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MODELING VOLATILITY IN EMERGING STOCK MARKETS OF INDIA AND CHINA

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Abstract

The study investigated the stock market volatility in the emerging stock markets of India and China using daily closing price from 1st January, 2005 to 12th May, 2009. The results detect the presence of non-linearity through BDSL test while conditional Heteroscedasticity is identified through ARCH-LM test. The findings reveal that the GARCH(1,1) model successfully captures nonlinearity and volatility clustering. The analysis suggests that the persistence of volatility in Chinese stock market is more than Indian stock market.

Keywords: Volatility clustering, nonlinearity, BDSL, GARCH

JEL Classification: G14, C32

1. Introduction

Volatility in equity market has become a matter of mutual concern in recent years for investors, regulators and brokers. Stock return volatility hinders economic performance through consumer spending.[2] Stock Return Volatility may also affect business investment spending.[3] Further the extreme volatility could disrupt the smooth functioning of the financial system and lead to structural or regulatory changes.

Volatility of stock returns in the developed countries has been studied extensively. After the seminal work of Engle(1982) on Autoregressive Conditional Heteroscedasticity (ARCH) model on UK inflation data and its Generalized form GARCH(Generalized ARCH) by Bollerslev (1986), much of the empirical work used these models and their extensions (See French, Schwert and Stambaugh 1987, Akgiray 1989, Schwert, 1990, Chorhay and Tourani,1994, Andersen and Bollerslev, 1998) to model characteristics of financial time series.

Starting with the pioneering work of Mandelbrot (1963) and Fama (1965), various features of stock returns have been extensively documented in the literature which are important in modeling stock market volatility. It has been found that stock market volatility is time varying and it also exhibits positive serial correlation (volatility clustering). This implies that changes in volatility are non-random. Moreover, the volatility of returns can be characterized as a long-

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[2] Garner A.C., 1988, Has Stock Market Crash Reduced Customer Spending? Economic Review, Federal Reserve Bank of Kanas City, April, 3-16.

[3] Gertler, M. and Hubbard, R.G.,1989, Factors in Business Fluctuations, Financial Market Volatility, Federal Reserve Bank of Kanas City, 33-72.

memory process as it tends to persist (Bollerslev, Chou and Kroner, 1992). Schwert (1989) agreed with this argument. Fama (1965) also found the similar evidence. Baillie and Bollerslev (1991) observed that the volatility is predictable in the sense that it is typically higher at the beginning and at the close of trading period. Akgiray (1989) found that GARCH (1, 1) had better explanatory power to predict future volatility in US stock market. Poshakwale and Murinde (2001) modeled volatility in stock markets of Hungary and Poland using daily indexes. They found that GARCH(1,1) accounted for nonlinearity and volatility clustering. Poon and Granger (2003) provided comprehensive review on volatility forecasting. They examined the methodologies and empirical findings of 93 research papers and provided syneptic view of the volatility literature on forecasting. They found that ARCH and GARCH classes of time series models are very useful in measuring and forecasting volatility.

There is relatively less empirical research on stock return volatility in emerging markets. Deregulation and market liberalization measures, rapid development in communication technology and computerized trading systems and increasing activities of multinational corporations have accelerated the growth of capital markets which are now moving towards global financial integration. The growing international integration of financial markets has prompted several empirical studies to examine features of volatility of stock markets across the world. However, we need a more systematic investigation of stock market volatility in emerging stock markets. This paper provides evidence on main features of volatility in the emerging stock markets of India and China. The rest of the paper is organized as follows. Section II provides research design used in the study. Empirical results are discussed in Section III. Section IV summarizes.

2. Research Design

Period of study

We collected data on daily closing price S&P CNX Nifty of Indian and SSE of Chinese stock price indices from 1st January, 2005 to 12th May, 2009. The period is the most recent one. The stock markets have become increasingly integrated. The crash of American financial markets triggered by subprime crisis has influenced not only USA but also the stock markets across the globe. These changes might have influenced the behavior and the pattern of volatility and therefore it will be instructive to study volatility in this period.

The Sample

It comprises of daily closing price of 1081 observations for two prominent stock market indices of the emerging economies of Asia namely India and China. Global Finance database is used for analyzing volatility. The NSE was incorporated in November 1992. The Nifty was launched on 3rd November, 1995 with a base value of 1000. It consists of 50 stocks listed on two criteria namely market capitalization and liquidity. The Shanghai composite index captures the price movement of all the shares listed on the Shanghai Stock Exchange (SSE). It is the largest in mainland China and fifth largest stock exchange in the world with more than 900 stocks listed on it. The reason for inclusion of China in the study is that it is the fastest developing economy in Asia followed by India. It is, therefore, insightful to study volatility of both the stock markets of India and China.

Methodology

Daily returns are identified as the difference in the natural logarithm of the closing index value for the two consecutive trading days.

Volatility is defined as;

$$\sigma = \sqrt{1/n-1\sum_{t=1}^{n}(R_t-\bar{R}^2} \quad \dots (1)$$

here $\bar{R}$ = Average return(logarithmic difference) in the sample.

In comparing the performance of linear model with its nonlinear counterparts, we first used ARIMA[4] models. Nelson (1990b) explains that the specification of mean equation bears a little impact on ARCH models when estimated in continuous time. Several studies recommend that the results can be extended to discrete time. We follow a classical approach of assuming the first order autoregressive structure for conditional mean as follows:

$$R_t = a_0 + a_1 R_{t-1} + \varepsilon_t \quad \dots (2)$$

where R_t is a stock return, $a_0 + a_1 R_{t-1}$ is a conditional mean and ε_t is the error term in period t. The error term is further defined as:

$$\varepsilon_t = \upsilon_t \sigma_t \quad \dots (3)$$

where υ_t is white noise process that is independent of past realizations of ε_{t-i}. It has zero mean and standard deviation of one. In the context of Box and Jenkins (1976), the series should be stationary before ARIMA models are used. Therefore, Augmented Dickey Fuller test (ADF) is used to test for stationarity of the return series. It is a test for detecting the presence of stationarity in the series. The early and pioneering work on testing for a unit root in time series was done by Dickey and Fuller (1979 and 1981). If the variables in the regression model are not stationary, then it can be shown that the standard assumptions for asymptotic analysis will not be valid. ADF tests for a unit root in the univariate representation of time series. For a return series R_t, the ADF test consists of a regression of the first difference of the series against the series lagged k times as follows:

$$\Delta r_t = \alpha + \delta r_{t-1} + \sum_{i=1}^{p}\beta_i \Delta r_{t-i} + \varepsilon_t \quad \dots (4)$$

$$\Delta r_t = r_t - r_{t-1}; r_t = \ln(R_t)$$

The null hypothesis is H_0: $\delta = 0$ and H_1: $\delta < 1$. The acceptance of null hypothesis implies nonstationarity. We can transform the nonstationary time series to stationary time series either by differencing or by detrending. The transformation depends upon whether the series is difference stationary or trend stationary.

One needs to specify the form of the second moment, variance, σ_t^2 for estimation. ARCH and GARCH models assume conditional heteroscedasticity with homoscedastic unconditional

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4 A process that combines Autoregressive process (AR) and Moving Average terms (MA) terms. AR process where the present observations depend on the previous observations and MA is a weighted average of the present and the recent past observations of a process.

error variance. That is, the changes in variance are a function of the realizations of preceding errors and these changes represent temporary and random departure from a constant unconditional variance. The advantage of GARCH model is that it captures the tendency in financial data for volatility clustering. It, therefore, enables us to make the connection between information and volatility explicit since any change in the rate of information arrival to the market will change the volatility in the market.

In empirical applications, it is often difficult to estimate models with large number of parameters, say ARCH (q). To circumvent this problem, Bollerslev (1986) proposed GARCH (p, q) models. The conditional variance of the GARCH (p,q) process is specified as

$$h_t = \alpha_0 + \sum_{j=1}^{q} \alpha_j \varepsilon_{t-j}^{2} + \sum_{i=1}^{p} \beta_i h_{t-i} \qquad \ldots (5)$$

with $\alpha_0>0$, $\alpha_1, \alpha_2, \ldots, \alpha_q \geq 0$ and $\beta_1, \beta_2, \beta_3, \ldots, \beta_p \geq 0$ to ensure that conditional variance is positive. In GARCH process, unexpected returns of the same magnitude (irrespective of their sign) produce same amount of volatility. The large GARCH lag coefficients β_i indicate that shocks to conditional variance takes a long time to die out, so volatility is 'persistent.' Large GARCH error coefficient α_j means that volatility reacts quite intensely to market movements and so if α_j is relatively high and β_i is relatively low, then volatilities tend to be 'spiky'. If $(\alpha + \beta)$ is close to unity, then a shock at time t will persist for many future periods. A high value of it implies a 'long memory.' The model is then tested for ARCH effect using ARCH-LM test to judge model adequacy. If ARCH-LM test results are statistically insignificant, the model will be adequate.

5. Empirical Results

The descriptive statistics for the return series include mean, standard deviation, skewness, kurtosis, Jarque-Bera and Ljung Box. ARCH-LM statistics are also exhibited in the Table 1.

The mean returns for Nifty and SSE are 0.00051 and 0.00062 respectively which are very close to zero indicating that the series are mean reverting. The return distribution is negatively skewed, indicating that the distribution is non-symmetric. Large value of Kurtosis suggests that the underlying data are leptokurtic or thick tailed and sharply peaked about the mean when compared with the normal distribution. Since GARCH model can feature this property of leptokurtosis evidence in the data.

The Jarque-Bera[5] statistics calculated and reported in the Table-1 to test the assumption of normality. The results show that the null hypothesis of normality in case of both the stock markets is rejected.

The Ljung-Box LB^2 (12) statistical value 623.70 and 118.81 for NSE and SSE respectively rejects significantly the zero correlation null hypothesis. It suggests that there is a clustering of variance. Thus, the distribution of square returns depends on current square returns as well as several periods' square returns, which will result in volatility clustering.

Stationarity condition of the Nifty and SSE daily return series were tested by Augmented Dickey-Fuller Test (ADF). The results of this test are reported in the Table 2.

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5 The B-J teat statistic is $T[skewness^2/6+(kurtosis-3)^2/24]$.

Table 1. Descriptive Statistics of Daily Returns

Statistic	*Nifty*	*SSE*
Observation period	January 2005-May 2009	January 2005-May 2009
Number of observations	1081	1081
Mean	0.00051	0.00062
Standard deviation	0.01933	0.02055
Skewness	-0.5401	-0.2713
Kurtosis	6.5667	5.4957
Jarque-Bera Statistics	624.93(2-tailed p=.000)	293.53(2-tailed p=.000)
Q^2(12)	623.70(0.000)	118.81(0.000)
ARCH LM statistics (at Lag =1)	37.56(2-tailed p=.000)	16.04(2-tailed p=.000)
ARCH LM statistics (at Lag =5)	189.84(2-tailed p=.000)	43.88(2-tailed p=.000)

Notes: ARCH LM statistic is the Lagrange multiplier test statistic for the presence of ARCH effect. Under null hypothesis of no heteroscedasticity, it is distributed as $\lambda^2(k)$. Q^2(K) is the Ljung Box statistic identifying the presence of autocorrelation in the squared returns. Under the null hypothesis of no autocorrelation, it is distributed as $\lambda^2(k)$.

Table 2. Unit Root Testing of Daily Returns of Nifty and SSE
Augmented Dickey-Fuller Test

Null Hypothesis	*Test statistics*				*Mackinnon Asymptotic*
Presence of Unit root	*Level*		*First Difference*		*Critical value @ 1% level*
	Nifty	*SSE*	*Nifty*	*SSE*	
Intercept	-1.54(0.52)	-1.00(0.76)	-30.73(0.00)	-32.83(0.00)	-3.44
Trend &Intercept	-1.20(0.92)	-0.67 (0.97)	-30.75(0.00)	-32.83(0.00)	-3.97
Trend coefficient	-0.00 (0. 93)	-0.00 (0.77)	-0.00(0.29)	0.00(0.48)	
None	0.17(0.74)	0.05(0.70)	-30.72(0.00)	-32.81(0.00)	-2.57

ADF statistics in level series shows presence of unit root in both the stock markets as their Mackinnon's value do not exceed the critical value at 1% level. It suggests that both the price series are nonstationary. The trend coefficients of both the series are statistically insignificant suggesting absence of any trend in both the markets. It is, therefore, necessary to transform the series to make it stationary by taking its first difference. ADF statistics reported in the Table 2 show that the null hypothesis of a unit root in case of both Nifty and SSE is rejected. The absolute computed values for both the indices are higher than the MacKinnon critical value at 1% level. Thus, the results of both the indices show that the first difference series are stationary.

Nonlinearity in the series is analyzed using BDSL test. The BDSL (Brock,Dechert,Scheinkman and LeBaron, 1996) test is a nonparametric test with the null hypothesis that a time series is independent and identically distributed. The alternative hypothesis includes both deterministic chaos as well as linear and nonlinear stochastic behaviour. It measures the statistical significance of the correlation dimension calculations. The correlation integral is the probability that any two points are within a certain length, 'e' apart in phase space. The correlation integrals are calculated according to equation 6.

$$C_m(e) = (1/N^2) \times \sum_{I,J=1}^{T} Z(e - |X_i - X_j|), i \neq j, \quad \dots (6)$$

where Z(e) =1 if $e - |X_i - X_j| > 0$, 0 otherwise. T = number of observations, e = distance, C_m = correlation integral for dimension m, N = length of the series, X_i, X_j = the index series.

The function Z in the equation 3 counts the number of points within a distance 'e' of one another. The correlation integral calculates the probability that two points that are part of two trajectories in phase space are 'e' units apart. The BDS statistics, W, is given by

$$W_N(e,T) = \left|C_n(e,T) - C_l(e,T)^N\right| \times \sqrt{T / S_N(e,T)} \quad \dots (7)$$

where $S_N(e,T)$ is the standard deviation of the correlation integrals. The test is able to locate many types of nonlinearity, nonstationarity and deterministic chaos. The null hypothesis is rejected with 95% and 99% confidence when W exceeds 1.96 and 3 respectively. If null hypothesis is rejected, we can say that the time series is nonlinear or has chaotic behavior.

We applied the BDSL test to the residuals of ARMA(1,0) models in both the stock markets. We used embedding dimensions of 2 to 8 and epsilons(e) ranging from half to two standard deviations. The results in Table 3 indicate significant BDSL statistics for both the Nifty and SSE, suggesting the presence of nonlinearity. It suggests that ARMA(1,0) model fails to capture nonlinearity in the data.

To test for heteroscedasticity, the ARCH-LM test is applied to residuals of ARIMA (1,0) equation. The results are reported in Table 1. The ARCH-LM test at lag length 1 and 5 indicate presence of ARCH effect in the residuals in both the stock markets. It implies clustering of volatility where large changes tend to be followed by large changes, of either sign and small changes tend to be followed by small changes (Engle, 1982 and Bollerslev, 1986). To explore the nature of volatility, GARCH (1,1) model is applied in the stock markets. The results of the estimated model are reported in Table 4. The GARCH model is tested for their fitness and adequacy using ARCH-LM test. The results are also presented in the Table 4. The findings indicate that there is no ARCH effect left after estimating the models because the results of ARCH-LM test statistics at lag length 5 reported in the Table 4 are statistically insignificant as its probability value is higher than 0.05. It, therefore, suggests that the estimated models are better fit and successfully account for time varying volatility.

The parameters estimates of the GARCH (1, 1) models in Tables 4 are all statistically significant. The estimates of β_1 are always markedly greater than those of α_1 and the sum $\alpha_1 + \beta_1$ is very close to but smaller than unity. It is observed that $\alpha_1 + \beta_1$ is equal to 0.984 for Nifty and 0.995 for SSE.

This is less than unity indicating stationarity condition is not violated. The sum of Chinese stock market is higher than Nifty of India which indicates a long persistence of shocks in volatility in SSE. As the lag coefficient of conditional variance β_1 is higher than the error coefficient α_1 implying that volatility is not spiky in both the stock markets. It also indicates that the volatility does not decay speedily and tends to die out slowly.

Table 3. BDS Test Statistic for Residuals from ARIMA(1,0) Model

M	*S&P CNX Nifty*	*SSE*
2	9.18	3.37
3	13.63	6.17
4	17.87	8.90
5	23.48	11.94
6	30.68	15.62
7	39.93	20.57
8	54.27	26.24
2	9.47	3.98
3	13.04	6.37
4	16.27	8.63
5	20.22	11.00
6	24.75	13.34
7	29.85	15.63
8	35.55	18.33
2	8.44	4.09
3	11.03	5.59
4	13.38	7.31
5	15.85	9.17
6	18.11	10.76
7	20.36	12.11
8	22.25	13.44
2	7.20	3.71
3	9.97	4.44
4	12.11	5.51
5	13.90	6.76
6	15.13	7.79
7	16.16	8.70
8	16.71	9.40

Note: Marginal significance Level of the statistics for a two tailed test is 1.96

Table 4. Coefficients of GARCH Model

Coefficients	*Nifty*	*SSE*
	GARCH(1,1)	*GARCH(1,1)*
α_0	0.0000(0.000)	0.0000(0.000)
α_1	0.146(0.000)	0.062(0.000)
β_1	0.838(0.000)	0.933(0.000)
$\alpha_1 + \beta_1$	0.984	0.995
Log liklihood	2922.26	2766.78
AIC	-5.41	-5.12
SBC	-5.38	-5.10
ARCH-LM test	4.38(0.50)	2.18(0.82)

Note: Figures in the parenthesis indicate probability Value.

The residuals from GARCH(1,1) process are tested for nonlinearity using the BDSL test. The results are reported in Table 5. It suggests that the nonlinearity is not present in the residuals. It indicates that the nonlinearity occurs due to volatility clustering is successfully captured by the GARCH model.

Table 5. BDS Test Statistic for Residuals from GARCH(1,1) Model

m	*S&P CNX Nifty*	*SSE*
2	-0.36	-1.15
3	0.32	-0.71
4	0.92	0.00
5	0.94	0.82
6	1.63	1.57
7	1.27	1.76
8	0.82	1.74
2	0.23	-0.59
3	0.46	-0.52
4	0.85	-0.29
5	0.67	0.27
6	0.37	0.47
7	0.24	0.61
8	0.32	0.70
2	-1.20	-0.04
3	-0.74	-0.27
4	-0.19	-0.33
5	0.43	0.03
6	0.90	0.23
7	1.16	0.35
8	1.00	0.35
2	-1.29	0.44
3	-0.90	-0.06
4	-0.29	-0.20
5	0.25	0.08
6	0.63	0.23
7	0.84	0.35
8	0.59	0.28

Note: Marginal significance level Of the statistics for a two tailed test is 1.96.

4. Summary

The volatility in the Indian and Chinese stock markets exhibits the persistence of volatility, mean reverting behavior and volatility clustering. The study used more than three years of recent daily data on Nifty and SSE to illustrate these stylized facts, and the ability of GARCH(1,1) to capture these characteristics. Daily returns in the stock markets exhibit nonlinearity and volatility clustering which are satisfactorily captured by the GARCH models. In both the markets, volatility tends to die out slowly. Results suggest that the volatility is more persistent in the Chinese stock market than the Indian stock market.

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