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STOCK PRICE VOLATILITY IN NSE INDICES: POST FINANCE CRISIS

D. Sumathi [1]
Research Scholar, Bharathiyar University,
Dr. S.N.S. Rajalakshmi College of Arts and Science (Autonomous),
Coimbatore

Dr. M. Uma Maheswari [2]
Head & Associate Professor,
Department of Management Studies,

Dr. S.N.S. Rajalakshmi College of Arts and Science (Autonomous),
Coimbatore

ABSTRACT
The extent of the global financial crisis during 2008 was hasty, and wedged the functioning and the enactment of financial markets. After the financial crisis markets were recovering and reckoning its pace in development. Due to the importance of this phenomenon, this study aims to explain the impact of the crisis on stock market behaviour through the study of the price volatility in various sectoral indices in NSE (National Stock Exchange). This paper investigates the patterns of linkage dynamics among three sectoral indices of NSE - CNX Auto, CNX Bank, CNX Pharma and NSE index -Nifty 50 between 2009 and 2015, by analysing the equity returns and price volatility in these indices post financial crisis using daily closure price. We apply the GARCH (1, 1), EGARCH (1, 1) and TGARCH (1, 1) framework to selected representative stock indices. The analysis indicates a long persistence of volatility in selected indices after the financial crisis in 2008. As a result of the analysis, the selected indices are modelled using TGARCH, which will be eventually used for forecasting the progress of the selected indices in the upcoming years. These findings have significant indications for both policymakers and investors by contributing to better insight the volatility of financial stocks in India especially NSE.

Keywords: Stock price volatility, Indian stock market, NSE sectoral indices, TGARCH.

1. Introduction:

The recent global financial crisis has considerably affected financial markets and is considered the most devastating crisis since the Great Depression of 1929. According to data from the World Federation of Exchanges, at the end of 2007 the world equity market capitalization was more than $64 trillion and sharply declined in 2009 to stand at $49 trillion—a drop of 22%, which is equal to 25% of global GDP for 2009. This crisis, which mainly originated in the US market, spread rapidly and dangerously to developed and emerging financial markets and to real economy around the world. Economic status of India is greatly developed after the introduction of new economic policy in 1991. The Indian Capital Market has perceived a marvellous progression since 1991. There was an outburst of investor interest during the nineties and an equity cult emerged in the country. To experience sustained growth statutory legislations have helped the capital market. Foreign Exchange Regulations Act is one such legislation in this direction. An important recent development has been the entry of Foreign Institutional Investors as participants in the primary and secondary markets for industrial securities. In the past several years, investments in developing countries especially in India have increased remarkably. This allows businesses to be publicly traded, or raise additional financial capital for expansion by selling shares of ownership of the company in a public market. History has shown that the price of shares and other assets is an important part of the dynamics of economic activity, and can influence or be an indicator of social mood. Nevertheless Indian capital market was also hit hard by the 2008 financial crisis.

Volatility refers to the amount of insecurity or risk about the size of variations in a security's value. A higher volatility means a security's value can potentially be spread out over a higher range of values whereas, lower volatility means a security's value does not oscillate dramatically, but changes in value over a period of time. Volatility is an indicator of a highly liquid stock market. Pricing of securities, depends on volatility of each asset. An increase in stock market volatility brings a large stock price change of advances or declines. The issues of price volatility have become increasingly important in recent times not only to the shareholders but also for the researchers. Emerging markets found to have four distinguishing features: average returns were higher, correlations with developed markets returns were low, returns were more predictable and volatility is higher. In fully integrated markets, volatility is strongly influenced by global factors, whereas in segmented markets, it is strongly influenced by local factors. This paper investigates the stock price volatility post 2008 financial crisis in selected sectoral indices of Indian stock market (NSE) where the influence is the mixture of global and local factors.

2. Review of Literature:

Volatility of stock returns in the developed countries has been studied extensively. Variance (or standard deviation) is often used as the risk measure in risk management. In the empirical modelling, when dealing with high-frequency financial data, **Engle R.F (1982)** establishes the ARCH model (autoregressive conditional heteroscedasticity) to solve self-relative and heteroscedasticity problems. **Bollerslev T (1986)** extends it into the GARCH model (generalized ARCH) to describe the phenomenon of volatility clustering of returns. **Akgiray V (1989)** found that GARCH (1, 1) had better explanatory power to predict future volatility in US stock market. **Poshakwale & Murinde (2001)** modelled volatility in stock markets of Hungary and Poland using daily indexes. They found that GARCH (1, 1) accounted for nonlinearity and volatility clustering. **Poon & Granger (2003)** provided comprehensive review on volatility forecasting. They examined the methodologies and empirical findings of 93 research papers and provided synaptic 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. However, the GARCH model cannot distinguish the difference of volatility between positive and negative information (the phenomenon of the violability asymmetries), thus, **Nelson D.B (1991)** develops the exponential GARCH model (EGARCH) which is the logarithmic expression of the conditional volatility used to capture the asymmetric effects. However, positive and negative volatility information is not considered in this analysis, therefore GARCH model is used instead of EGARCH. Later, a number of different specifications of these models and extensions were derived. **Zakoian (1994**) proposed Threshold GARCH (TGARCH) model, which was used to identify the relation between asymmetric volatility and return.

Goudarzi & Ramanarayanan (2010) examined the volatility of Indian stock market using BSE 500 stock index as the proxy for ten years. ARCH and GARCH models were estimated and the best model was selected using the model selection criterion. The study revealed that the GARCH (1, 1) was the best suited model for explaining the volatility clustering in the time series for the given period. Further, **Goudarzi & Ramanarayanan (2011)** another study, they investigated the volatility of BSE 500 stock index and modelled two non-linear asymmetric model viz., EGARCH (1,1) and TGARCH (1,1) and found that TGARCH (1,1) model was found to be the best preferred model as per AIC, Schwarz Information Criterion (SBIC) and Log Likelihood criteria. **Vijayalakshmi & Gaur (2013)** used eight different models to forecast volatility in Indian and foreign stock markets. **Ragunathan S (2015)** analysed the presence of Volatility in Indian Stock market and studied the asymmetric nature and persistence behaviour of volatility in the Indian market using the GARCH framework. In this study ARCH effect is significantly weak when compared to the Garch effect, which implies the weak reaction of conditional variance to shock.

There is relatively less empirical research on comparing stock return volatility in emerging markets like India. Deregulation and market liberalization measures, rapid development in communication technology and computerized trading systems and increasing activities of multinational corporations have fast-tracked the growth of capital markets which indicates the tendency towards global financial integration. The growing international integration of financial markets has prompted several empirical studies to examine features of volatility of stock markets. However, we need a more methodical exploration of stock market volatility in Indian stock market. This paper provides evidence on main features of volatility of the market using TGARCH in selected indices of NSE.

3. Research Objective:

It is argued that modelling volatility is difficult in emerging markets, especially in segmented markets. The stock markets have become increasingly integrated and 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 behaviour and the pattern of volatility and therefore it will be instructive to study volatility after the financial crisis. Volatility, in simple words, is the variation in the price of financial assets during a period of time. It is the amount by which the price of a financial asset such as share of a company has fluctuated or is expected to oscillate during a period. The objective of this study is to find out the existence of stock price volatility in the selected sectoral indices of NSE post finance crisis in 2008 and to model and forecast the stock price volatility in the selected sectoral indices of NSE based on the data from post finance crisis.

4. Research Methodology:

A. Sample

This research study is based on secondary data, which is mainly collected from NSE website. CNX Nifty indices were used as proxy to the stock market. The daily closing price of NSE index Nifty 50, NSE sectoral indices like CNX Auto, CNX Bank and CNX Pharma from 1st January, 2009 to 31st October, 2015 were collected and used to analyse the existence of the price volatility post financial crisis.

B. Methodology

Daily returns are identified as the difference in the natural logarithm of the closing index value for the two consecutive trading days. The daily closing price collected during the period of study for the selected indices are converted into returns. Volatility is defined as:

$$\sigma = \sqrt{\frac{1}{n-1} \sum_{i=1}^{n} (Ri - \bar{R})^2} \quad (1)$$

$\bar{R}$ – Average log return for the collected samples.

Under descriptive statistics, the Mean, Median, Minimum, Maximum, Standard Deviation, Skewness and Kurtosis of Daily log returns are calculated to specify the distributional properties of the daily return series of Nifty market index during the study period. Normality tests are used to check whether the dataset is distributed normally. More precisely, the tests are a form of model selection and can be interpreted in several ways, depending on one's interpretations of probability. In descriptive statistics terms, one measures a goodness of fit of a normal model to the data – if the fit is poor then the data are not well modelled in that respect by a normal distribution, without making a judgment on any underlying variable. **Jarque and Bera (1980)** proposed the Jarque–Bera (J-B) test is a goodness-of-fit test to find whether the data have the Skewness and Kurtosis matching a normal distribution. The test statistic JB is defined as:

$$JB = \frac{n-k+1}{6}\left(S^2 + \frac{1}{4}(C-3)^2\right) \quad (2)$$

Where n is the number of observations (or degrees of freedom in general); S is the sample skewness, C is the sample kurtosis, and k is the number of repressors.

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. A nonzero mean indicates the regression will have a constant term. The three basic regression models are:

No constant, no trend:

$$\Delta r_t = \gamma\ r_{t-1} + \sum_{i=1}^{p} \beta_i\ \Delta r_{t-1} + \varepsilon_t \quad (3)$$

Constant, no trend:

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

Constant and trend:

$$\Delta r_t = \alpha + \gamma\ r_{t-1} + \lambda_t + \sum_{i=1}^{p} \beta_i\ \Delta r_{t-1} + \varepsilon_t \quad (5)$$

In empirical applications, it is often difficult to estimate models with large number of parameters, say ARCH (q). In an ARCH (1) model, next period's variance only depends on last period's squared residual so a crisis that caused a large residual would not have the sort of persistence that we observe after actual crises. To circumvent this problem, Bollerslev (1986) proposed Generalized ARCH (p, q) or GARCH (p, q) modes. The GARCH (1, 1) process is often preferred by financial modelling professionals because it provides a more real-world context than other forms when trying to predict the prices and rates of financial instruments. The conditional variance of the GARCH (1, 1) process is specified as:

$$\sigma_t^2 = \alpha_0 + \alpha_1\ a_{t-1}^2 + \beta_1 \sigma_{t-1}^2 \quad (6)$$

With $\alpha_0 > 0$, $\alpha_1 \geq 0$, $\beta_1 \geq 0$ and $(\alpha_1 + \beta_1)$ is less than 1 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_1 indicate that shocks to conditional variance takes a long time to die out, so volatility is 'persistent.' Large GARCH error coefficient α_1 means that volatility reacts quite intensely to market movements and so if α_1 is relatively high and β_1 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 main drawback of symmetric GARCH is that the conditional variance is unable to respond asymmetrically to rise and fall in the stock returns. Hence, number of models have been introduced to deal with the issue and are called asymmetric models viz., EGARCH, TGARCH and PGARCH, which are used for capturing the asymmetric phenomena. To study the relation between asymmetric volatility and return, the EGARCH (1, 1) and TGARCH (1, 1) models are used in the study.

EGARCH model is based on the logarithmic expression of the conditional variability. The presence of leverage effect can be tested and this model enables to find out the best model, which capture the symmetries of the Indian stock market (Nelson 1991) and hence the following equation:

$$\ln(\sigma_t^2) = \omega + \beta_1 \ln(\sigma_{t-1}^2) + \alpha_1 \left\{ \left| \frac{\varepsilon_{t-1}}{\sigma_{t-1}} - \sqrt{\frac{\pi}{2}} \right| \right\} - \gamma \frac{\varepsilon_{t-1}}{\sigma_{t-1}} \qquad (7)$$

The left-hand side is the log of the conditional variance. The coefficient γ is known as the asymmetry or leverage term. The presence of leverage effects can be tested by the hypothesis thatγ < 0. The impact is symmetric if γ ≠ 0.

The generalized specification of the threshold GARCH for the conditional variance (Zakoian 1994) is given by:

$$\sigma_t^2 = \omega + \alpha_1 \varepsilon_{t-1}^2 + \gamma \varepsilon_{t-1}^2 I_{t-1} + \beta_1 \sigma_{t-1}^2 \qquad (8)$$

The γ is known as the asymmetry or leverage parameter. In this model, good news ($\varepsilon_{t-1} > 0$) and the bad news ($\varepsilon_{t-1} < 0$) have differential effect on the conditional variance. Good news has an impact of α_i, while bad news has impact on $\alpha_i + \gamma_i$. Hence, if γ is significant and positive, negative shocks have a larger effect on σ_t^2 than the positive shocks.

5. Data Analysis & Discussion:

Table 1 reveals the descriptive statistics of the of NSE index Nifty 50, NSE sectoral indices like CNX Auto, CNX Bank and CNX Pharma from 1st January, 2009 to 31st October, 2015.

Table 1

Descriptive Statistics

Index / Statistic	Mean	Median	Standard Deviation	Skewness	Kurtosis
Nifty 50	0.0005919	0.00064319	0.012773	1.0387	16.741
CNX Auto	0.0011999	0.00107060	0.013708	0.57068	7.1183
CNX Bank	0.0007344	0.00089264	0.017795	0.42173	6.7697
CNX Pharma	0.0010145	0.00089440	0.011076	0.039232	9.7612

Source: computed by the researcher using Gretl on the basis of secondary data collected

The mean of the returns is positive, indicating the fact that price has increased over the period of time. The descriptive statistics shows that the returns are positively skewed, indicating that there is a low probability of earning returns which is higher than the mean value. The Kurtosis of the series is > 3, which implies that the return series is fat tailed and does not follow a normal distribution. This is further confirmed by Jarque-Bera test statistics in Table 2, which is significant at 1% level and hence the null hypothesis of normality is rejected. This shows that the return values are not normally distributed.

Table 2

Normality Test - Jarque-Bera (J-B)

Index / Statistic	Jarque-Bera test	P-Value
Nifty 50	20085.7	~ 0.000
CNX Auto	3668.47	~ 0.000
CNX Bank	3285.01	~ 0.000
CNX Pharma	6725.72	~ 0.000

Source: computed by the researcher using Gretl on the basis of secondary data collected

Table 3 shows the presence of unit root in the series tested using ADF. The p values are < 0.05, which lead to conclude that the data of the time series for the entire study period is stationary.

Table 3

Unit Root Test - ADF

Index / Statistic	Augmented Dickey Fuller Test		
	Model 1 (no constant, no trend)	Model 2 (constant, no trend)	Model 3 (constant, trend)
Nifty 50	-38.8232	-38.8906	-38.9051
CNX Auto	-14.7146	-15.1063	-15.2664
CNX Bank	-28.5525	-28.6093	-28.615
CNX Pharma	-8.53977	-10.3468	-10.3442

Source: computed by the researcher using Gretl on the basis of secondary data collected

The critical values at 1% for Augmented Dickey Fuller Test for Model 1, Model 2 and Model 3 are -2.58, -3.43 and -3.96 respectively. The calculated values are more negative than the critical values, which indicates that the null hypothesis of a unit root will be rejected at 1%. And it may be concluded that the returns of the select indices are stationary. After volatility clustering is confirmed with return series and stationarity using ADF test, the study focuses on determining the best fitted GARCH model to the return series. Therefore, GARCH model is used for modelling the volatility of return series in the selected indices of Indian stock market (NSE).

Table 4

GARCH (1, 1) – Coefficients

Index / Statistic	α_0	α_1	β_1	$\alpha_1 + \beta_1$	AIC	Log-likelihood
Nifty 50	1.73e-06	0.0623	0.9272	0.9895	−10323.8	5166.9
CNX Auto	2.33e-06	0.0441	0.9441	0.9882	−9869.1	4939.5
CNX Bank	4.06e-06	0.0566	0.9296	0.9862	−9129.3	4569.6
CNX Pharma	0.59e-06	0.0305	0.9652	0.9957	−10631.3	5320.6

Source: computed by the researcher using Gretl on the basis of secondary data collected

To explore the nature of volatility, GARCH (1, 1) model is applied in the selected stock markets. The results of the estimated model are reported in Table 4, which indicates the parameters estimates of the GARCH (1, 1) model and these values are all statistically significant. The estimates of β_1 are always marked greater than those of α_1 and the sum $\alpha_1 + \beta_1$ is very close to but smaller than unity. These values are less than unity, which indicates that the stationarity condition is not violated. As the lag coefficient of conditional variance β_1 is higher than the error coefficient α_1 implying that volatility is not spiky in all the stock markets. It also indicates that the volatility does not decay speedily and tends to die out slowly. In order to capture the asymmetries in the return series, two variants of GARCH models namely EGARCH (1, 1) and TGARCH (1, 1) are used.

Table 5

EGARCH (1, 1) – Coefficients

Index / Statistic	ω	α_1	γ	β_1	$\alpha_1 + \beta_1$	AIC	Log-likelihood
Nifty 50	-0.2287	0.1492	-0.0712	0.9872	1.1364	-10349.4	5189.7
CNX Auto	-0.1851	0.1105	-0.0303	0.9884	1.0989	-9901.5	4965.7
CNX Bank	-0.1692	0.1067	-0.0376	0.9894	1.0961	-9140.5	4585.3
CNX Pharma	-0.1252	0.0818	0.0249	0.9929	1.0747	-10637.8	5333.9

Source: computed by the researcher using Gretl on the basis of secondary data collected

The asymmetrical EGARCH (1, 1) model is used to estimate the returns of the selected indices and the results are presented in table 5. The term γ captures the asymmetric effect in both models. In this model, α is the GARCH term that measures the impact of last period's variance of the forecast. A positive α indicates volatility clustering implying that positive stock price changes are associated with further positive changes and the other way around. The ARCH term β is the measure of the effect of news about volatility from the previous period on current period volatility. The presence of leverage effect may be tested by the null hypothesis that the coefficient of the last term in the regression is negative ($\gamma < 0$) for Nifty 50, CNX Auto and CNX Bank. Thus, for a leverage effect, we would see $\gamma > 0$ for CNX Pharma. The impact is asymmetric if this coefficient is different from zero ($\gamma \neq 0$). Ideally γ is expected to be negative implying that bad news has a bigger impact on volatility than good news of the same magnitude. The sum of the ARCH and GARCH coefficients, that is, $\alpha + \beta$ indicates the extent to which a volatility shock is persistent over time. The stationary condition is $\alpha + \beta < 1$. Since the value of γ is non-zero, the EGRACH model supports the existence of asymmetry in volatility of stock returns. But on the basis of this model we cannot say whether good news or bad news that increases volatility. This aspect of volatility modelling is captured by Threshold GARCH model.

Table 6

TGARCH (1, 1) – Coefficients

Index / Statistic	ω	α_1	γ	β_1	$\alpha_1 + \beta_1$	AIC	Log-likelihood
Nifty 50	1.86e-06	0.0346	0.0823	0.9151	0.9597	-10335.6	5182.8
CNX Auto	2.17e-06	0.0474	0.1622	0.9409	0.9883	-9886.2	4958.1
CNX Bank	3.06e-06	0.0419	0.3050	0.9437	0.9856	-9144.5	4587.3
CNX Pharma	0.73e-07	0.0308	-0.2150	0.9624	0.9932	-10637.3	5333.6

Source: computed by the researcher using Gretl on the basis of secondary data collected

In this model, good news, $\varepsilon_{t-1} > 0$ and bad news, $\varepsilon_{t-1} < 0$ have differential effects on the conditional variance; good news has an impact of the factor α, while bad news has an impact $\alpha + \gamma$. If $\gamma > 0$, then bad news increases volatility, and we say that there is a leverage effect. If $\gamma \neq 0$, the news impact is asymmetric.

6. Conclusion:

The financial crisis in 2008 was a major disruption to the financial sector. There has been discussion about the causes and consequences that led to the failure or near failure of many large financial institutions and there have been many proposals to assure that a similar credit crisis will be less likely to happen in the future. The study revealed that volatility in the selected indices of Indian stock markets exhibits the persistence of volatility. The study used daily data on Nifty 50, CNX Auto, CNX Bank and CNX Pharma between 2009 and 2016 to illustrate these stylized facts, and the ability of GARCH (1, 1), EGARCH (1, 1) and TGARCH (1, 1) to capture these characteristics.

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