNX Nifty, the ARCH term coefficient is 0.104788 and the GARCH term is 0.881208. It also shows high persistence and low reaction. The sign of both the coefficients is positive as required by GARCH model. The major information

Table 5: AIC and SIC results for different model distributions.

Method	Parameter	S&P BSE	CNX Nifty	ShanghaiComposite	ShenzhenComposite
Normal Distribution	Akaike info criterion	-5.668892	-5.66624	-5.167832	-5.148661
	Schwarz criterion	-5.664308	-5.661687	-5.163249	-5.144108
	Log likelihood	16500.47	16623.08	15042.39	15105.02
Student's t distribution	Akaike info criterion	-5.706308	-5.711062	-5.366064	-5.271594
	Schwarz criterion	-5.700578	-5.705371	-5.360335	-5.265902
	Log likelihood	16610.36	16755.55	15620.25	15466.58
Generalized error distribution	Akaike info criterion	-5.699041	-5.702304	-5.356022	-5.255281
	Schwarz criterion	-5.693311	-5.696613	-5.350292	-5.24959
	Log likelihood	16589.21	16729.86	15591.02	15418.74

(88.12%) comes from the previous day's volatility. The sum of the above two coefficients is 0.985996, the closer the sum of parameters to the unity, the greater is the volatility persistence. For Shanghai Composite Indexthe ARCH term coefficient is 0.117651 and the GARCH term is 0.879050. It also shows high persistence and low reaction. The sign of both the coefficients is positive as required by GARCH model. The major information (87.91%) comes from the previous day's volatility. The sum of the above two coefficients is 0.996701, the closer the sum of parameters to the unity, the greater is the volatility persistence. And for Shenzhen Composite Index the ARCH term coefficient is 0.143416 and the GARCH term is 0.849399. 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 (84.94%) comes from the previous day's volatility. The sum of the above two coefficients is 0.992815, the closer the sum of parameters to the unity, the greater is the volatility persistence. It is evident that both the Chinese markets are of more volatility persistent than Indian Indices as the sum of the parameter for the Chinese markets is closed to unity.

Table 6: Results of GARCH (1, 1)

Indices	ω		β	α + β
S&P BSE Sensex	3.96E-06	0.106831***	0.881095***	0.987926
CNX Nifty	4.34E-06	0.104788***	0.881208***	0.985996
Shanghai Composite	6.64E-06	0.117651***	0.879050***	0.996701
Shenzhen Composite	8.46E-06	0.143416***	0.849399***	0.992815

*Note***Significance @ 1%, ω: constant, α: ARCH term and β: GARCH term.*

7.2 The Garch-in-Mean (Garch-M) Model

The risk is an important element of the financial world at the present time. Estimation of the market risk is one of the major problems faced by different types of financial institutions each day. Engle, Lilien, and Robins (1987) proposed GARCH-M model, suitable for the estimation of risk as model uses conditional variance instead of the unconditional variance. GARCH (1, 1)-M model can be written as

Mean equation: $r_t = \mu + \lambda\sigma t^2\ \tau + \varepsilon t$ .... (4)

Variance equation: $\sigma^2 t = \omega + \alpha\varepsilon^2{}_{t-1} + \beta\sigma^2{}_{t-1}$ ....(5)

The parameter λ in the mean equation and it is called as a risk premium. A positive λ indicates that the return is positively related to its volatility, i. e. a rise in mean return is caused by an increase in conditional variance as a proxy for increased risk. Table 6 shows results of GARCH –M model which reveals the risk and influence of internal and external shocks of respective index. Considering each index separately as dependent variable we could see, the sign of coefficients as positive and the *p* values are not significant in all the cases except Shenzhen composite. Shenzhen composite shows the highest coefficient with a significant *p*-value. If Standard Deviation is more and the *p*-value is significant then it is a risky asset, in other words, higher Standard Deviation indicates higher volatility and it is constituted as the asset is more risky, in this study Shenzhen Composite Index is arisky asset which seems to have more Standard Deviation than other markets. ARCH and GARCH terms which are also significant to explain respective index return here. The null hypothesis is rejected to indicate that there are clustering volatility and ARCH effect in this model. That means the internal causes are significant to explain the volatility of all the Indian and Chinese index return. In other words, internal shocks influence the variability of all the Indian and Chinese Indices.

When we check the external causes to influence the volatility of S & P BSE & CNX Nifty taking Shanghai and Shenzhen composite as the variance regressor and Vice Versa It reveals that Shanghai and Shenzhen return volatility cannot

Table 7: Results of Garch– M

	S&P BSE			*CNX Nifty*		
Variable	*Coefficient*	*z-Statistic*	*Prob.*	*Coefficient*	*z-Statistic*	*Prob.*
	0.039186	0.998103	0.3182	0.053417	1.308955	0.1905
ω	0.000004	5.468044	0.000	0.000004	5.58418	0.000
	0.107307	11.48321	0.000	0.105478	11.26346	0.000
β	0.880508	93.53645	0.000	0.87989	89.90078	0.000
SSE	-0.000005	-0.08809	0.9298	0.00006	0.906406	0.3647
SHZ	0.000003	0.043181	0.9656	-0.000056	-0.838798	0.4016
	Shanghai Composite			*Shenzhen Composite*		
Variable	*Coefficient*	*z-Statistic*	*Prob.*	*Coefficient*	*z-Statistic*	*Prob.*
	0.021783	0.923392	0.3558	0.109359	3.277571	0.001
ω	0.000007	6.566839	0.000	0.000008	6.055718	0.000
	0.120785	10.75254	0.000	0.145452	11.68427	0.000
β	0.876559	100.7889	0.000	0.846379	81.20979	0.000
BSE	-0.000426	-7.05727	0.000	0.000127	0.755783	0.4498
NFTY	0.000003	0.035466	0.972	0.000413	2.733905	0.0063

affect Indian markets as S & P BSE & CNX Nifty return volatility, as *p*-value, not significant., that means that Chinese market's volatility cannot transmit to Indian stock markets. But there is an interesting result that the Indian volatility gets transmitted to Chinese market volatility. The Chinese market is indeed affected by the volatility of Indian market as the table 5 reveals that BSE returns volatility affect Shanghai return volatility, Also CNX Nifty volatility transmitted to Shenzhen return as the p values are significant.

8. Concluding Remarks

The leading 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 to assess risks and volatility. The daily closing prices of S & P BSE Sensex, CNX Nifty, Shanghai Composite, and Shenzhen Composite Index from 1/01/1992 to 31/12/2015 were analysed applying GARCH models with an aim to capture the symmetric effect of the indices for the study period. GARCH (1,1), and GARCH-M (1,1) models are employed in the study after doing the preliminary checks such as stationarity, diagnostic checks, volatility clustering and ARCH LM test.

GARCH (1, 1) reveals that both the Chinese markets are of more volatility persistent than Indian Indices as the sum of the parameter for the Chinese markets is close to unity. The result of GARCH –M model discloses risk and internal and external shocks influence of respective index and found Shenzhen Composite Index is arisky asset which seems to have more Standard Deviation than other markets.

We also checked the external causes to influence the volatility of each country's index taking Chinese indices as the variance regressor for Indian indices and vice-versa and found that Shanghai and Shenzhen return volatility cannot affect Indian market, but Chinese market are indeed affected by the volatility of Indian market as BSE return volatility affect Shanghai return volatility, also CNX Nifty volatility transmitted to Shenzhen return.

It's important for the investors to be aware of the possible risks in times of volatility. A précised investment strategy with the coverage to different areas of the market can assist fund managers or investors for the ups and downs of the market, and perhaps they can get the advantage of opportunities when it strikes.

Choosing to stay invested can be the best option for any investors and fund manger if they are confident in their strategy, however, if at all they trade during volatility, it is also important for them to understand the influence of the market on their trade.

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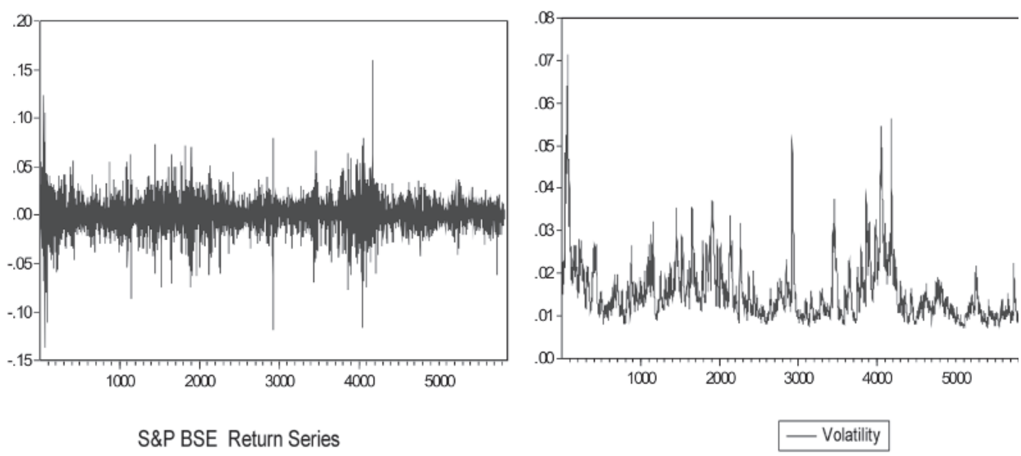
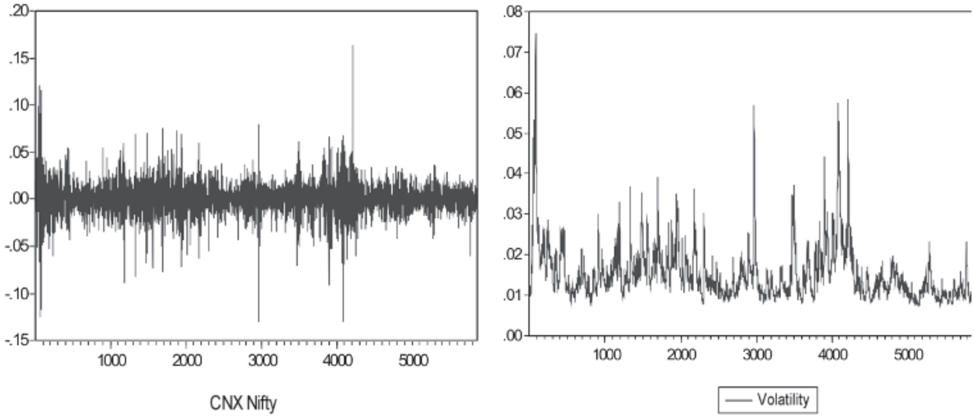
ANNEXURE

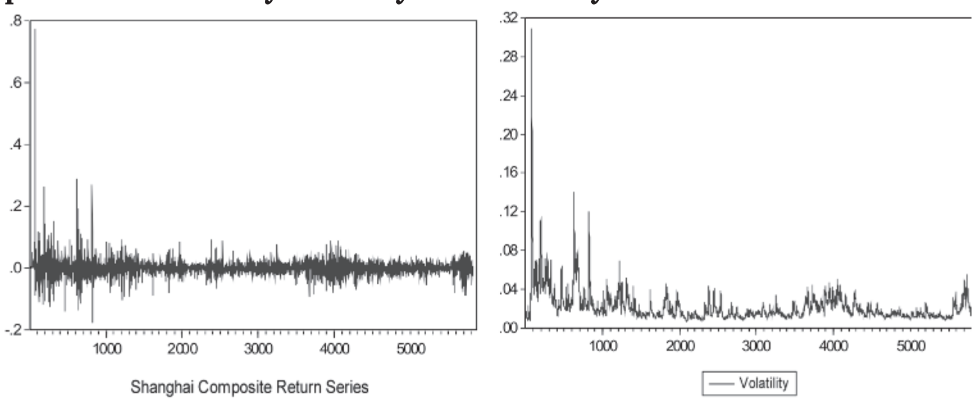
Graph. 1: S&P BSE: Change in the log of daily index price and the daily volatility from January 1992 to December 2015



Graph. 2: CNX Nifty Change in the log of daily index prices and the daily volatility from January 1992 to December 2015



Graph. 3: Shanghai Composite Index: Change in the log of daily index prices and the daily volatility from January 1992 to December 2015



Graph. 4: Shenzhen Composite Index: Change in the log of daily index prices and the daily volatility from January 1992 to December 2015