Modelling Stock Market Volatility: A Study of NIFTY Returns

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Abstract

The Present paper attempted to explore stock market volatility patterns using both symmetric as well as asymmetric models particularly whether negative and positive news have same impact on the stock market volatility or there is difference in their impact and along with whether FIIs influence the volatility. The monthly data on closing stock prices were taken from website of National Stock Exchange from 1st January 1999 to 31st May 2019 and for foreign Institutional investment, Reserve Bank of India's website was considered. Augmented Dickey Fuller test of unit root was employed to check the stationarity of the data. To find the asymmetry affect two tests from GARCH family, Exponential GARCH model and Threshold GARCH model were used. The study found the clear presence of asymmetry in the return series meaning thereby any negative news in the market have a larger impact on the volatility than any positive shock. FIIs found to have positive but insignificant impact on stock market volatility of NSE in India for the study period. But GARCH-M model found no evidence of risk premium indicating no reward for assuming additional risk. Finally the study affirms GARCH (1,1) and E-GARCH are the better performers in symmetric and asymmetric category of techniques respectively following the lowest values of Akaike information criteria and Schwartz information criteria.

Key Words: *Volatility, FIIs, GARCH, Stationarity, NIFTY, symmetric and Asymmetric*

INTRODUCTION

Financial markets and stock markets in particular are subject to uncertainty. Exchange rates, Stock market volatility has now days become a very critical issue due to financial integration and globalization all over the world. Volatility is one of the main characteristic of financial markets today and forecasting and modeling of financial market has became an important empirical research topic in past few decades (Gabriel 2012). Volatility is a method of measuring how much the current price of an asset varies from its average price. Higher the variation greater the volatility. It is a standard measure of financial market vulnerability of an economy (Kaur and Dhillon, 2015).Greater price fluctuations increase the chances of uncertainty about future returns. Such kind of volatility makes it difficult for companies to raise the investible funds in the capital market (Islam, 2013). Volatility can be categorized as historical and implied. Implied volatility is calculated by taking market price of market traded derivatives. To measure historical volatility three methods are used such as exponentially weighted moving average, simple volatility and GARCH model. Conditional volatility plays a very significant role in many financial activities and expected return on any assets is directly based on its covariance with one or many pricing factors. Various portfolio risk hedging and diversification strategies are build on capability to anticipate variances and covariances (Karmakar 2006). In the present study we applied the basic GARCH (1,1) and GARCH –in mean model and other extensions of GARCH model commonly known as asymmetric models. E-GARCH and T-GARCH popularly used by researcher to find asymmetric relationship. Stock market index act as a barometer of economy and volatility of the market sometimes hinders the investors to invest in the market due to high risk factors. It is generally believed that foreign capital inflows have great influence on economic behavior of countries. In Indian capital FIIs have gained an indispensable role (Saxena,2011). In such a scenario it becomes imperative to gauge the risk associated with investment in general and in particular that whether there is any difference in the impact of positive or negative shocks in the stock market and whether daily investment by foreign institutional investors in the Indian stock market affects the market volatility.

REVIEW OF LITERATURE

Batra (2004) examined the dynamic patterns of in Indian stock market for a period of 24 years taking from 1979 to 2003 on a monthly data. The study investigated the volatility patterns for different phases in the market. Applying asymmetric GARCH model study claims that during the balance of payment crisis period and start of economic reforms was the most volatile period in Indian securities market but FIIs arrival in Indian stock market shows no evidence of direct influence on the volatility of stock market.

Islam(2013)covering a period from 2/1/2007 to 31/12/2012 and considering 1477, 1461 and 1493 observations from kuala Lumpur composite index of Malaysia, Jakarta stock exchange composite index of Indonesia and Straits times index of Singapore respectively employed two symmetric GARCH models namely GARCH (1,1) and GARCH in mean. GARCH in mean found positive correlation between risk and return of all the three different markets but only for Indonesian has strong evidence of volatility than other two markets, the estimated coefficient of risk premium has come out to be statistically significant explain that higher risk leads to higher returns. Both the models have done a good job by removing more than 96% of autocorrelation in the series. However GARCH in mean performs slightly better in case of Indonesia and Singapore market whereas GARCH (1,1) performed a bit better in case of Malaysia.

Floros (2008)taking daily data of two markets indices for Egypt CMA general index and TASE-100 index for Israeli for a period of 1997-2007 employed GARCH –in- mean model and reported positive but insignificant between increased expected risk and increased expected return indicating that higher expected risk does not necessarily bring higher expected return in these markets.

Banumathy and Azhagaiah (2015) on daily of data of closing prices of S&P CNX NIFTY from 1st January 2003 to 31st December 2012 applied GARCH family of volatility models both symmetric as well as asymmetric. The study employed GARCH (1,1) and GARCH in mean as symmetric model and E-GARCH and T-GARCH in asymmetric category of model. Based on Akaike information criteria and Schwarz Information criteria the study found that GARCH (1,1) modelproved to be most suitable in present data series to apprehend the symmetric volatility and to measure asymmetric effect T-GARCH model performed better. The study further asserted that GARCH-M (1,1) revealed the presence of positive but insignificant risk premium meaning thereby that higher risk does not here lead to more returns. The leverage effect measured by parameters of T-GARCH (1,1) and E-GARCH also affirm that negative shocks or events have significant effect on conditional volatility.

Ahmed and Aal (2011) investigated the volatility of returns taking data from Egyptian stock market from 1998 to 2009. The study claims that E-GARCH is the best suited model.(Bahadur 2008).

Goudarzi and Ramanarayanan (2010) estimated volatility of Indian stock market considering BSE 500 stock index for ten years. The decision regarding the best fitted model based on Akaike Information criteria and Schwarz Information criteria study concluded that for explaining volatility clustering and mean reverting in the series, GARCH (1, 1) model was most applicable one amongst the various GARCH models.

Karmakar (2005) in his study examined the volatility model to measure the stock market volatility in Indian context. The study also attempted to estimate the presence of leverage effect in Indian stock market. The research concluded that GARCH (1,1) model is fairly best forecast of market volatility in present data.

Vijyalakshmi and Gaur (2013) applied eight different models for volatility forecast in both Indian and foreign stock markets. A study period from 2003 to 2013 was considered taking NSE and BSE as a proxy of Indian stock market and exchange rate data for Indian rupee and foreign currency. Forecast statistics reveals that TARCH and PARCH are appropriate volatility forecast for stock market evaluation in Indian case whereas for foreign exchange market ARMA (1,1) ARCH (5) and E-GARCH perform well.

OBJECTIVES OF THE STUDY

The primary objective of the study is to examine the volatility of Indian stock market based on NIFTY index return series. The paper attempts to:

- To investigate for the presence of leverage effect in NIFTY returns series.
- To find out whether there exists a risk return relationship.
- To investigate the contribution of foreign institutional investment on stock market volatility.
- To examine the stock market volatility patterns with symmetric as well asymmetric models.

RESEARCH METHODOLOGY

Volatility has been estimated on returns series and for the purpose daily returns were calculated by considering the daily closing stock prices data from NIFTY index. Total 5008 observations were considered for the study for time period 1st January 1999 to 31st May 2019 excluding the public holidays. Log value of first difference of daily closing price is taken to calculate the return series which is as under:

$$rt = \log \frac{ct}{ct-1}$$

Where rt is daily logarithmic NIFTY returns at time t, pt denotes closing price for time t andc_{t-1} is the price in the corresponding period at time t_{-1}. Daily data on FIIs were collected from website of NSDL. Statistical tools such as Augmented Dicky Fuller test (ADF), ARCH-LM test and GARCH family symmetric as well as asymmetric models have been employed and analyzed using E-views 10 student version software package.

Stationarity check

The pre-conditional here to test whether the series are stationary or non stationary and for the purpose to verify unit root test has been referred by conducting commonly used test in the literature, Augmented Dickey Fuller test.

Test for Heteroskedasticity

Before we proceed to apply the GARCH model, it is necessary to confirm the presence of heretoskedasticity in residuals. To test the evidence of heteroskedasticity in residuals of return series, Lagrange Multiplier test for Autoregressive conditional heteroskedasticity commonly known as (ARCH-LM)has been performed.

Volatility Measurement

This part discusses the main methodologies used in the study to model the stock market volatility. GARCH family techniques are employed in the present study. Asymmetric models were applied to capture the asymmetric phenomena to study the relationship asymmetric volatility and return. T-GARCH (1,1) and E-GARCH (1,1) two mostly used models in literature has been considered due to their superiority over the symmetric models as these are competent to arrest asymmetries in terms of negative as well as positive shocks in the market. Two symmetric models were also used i.e GARCH (1,1) model and GARCH –in- mean model.

The Exponential GARCH model

This model verifies the presence of leverage effect in the data based on the logarithmic expression of conditional variance. Nelson 1991 given the general exponential GARCH:

$$\log\sigma_t^2 = wt + \sum_{k=1}^{\infty} \beta k g(Zt - k),$$

$$g(Z_t) = \Theta Zt + \Upsilon(|Z_t|) - E(|Z_t|)$$

The first equation is mean equation and second one is variance equation.$\sigma_t^2$is the conditional variance. As log σ_t^2may be negative, parameters assume no sign constraint.

Threshold GARCH model

Is another variant of asymmetric models, Zakoian 1994 has given the generalized specification of Threshold GARCH model as follows:

$$\sigma_t^2 = \omega + \alpha^1 \varepsilon_{t-1}^2 + \Upsilon d_{t-1} \varepsilon_{t-1}^2 + \beta_1 \sigma_{t-1}^2$$

In the above model Υ term is introduced as a leverage parameter. This model explains good news ($\varepsilon_{t-1} > 0$) and bad news ($\varepsilon_{t-1} < 0$) have differential effects on conditional variance. $\alpha_i$represent impact of good news while $\alpha_i + \Upsilon_i$ reflect impact of bad news. Thus if Υ comes out positive and significant, it implies negative shocks have a larger effectthan positive effect.

GARCH 1,1

It the basic and simplest GARCH model still good enough to capture the volatility effect present in the data. It is symmetric model usually applied to capture volatility clustering but comes with the only limitation it is unable to handle asymmetric shocks in the market.

GARCH –in Mean Model

This method generally helps to measure the risk return relationship, in finance generally. Return of security may be affected by its volatility or risk factor. In this method GARCH term is directly introduced in mean equation to capture the relationship as given below:

Mean equation: $r_{t=} \mu + \lambda \sigma t^2{}_{\tau} + \varepsilon_t$

Variance equation: $\sigma_t^2 = \omega + \alpha\, \varepsilon_{t}^2{}_{-1} + \beta\, \sigma^2{}_{t-1}$

A significant and positive value of the parameter λ reflects that higher mean return is caused by higher risk (Banumathy and Azhagaiah 2015).

RESULTS AND DISCUSSION

Descriptive statistics on NIFTY return and FIIs are compiled in table 1. Descriptive statistics indicate that daily return of NIFTY are negatively skewed which denotes high probability of earning returns greater than average returns and excess kurtosis stating leptokurtic distribution of returns. Jaqrue-Bera test statistics reveals the series are non-normal which the common phenomenon of financial time series.

Daily closing prices of NIFTY were converted into daily logarithmic returns to make the series stationary. Figure no. 1 describes the volatility clustering of return series NIFTY index for the study period from January 1999 to 31 May 2019. It is apparent from figure 1 that periods of high volatility are followed by periods of high volatility for a persistent period and periods of low volatility are chased by periods of low volatility.

Table 1 Descriptive Statistics

Variable	Skewness	Kurtosis	Jarque-Bera Statistics	P-Value
NIFTY Returns	-0.159514	11.70617	15834.48	0.0000
FIIs	2.956358	40.69735	303829.2	0.0000

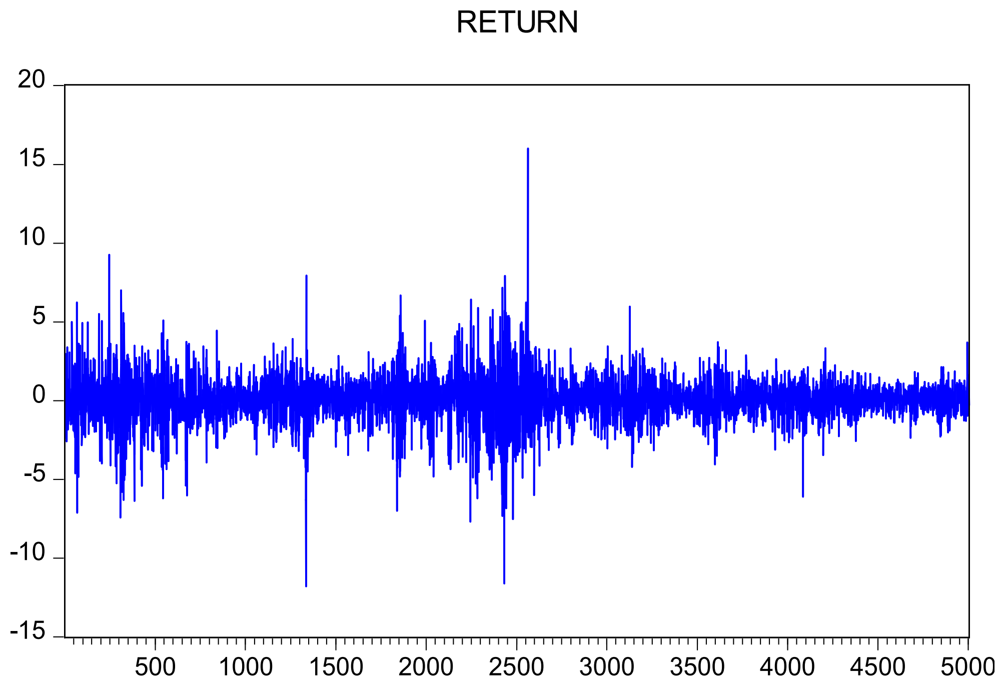

Table 2 Results of unit root test

Series		ADF Unit Root Test Statistics		
		None	**With Intercept**	**With Trend and Intercept**
FII	**At Level**	-13.00616 (0.0000)	-13.48360 (0.0000)	-13.49108 (0.0000)
	At First Difference	-28.42364 (0.0000)	-28.42093 (0.0000)	-28.42635 (0.0000)
NSER	**At Level**	-50.56725 (0.0001)	-50.64950 (0.0001)	-50.64587 (0.0000)
	At First Difference	-24.93288 (0.0000)	-24.93036 (0.0000)	-24.93538 (0.0000)

Table 3Statistics of ARCH-LM test

	Null Hypothesis	**F-statistics**	**Probability**
F-Statistics(NIFTY)	No Heteroskesdasticity	256.8185	0.0000
Obs*R-squared		244.3789	0.0000

From table 2 it is inferred that the p values of ADF are <0.05 for both return series of NIFTY and FIIs which states that both the variables are stationary. Test statistics rejects the hypothesis at 1 percent level with critical value -50.64 of NIFTY returns and -13.48 of unit root test. Hence the test results certify that both the series are stationary. Further ARCH-LM test was performed to detect the presence of ARCH effects in the residuals of NIFTY return series. Table 3 shows the test statistics of ARCH-LM which affirm the existence of ARCH effects since p value < 0.05, null hypothesis of 'no ARCH effect is rejected at 1 percent level. Thus the results call for the estimation of GARCH family models. After confirming the volatility clustering of return series, checking for stationarity with ADF technique and heteroskedasticity effect applying ARCH-LM test, study attempts to determine the best fitted model and impact of FIIs on volatility of return. Accordingly GARCH model is used for modeling volatility of returns. Four models have been usedi.e to capture the asymmetries in the return series viz., T-GARCH and E-GARCH and two symmetric models GARCH 1,1 and GARCH-M 1,1. In all the models maximum likelihood method is referred assuming student t distribution of u_{t}..Table 4 & 5 present the results of E-GARCH and T-GARCH respectively where ϒ term measures the leverage or asymmetric effect in both the models. In E-GARCH model, the leverage coefficient ϒ is negative and statistically significant at 1% level of significance indicating the presence of leverage effect in return series. The diagnosis report negative correlation between past return and future return that is leverage effect. The table explains aggregate of α (ARCH) and β (GARCH) coefficient is greater than one indicating that conditional variance is explosive. Coefficient of FIIs is positive but insignificant meaning thereby that FIIs does not affect the volatility of returns of NIFTY index on Indian stock market for the study period. Another variantof asymmetric volatility,T-GARCH, results are shown in table 5 which reveals leverage effect is positive and significant at 1percent confidence level indicating asymmetric effect is accepted for the study period. Table 6 and 7 describes the results of GARCH 1, 1 and GARCH-M 1, 1. The results of GARCH 1,1 and GARCH-M 1,1 indicate that coefficients of GARCH parameters α and β are positive and statistically significant, evidencing that the news on volatility from past have significant impact on current period volatility. The value of β coefficient is high0.89 in both the modelswhich denotes persistent volatility clustering. Further it is inferred from the results that aggregate of estimated coefficients α and β are 0.988 but less than 1 implying GARCH process is mean reverting meaning thereby the existence of long periods of volatility clustering both models. Coefficient λ as a proxy of risk premium in mean equation is found positive but not statistically significant explaining, no evidence of GARCH in mean which simply mean increased risk does not necessarily produce excess returns. The decision regarding best suited model to capture both symmetric as well as asymmetric effect is based upon the minimum AIC and SIC values. Besides AIC and SIC (3.200, 3.211) respectively are low in E-GARCH model as compared to T-GARCH for which values are 3.202 and 3.213.In symmetric models AIC and SIC values are low in case of GARCH 1,1 model.

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Table 4 Results of E-GARCH test

Variable	Coefficient	Std.Error	z-statistics	Prob.
C	0.061837	0.015411	4.012525	0.0001
AR(1)	0.080578	0.014523	5.548101	0.0000
		Variance Equation		
Intercept	-0.146000	0.012091	-12.07474	0.0000
ARCH	0.199517	0.016020	12.45405	0.0000
GARCH	0.977484	0.003807	256.7663	0.0000
Leverage	-0.102460	0.010677	-9.596488	0.0000
FIIs	6.01E-06	6.70E-06	0.896569	0.3699
Durbin Watson Stat	2.026518			
$Q^2(1)$	0.0702			0.791
$Q^2(36)$	26.772			0.868
Obs*R-squared(ARCH)LM	0.070114			0.7912
AIC				3.200875
SIC				3.211292

Table 5 Results of T-GARCH test

Variable	Coefficient	Std.Error	z-Statistics	Prob.
C	0.066871	0.015559	4.297844	0.0000
AR(1)	0.079506	0.014855	5.352121	0.0000
		Variance Equation		
Intercept	0.032895	0.006308	5.214967	0.0000
ARCH	0.032967	0.009403	3.505848	0.0005
GARCH	0.882170	0.009449	93.35635	0.0000
Leverage(TARCH)	0.138966	0.016453	8.446011	0.0000
FIIs	1.72E-06	6.46E-06	0.266119	0.7901
Durbin Watson Stat	2.024376			
$Q^2(1)$	0.5184			0.472
$Q^2(36)$	21.427			0.974
Obs*R-squared(ARCH)	0.518046			0.4717
AIC				3.202942
SIC				3.213359

Table 6 Results of GARCH 1,1 Model

Variable	Coefficient	Std.Error	z-Statistics	Prob.
μ C	0.088831	0.015531	5.719754	0.0000
AR(1)	0.072691	0.014770	4.921674	0.0000
		Variance	Equation	
ω C	0.028399	0.005985	4.745308	0.0000
α RESID(-1)^2	0.093122	0.008987	10.36193	0.0000
β GARCH(-1)	0.895253	0.009112	98.24997	0.0000
α + β	0.988375			
FIIs	-8.70E-06	5.55E-06	-1.568476	0.1168
Durbin Watson Stat	2.010474			
$Q^2(1)$	0.8926			0.345
Q^2 (36)	24.257			0.932
Obs*R-squared(ARCH)LM	0.891967			0.3449
AIC				3.218152
SIC				3.227267

Table 7 Results of GARCH- M 1,1 Model

Variable	Coefficient	Std.Error	z-Statistics	Prob.
GARCH (Risk Premium) λ	0.020845	0.013388	1.557001	0.1195
μ C	0.065170	0.021595	3.017796	0.0025
AR(1)	0.072174	0.014832	4.866262	0.0000
		Variance Equation		
ω C	0.028948	0.006056	4.779734	0.0000
α RESID(-1)^2	0.093772	0.009060	10.34976	0.0000
β GARCH(-1)	0.894375	0.009195	97.27110	0.0000
α + β	0.988147			
FIIs	-9.06E-06	5.57E-06	-1.625055	0.1042
Durbin Watson Stat	2.004563			
$Q^2(1)$	0.9408			0.332
$Q^2(36)$	24.358			0.930
Obs*R-squared(ARCH)LM	0.940137			0.3322
AIC				3.218043
SIC				3.228460

CONCLUSION

In financial markets, modeling and forecasting the volatility of stock market returns has now days become a lush field of research. Two asymmetric modelssuch as Exponential GARCH model and Threshold GARCH model are used to capture the asymmetric volatility present in Indian stock market along with basic GARCH 1,1 and GARCH in mean models of symmetric effect. The study finds strong evidence of asymmetry and reveals that negative shocks have larger impact on the market volatility than the positive news. But no risk return relationship was found in GARCH in mean model.As taken in earlier studies (Banumathy and Azhagai, 2015) based on the AIC and SIC value Exponential GARCH model performs better with lowest values 3.200 and 3.211 respectively. Hence GARCH 1,1 come out to be the best fitted model among symmetric models with minimum AIC and SIC 3.218 and 3.228similar with (Kaurand Dhillon, 2015) (Ahmed and Aal, 2011). FIIs show positive but insignificant impact on stock market volatility. Q-statistics of correlogram of squared standardized residuals for all the models are insignificant verifying the correctness of the variance equation specification indicating no remaining ARCH in variance equation.

LIMITATIONS OF THE STUDY

- The study suffers from the limitation of considering only CNX NIFTY index return and other index, Bombay Stock Exchange has not beentaken.
- Intraday volatility calculation is not performed.

REFERENCES

Ahmed, M., and A. E. Aal. 2011. 'Modelling and Forecasting Time VaryingStockReturnVolatility in theEgyptianStockMarket.' *International ResearchJournal of Finance and Economics* 78:96–113.

Ahmed M.Elsheikh Ahmedand SulimanZakaria 2011. 'Modeling Stock Market Volatility Using GARCH Models Evidence From Sudan' *International Journal of Business and Social Science Vol.2 No.23(Special Issue December 2011)*

Bahadur, S. G. C. 2008. 'Volatility Analysis of Nepalese Stock Market.'*TheJournal of Nepalese Business Studies* 1 (1):

Banumathy Krunanithy and Azagaiah Ramachandran ,2015. 'Modeling Stock Market Volatility: Evidence from India' *Managing Global Transitions 13(1): 27-42*

Batra,Amita 2004. "Stock Return Volatility Patterns in India" *Indian Council for Research on International Economic Relations, working Paper No:124*

Floros, C. 2008. ‘Modelling Volatility Using garch Models: Evidencefrom Egypt and Israel.’ *Middle Eastern Finance and Economics* 2:31–41.

Bologna, P. (2000). “Index Futures Activity and Stock Market Volatility: An Empirical Analysis Of The Italian Stock Exchange”. *Giornale Degli Economisti E Annali Di Economia, 59 (Anno 113)*(1), nuova serie, 49-86. Retrieved January 25, 2020, from www.jstor.org/stable/41954947

Gabriel S.A. 2012. “Evaluating the Forecasting Performance of GARCH Models. Evidence from Romania” *Procedia: Social and Behavioral Sciences, Vol.62, PP,1006-1010.* Retrieved January 29, 2020 from www.sciencedirect.com

Goudarzi, H., and C. S. Ramanarayanan. 2010. ‘Modelling and Estimationof Volatility in Indian Stock Market.’ *International Journal of Businessand Management* 5 (2): 85–98.

Hameed, A., Ashraf, H., & Siddiqui, R. (2006). Stock Market Volatility and Weak-form Efficiency: Evidence from an Emerging Market [with Comments]. *The Pakistan Development Review,45*(4), 1029-1040. Retrieved January 25, 2020, from www.jstor.org/stable/41260666

Islam Aminul M 2013. ‘Estimating Volatility of Stock Index Returns by Using Symmetric GARCH Models’ *Middle-East Journal of Scientific Research 18(7): 991-999,2013 ISSN 1990-9233DOI: 10.5829/idosi.mejsr.2013.18.7.11806*

Kalu O Emenike and Chinwe Confidence Opera 2014. ‘The Relationship Between Stock Returns Volatility and Trading Volume In Nigeria’*Business Systems and Economics Vol.4 (2),2014*

Karmakar, M. 2005. ‘Modelling Conditional Volatility of the Indian StockMarkets.’*Vikalpa*30 (3): 21-37.

Karmakar, M. 2006. “Stock Market Volatility in the Long Run, 1961-2005” *Economic and Political Weekly, Vol.41, No.18, Pp1796-1802.*

McKenzie and Mitchel. 1998. ‘Generalised Asymmetric Power ARCH Modeling of Exchange Rate Volatility’

Nelson, D.B. 1991 ‘Conditional Heteroskedasticity in Asset Returns: A New Approach’ *Econometrica 59 (2):347-370.*

Saxena P. Swani 2011 “FII Flows and Stock Market Volatility: Exploring Causal Link”*presented in International conference on practice and Research in Management, Department of Management, Dayalbagh Educational Institute, Agra*

Vijayalakshmi, S., and S. Gaur. 2013. ‘ModellingVolatility: Indian Stock and Foreign Exchange Markets.’ *Journal of Emerging Issues in Economics,Finance and Banking* 2 (1): 583–98.