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Long Memory Property In Return and Volatility: Evidence from the Indian Stock Markets

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Abstract

The paper examines the existence of long memory in the Indian stock market using ARFIMA, FIGARCH models. The data set consists of daily return of BSE and NSE stock indices and long memory tests are carried out both for the returns and volatilities of these series. The results of ARFIMA model suggests the absence of long memory in return series of the Indian stock market. The results of FIGARCH model indicate strong evidence of long memory in conditional variance of the stock indices. The long memory property of the BSE market is revealed to be stronger than NSE.

Keywords: ARFIMA, GARCH, long memory, FIGARCH

JEL classification: C22, C50

1. Introduction

Long memory dynamics are important pointers for identifying presence of nonlinear relations in conditional mean and variance of financial time series. The modelling of stock market volatility has been a considerable field of research after the introduction of ARCH and GARCH classes of models by Engle(1982) and Bollerslev(1986). It has been found that stock market volatility is time varying and exhibits positive serial correlation (volatility clustering).This implies that changes in volatility are non-random. However, these models do not account for long memory in volatility. The long memory is often found in conditional mean and variance of a financial time series at the same time. Slow mean-reverting at hyperbolic rate decay in autocorrelation functions of return and volatility is defined as long memory in return and volatility. Based on this idea, the empirical works of Baillie, Han and Kwon(2002) and Beine, Laurent and Lecourt (2003) have focussed on analysing dual long memory property in conditional mean and variance. The empirical findings act as evidence for presence of long memory in return and volatility of returns.

Mendes and Kolev(2006) found that the presence of long memory in conditional variance hid its true dependence structure. Madlebrot(1971) implied that the perfect arbitrage was not possible when returns displayed a long-range dependence. The derivative pricing models become ineffective in the presence of long-range dependence. Hence, the presence of long memory has important theoretical and practical implications. The study of long memory property in return and volatility of stock markets of India has received little attention. In the light of this background, the primary aim of this paper is to investigate the dual long memory property in the returns and volatility of Stock Markets of India using ARFIMA-FIGARCH model.

The rest of the paper is organized as follows. Section 2 presents a brief review of previous work on long memory property in return and volatility. Section 3 discusses ARFIMA-GARCH model. Section 4 provides the statistical properties of data and the estimation results of the ARFIMA-FIGARCH models. Section 5 summarizes.

2. Literature Review

Modelling long memory properties in stock market return and volatility has become an interesting research area in recent years. The existence of long memory in returns and volatility suggests the presence of dependencies among observations. Kasman, Kasman and Torun(2009) found that Long memory in these series were related with the high autocorrelation function which decays hyperbolically and finally died out. In contrast, if correlation between distant observations is negligible, the series possesses short memory and exhibits exponential decaying observations.

Granger and Joyeux(1980) and Hosking(1981) found that fractionally integrated series could capture long memory property and proposed fractionally integrated autoregressive moving average (ARFIMA) model. It is characterized by hyperbolic decaying of autocorrelation function. Lo (1991), Jacobson(1996), Crato and Lima(1994) and Tolvi(2003) used ARFIMA model to investigate the presence of long memory in stock market returns. Besides numerous studies examine long memory in stock return, Ding and Granger(1996), Lobato and Savin(1998), Comte and Renaut(1998) and Andreano(2005) investigated the long memory in volatility. They showed that the autocorrelation function of the squared daily return decayed very slowly. Baillie et al.(1996) developed fractionally integrated generalized conditional heteroscedasticity(FIGARCH) model to allow for fractionally integrated process of conditional variance.

Korkmaz, Cevik and Ozatae(2009) detected long memory property in volatility of returns in Istanbul stock exchange of Turkey. Jeffery and Thupayagale (2008) found the evidences of long memory in volatility for South Aftica and Zimbabwe, whereas no such evidence was found in Botswana.

Kang and Yoon (2007) suggest that ARFIMA-FIGARCH model can provide a useful way of examining the relationship between conditional mean and variance of a process exhibiting the long memory property. Moreover, Kasman et. Al (2009) found that these models offer greater flexibility to analyze long memory property in return and volatility with fractionally differencing process.

Kumar(2004) analyzed the long memory property of Indian stock markets of National Stock Exchange(NSE) and Bombay Stock Exchange(BSE) by examining trade volume series using ARFIMA-GARCH models during 1995 to 2003. The study found that the the trade volume series exhibited strong evidence of long memory. The study has made no attempt to investigate long memory property in return and volatility of Indian stock indices. There has been no comprehensive study of long memory in return and volatility in India, which is one of the fasted growing emerging stock markets. Hence, the present paper is devoted to this issue in two premier Indian stock exchanges namely NSE and BSE.

3. Methodology

3.1 ARFIMA-FIGARCH model

Granger and Joyeux (1980) and Hosking (1981) introduced ARFIMA to test long memory property in the asset returns. The purpose of this model to consider fractionally integrated process I(d) in the conditional mean. The ARFIMA (n,ξ,s) model can be expressed as follows:

$$\psi(L)(1-L)^{\xi}(y_t-\mu)=\theta(L)\varepsilon_t \tag{1}$$

$$\varepsilon_t = z_t\sigma_t, \quad z_t \sim N(0,1) \tag{2}$$

Where ε_t is independent and identically distributed with variance σ^2 and L denotes the lag operator and replacing with difference operator (1-L) of an ARIMA process with the fractional difference operator $(1-L)^{\xi}$, where ξ denotes the degree of fractional integration. The differencing parameter ξ need not be an integer, but the integer value of ξ leads to a traditional ARMA models. If $0 < \xi < 0.5$, all autocorrelations are positive implying long memory while they are negative if $-0.5 < \xi < 0$. The negative values indicate that the process exhibits negative dependence between distant observation suggesting anti-persistence. The process is said to be stationary when $\xi = 0$. For $\xi = 1$, the process follows a unit root process.

$\psi(L) = 1 - \psi_1 L - \psi_2 L^2 - \ldots . \psi_n L^n$ and $\theta(L) = 1 + \theta_1 L + \theta_2 L^2 + \ldots + \theta_s L^s$ are the autoregressive (AR) and moving-average (MA) polynomials.

The extension of the ARFIMA representation in squared errors (ε^2) is FIGARCH model of Baillie et al. The FIGARCH (p,d,q) can be expressed as follows:

$$\phi(L)(1 - L)^d \varepsilon^2 = \omega + [1 - \beta(L)]v_t \tag{3}$$

$V_t = \varepsilon_t^2 - \sigma_t^2$ is mean zero serially uncorrelated error, ε_t^2 is the squared error of the GARCH process. The $\{V_t\}$ process is integrated as the "innovations" for the conditional variance (σ_t^2). If d=0, the FIGARCH (p, d, q) process reduces to a GARCH (p,q) process and if d=1, the FIGARCH process becomes an integrated GARCH process. Rearranging the terms in Eq.(3), one can write the FIGARCH model as follows:

$$[1 - \beta(L)]\sigma_t^{\,2} = \omega + [1 - \beta(L)(1 - L)^d]\varepsilon_t^2. \tag{4}$$

The conditional variance equation of ε_t^2 is obtained by:

$$\sigma_t^2 = \frac{\omega}{[1 - \beta(L)]} + \left[1 - \frac{\phi(L)}{[1 - \beta(L)}(1 - L)^d\right]\varepsilon_t^2 \tag{5}$$

That is

$$\sigma_t^2 = \frac{\omega}{[1 - \beta(1)]} + \lambda(L)\varepsilon_t^2 \tag{6}$$

where $\lambda(L) = \lambda_1 L + \lambda_2 L^2 \ldots$ Baillie et al. (1996) mention that the impact of a shock on conditional variance of FIGARCH(p,d,q) processes decrease at a hyperbolic rate when $0 \le d \le 1$. Hence, the long term dynamic is taken into account by the fractional integrated parameter d and the short dynamic is captured through traditional GARCH model parameters.

Baillie et al (1996) through simulations demonstrated that Quasi maximum likelihood (QMLE) estimation method performs better in case of high frequency financial data. Therefore, we use QMLE method to estimate the results of ARFIMA-FIGARCH model.

3.2 The adjusted Pearson goodness-of-fit Test

The adjusted Pearson goodness-of-fit test can access the relevance of various estimated distributions like normal and skewed Student-t distribution. It compares the empirical distribution with theoretical innovations. Palm and Vlaar(1997) classify the residuals in cells corresponding to their magnitude to implement the test. The Pearson goodness-of-fit statistics for a given number of cells denoted g is given as follows:

$$P(g) = \frac{\sum_{i=1}^{g} (n_i - En_i)^2}{En_i} \quad \textbf{(7)}$$

Where n_i is the number of observations in cell i, and En_i is the expected number of observations. Under the null hypothesis of a correct distribution, P(g) statistics is distributed as $\chi^2(g-1)$. Since there is no consensus on the proper choice of g in literature, we set g equal to 60 for our sample size.

4. Empirical Results

4.1 Preliminary Analysis of Data

We consider daily returns of two most popular and widely quoted stock indices-Bombay Stock Exchange and National Stock Exchange of India. The Bombay Stock Exchange is the oldest stock exchange in Asia. The BSE sensitivity index(SENSEX) is launched in 1986. It comprises 30 shares and its base year is 1978-79. The major criteria for selection of a scrip in the BSE Sensex is large market capitalization. Besides this criteria, other criteria like number of trades, average value of shares traded per day as a percentage of total number of outstanding shares are considered for inclusion in Sensex. Another index which has become popular in a short span of time is the S&P CNX Nifty of National Stock Exchange of India. The National stock exchange began equity trading in November 1994. NSE introduced this index to reflect the market movements more accurately, provide for managers with a benchmark for measuring portfolio performance. The S&PCNX Nifty launched comprises of 50 scrips which are selected on the basis of low impact cost, high liquidity and market capitalization. The dataset consists of daily closing prices starting from January 2, 2008 to August 10, 2011 covering 890 observations. The period is the most recent. The economy has also been affected by global financial crisis at different point in time during the period, leading to some fluctuations in the stock prices. This study which uses the data set covering the crisis period is, therefore, relevant and instructive for the analysis.

The daily stock returns are defined as logarithmic difference of the daily closing price of respective indices. The descriptive statistics of these two indices are reported in Table 1.

Table 1. Descriptive statistics of sample return series

Descriptive Statistics	BSE	NSE
Mean	-0.0002	-0.0001
Standard Deviation	0.0203	0.0199
Skewness	0.2873	0.1705
Kurtosis	9.6177	11.0789
Jarque-Bera	1632.57	2419.23
Q(20)	32.07	35.77
Qs(20)	279.94	195.76

All the return series reveal that they do not correspond with normal distribution assumption. Jarque-Bera statistics suggest that there are significant departures from normality. We examine the null hypothesis of white noise using the Box-Pierce statistics of the return residuals(Q(20) and squared return residuals Qs((20)). From the results, we certainly reject the null hypothesis of white noise. It also indicates that the series are autocorrelated.

4.2 Unit Root Tests

Before investigating the long memory in return and volatility, we check the series for a presence of unit root. We have employed three unit root tests--ADF(Augmented Dickey Fuller), PP(Philips-Peron) and KPSS(Kwiatkowski, Phillips, Schmidt and Shin) to determine if the individual return series are stationary or not. Three tests differ in the null hypothesis. The null hypothesis of the ADF and PP test is that a time series contains unit root while KPSS test has the null hypothesis of stationarity.

The empirical results of all the three tests are presented in Table 2.

Table 2. Unit Test Results

Test	BSE	NSE
ADF	-27.65(0.000)*	-28.32(0.00)
PP	-27.61(0.000)*	-28.33(0.00)
KPSS	0.264**	0.274

Notes: * Mackinnon's 1% critical value is -3.435 for ADF and PP tests.

** A KPSS critical value is 0.739 at 1% significant level.

Large negative values for ADF and PP tests for both return series reject the null hypothesis of a unit root at the 1% significant level. Additionally, the statistics of the KPSS test indicate that return series are stationary. Thus both the series are stationary and suitable for subsequent long memory tests in this study.

4.3 Estimation Results of ARFIMA Models

We estimate different orders of ARFIMA models of (n,s) and compare the performance of the ARFIMA models to determine the adequate orders in detecting long memory property in return series. Following Cheung(1993), we consider all possible combinations for the ARMA(n,s) with maximum n=0,1,2 and s=0,1,2.

The results of the models are reported in Table 3. The results indicate that the long memory parameter ξ and coefficients of all AR and MA are insignificant in all cases. It clearly suggests that there is no evidence of long memory in both BSE and NSE return series. It is consistent with weak-form market efficiency. Model selection criteria select ARFIMA (0,0,0) model. We, therefore, consider ARMA (0,0) model with GARCH class of models to analyze long memory in volatility of return series.

The diagnostic statistics in Table 3 indicate that the significant departure from normality with large excess kurtosis and skewness. The J-B statistics also suggest that the residuals appear to be leptokurtic. In addition, ARCH statistics are highly significant implying the presence of ARCH effects in the standardized residuals. It, therefore, implies that we need GARCH models to capture long memory property in the Indian stock market.

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Table 3. Estimation of ARFIMA models for (a) BSE and (b) NSE

(n, ξ ,s)	(0, ξ ,0)	(0, ξ ,1)	(0. ξ ,2)	(1, ξ ,0)	(1, ξ ,1)	(1, ξ ,2)	(2, ξ ,0)	(2, ξ ,1)	(2, ξ ,2)
(a)									
μ	-0.02 (0.769)	-0.02 (0.78)	-0.02 (0.77)	-0.01 (0.79)	-0.02 (0.76)	-0.02 (0.76)	-0.02 (0.77)	-0.01 (0.81)	-0.02 (0.78)
ψ_1				0.07 (0.17)	-0.37 (0.67)	0.76 (0.00)	0.08 (0.201)	0.57 (0.08)	0.07 (0.9)
ψ_2				-			-0.033 (0.41)	-0.02 (0.19)	-0.32 (0.93)
ξ	0.00 (0.98)	0.00 (0.98)	0.00 (0.97)	0.00 (0.89)	0.00 (0.98)		0.00 (0.97)	0.00 (0.98)	0.00 (0.96)
θ_1	-	0.06 (0.21)	-0.02 (0.77)	-	0.36 (0.77)	-0.66 (0.00)	-	-0.04 (0.06)	-0.00 (0.99)
θ_2	-	-	-0.03 (0.12)	-	-	-0.06 (0.13)	-	-	-0.00 (0.99)
ln(L)	-1889.73	-1887.23	-1886.89	-1887.31	-1888.74	-1887.91	-1886.86	-1888.93	-1886.86
AIC	4.231	4.25	4.254	4.259	4.269	4.265	4.38	4.28	4.27
Skewness	0.287**	0.31**	0.29**	0.31**	0.28**	0.33**	0.29**	0.34**	0.29**
Excess Kurtosis	6.62*	6.47*	6.45*	6.44*	6.63*	6.36*	6.46	6.02*	6.45*
J-B	1632.6*	503.7*	505.2*	500*	525.78*	486.95*	504.56*	448.87*	506.78*
Q(20)	**523.86***	**1561.6***	**1556.1***	**1550.3***	1638.9*	1513.4*	1550.4*	1357.8*	1551.1*
ARCH(5)	13.63*	13.76*	13.58*	13.82*	13.64*	14.03*	13.60*	14.61*	13.56*
(b)									
μ	-0.01 (0.82)	-0.014 (0.84)	-0.014 (0.83)	-0.01 (0.84)	-0.00 (0.84)	-0.02 (0.85)	-0.01 (0.82)	-0.014 (0.8)	-0.02 (0.98)
ψ_1	-	-	-	0.05 (0.36)	-0.19 (0.94)	0.05 (0.96)	0.049 (0.41)	0.05 (0.96)	0.049 (0.96)
ψ_2	-	-	-		-	-	-0.011 (0.77)	-0.01 (0.89)	-0.011 (0.96)
ξ	0.00 (0.97)	0.00 (0.98)	0.00 (0.87)	0.00 (0.95)	0.00 (0.96)	0.01 (0.97)	0.00 (0.98)	0.00 (0.98)	0.00 (0.98)
θ_1	-	0.04 (0.39)	0.05 (0.42)	-	0.21 (0.93)	0.00 (0.98)	-	0.00 (0.99)	-0.00 (0.98)
θ_2	-	-	-0.01 (0.85)	-	-	-0.01 (0.91)	-	-	-0.00 (0.97)
ln(L)	-1875.6*	-1874.5*	-1874.5*	-1874.4*	-1895*	-1894.49*	-1874.4*	-1874.5*	-1874.0*
AIC	4.24	4.23	4.233	4.231	4.234	4.235	4.23	4.234	4.237
Skewness	0.17**	0.19**	0.18**	0.20**	0.17**	0.18**	0.18**	0.19**	0.18**

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Excess Kurtosis	8.08*	7.91*	7.90	7.89*	8.02*	8.90*	7.89*	8.90*	7.89*
J-B	2419.2*	2321*	2314.6	2307.1*	2383.8*	2313.3*	2312.1*	2313.6*	2312.4*
Q(20)	703.82	682.07	681.6*	678.77*	696.2*	681.3*	681.53*	681.6*	882.1*
ARCH(5)	10.65*	10.84*	10.79*	10.89*	10.67*	10.78*	10.79*	10.77*	10.76*

Notes: QMLE standard errors are reported in the parentheses below corresponding parameter estimates. Ln(L) is the value of the maximized Gaussian Likelihood and AIC is the Akaike Informatin criteria. The Q(20) is the Ljung Box test statistics with 20 degree of freedom based on the standardized residuals. The ARCH(5) denotes the ARCH test statistic with lag 5. The skewness and kurtosis are also based on standardized residuals. * and ** denote significance levels at 1% and 5% respectively.

4.3 Estimation results of FIGARCH models

We compare the performance of GARCH, IGARCH and FIGARCH models in modelling a long memory volatility process and determine its best fitting order. We used ARFIMA (0,0,0) model in mean equation. The results of the models are presented in Table 4. The model selection criteria based on AIC and Ljung-Box Q statistics. The model which has lowest AIC and passes Q-test simultaneously is used. The model selection criteria suggest FIGARCH(1,1,1) model in both the stock market of India. The sum of estimates of ϕ_1 and β_1 is close to one for all the indices, indicating that the volatility is highly persistence. In particular, the estimates of β_1 in GARCH model are very high, suggesting a strong autoregressive component in the conditional variance process. The long run memory parameter d is statistically significant in the Indian stock markets implying prevalent of long memory in volatility. Comparing the degree of parameter d between the BSE and NSE stock markets, the long memory property in NSE market is less than that in its counterpart. The reasons might be related to market microstructure. NSE has been providing investors' better platform to adopt broader investment strategy and gather information through better usage of information technology. The results also indicate that the β_1 estimates are lower in the FIGARCH than those of GARCH models. These results are in line with the findings of Baillie et al.(1996) who show that there is an upward bias in GARCH estimates in the presence of long memory due to the fact that GARCH model does not take into account the long memory component of the volatility process.

Examining the distributional property, the standardized residuals exhibit excess kurtosis and skewness. This justifies the use of skewed Student-t distribution. The statistically insignificant value of P(60) test suggest the relevance of the Student-t distribution for the BSE and NSE returns.

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Table 4. Estimation Results of GARCH models (a) BSE and (b) NSE

(p,d,q)	GARCH (1,0,1)	IGARCH (1,1,1)	FIGARCH (1,d,0)	FIGARCH (1,d,1)
(a)				
μ	0.046 (0.33)	0.047 (0.33)	0.065 (0.21)	0.047 (0.30)
ω	0.028 (0.09)	0.026 (0.07)	0.044 (0.72)	0.031 (0.33)
β_1	0.889 (0.00)	0.889 (0.00)	0.787 (0.00)	0.712 (0.00)
d	-	1	0.854 (0.00)	0.702 (0.00)
ϕ_1	0.107 (0.00)	0.111 (0.00)	-	0.07 (0.31)
ln(L)	-1694.45	-1694.5	-1704.5	-1688.91
AIC	3.828	3.826	3.848	3.817
Q(20)	19.15 (0.51)	19.11 (0.51)	20.249 (0.44)	20.173 (0.44)
Qs(20)	8.017 (0.978)	8.152 (0.976)	8.578 (0.979)	8.328 (0.973)
ARCH(5)	0.587 (0.709)	0.601 (0.699)	0.561 (0.730)	0.544 (0.742)
Skewness	0.15**	0.15**	0.12	0.14**
Excess Kurtosis	2.14*	2.13*	2.22*	2.11*
p(60)	44.57 (0.83)	54.30 (0.50)	61.73 (0.24)	60.51 (0.22)
(b)				
μ	0.057 (0.25)	0.058 (0.24)	0.068 (0.13)	0.059 (0.23)
ω	0.031 (0.07)	0.028 (0.07)	0.059 (0.12)	0.034 (0.32)
β_1	0.888 (0.00)	0.888 (0.00)	0.693 (0.036)	0.649 (0.00)
d	-	1	0.743 (0.04)	0.650 (0.00)
ϕ_1	0.108 (0.00)	0.112 (0.00)	-	0.109 (0.21)
ln(L)	-1685.75	-1685.81	-1684.66	-1683.86
AIC	3.808	3.806	3.805	3.704
Q(20)	17.45 (0.56)	18.35 (0.56)	19.84 (0.47)	19.11 (0.51)

Qs(20)	5.80 (0.99)	5.96 (0.98)	6.48 (0.99)	5.91 (0.99)
ARCH(5)	0.338 (0.89)	0.348 (0.88)	0.416 (0.84)	0.323 (0.123)
Skewness	0.17*	0.17*	0.16*	0.18*
Excess Kurtosis	3.40*	3.43*	3.64*	3.41*
p(60)	54.29 (0.46)	47.81 (0.74)	63.08 (0.18)	71.73 (0.13)

Notes: P(60) is the Pearson goodness-of-fit statistic for 60 cells. The ARCH(5) and P(60) tests are computed on the standardized residuals. * and ** indicate rejection at 1% and 5% significance level, respectively.

5. Conclusions

The study examined the long memory property in the Indian stock markets. The results of ARFIMA model indicate that there is no existence of long memory property in the stock returns. The absence of long memory in asset returns supports the weak form market efficiency hypothesis. We investigate the long memory property in conditional variance series of Indian stock markets. The ARMA-GARCH(1,0,1), ARMA-IGARCH(1,1,1), ARMA-FIGARCH (1,d,0) and ARMA-FIGARCH(1,d,1) were estimated. The estimation results indicate that ARMA-FIGARCH (1,d,1) model better explains long memory property in conditional variance of return series. The results suggest that there is a prevalence of long memory property in volatility of Indian stock markets. Therefore, long memory models such as FIGARCH are recommended for volatility forecasting. In addition, the long memory property of the BSE market is revealed to be much stronger than NSE. It could be said that NSE might be having better process of market development and greater participation of competing investors than BSE which could lead to better informational efficiency in volatility in comparison to BSE. The evidence of long memory in volatility, however, shows that uncertainty or risk is an important determinant of the behaviour of daily stock data in the Indian stock markets. High frequency data at minute frequency would be useful in understanding the dynamics of the markets. Diebold and Inoue (2001) detected the linkage between regime switching and long memory property. Therefore, non linear models like regime switching might provide valuable insight over the dynamics of stock return, which could be an area for future research.

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