Stock Price Volatility in European & Indian Capital Market: Post-Finance Crisis

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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 behavior and interdependence among the markets through the study of the price volatility. This paper investigates the patterns of linkage dynamics among three European stock markets - France, Germany, UK and Indian Stock market between 2009 and 2016, by analyzing the investigate equity returns and price volatility among these markets post financial crisis using daily closure price. We apply the GARCH (1, 1) (General Autoregressive Conditional Heteroscedasticity) framework to on selected representative stock indices. The findings reveal that the GARCH (1, 1) model successfully captures nonlinearity and existence of volatility. The analysis suggests indicates a long persistence of volatility in Indian and German stock market, when compared to the French and UK Stock market after the financial crisis in 2008. These findings have significant insinuations for both policymakers and investors by contributing to better understanding the volatility of financial stocks in Europe and India.

Keywords: Stock Price volatility, Indian Stock Market, European Stock Market, GARCH, Financial Crisis
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 imitated by the introduction of new economic policy in 1991. The Indian Capital Market has perceived a marvelous progression. 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 have increased remarkably. Among the developing countries, India has received considerable capital inflows in recent years. 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. The liquidity that an exchange affords the investors gives them the ability to quickly and easily sell securities. This is an attractive feature of investing in stocks, compared to other less liquid investments such as real estate. Some companies actively increase liquidity by trading in their own shares. 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 is a symptom 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 to the Indian investors, Regulators, brokers, policy makers, dealers and researchers. Share prices also affect the wealth of households and their consumption. 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. They argued that modeling volatility is difficult in emerging markets, especially in segmented markets. In fully integrated markets, volatility is strongly influenced by global factors, whereas in segmented markets, it is strongly influenced by local factors. 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 fluctuate during a period. This paper investigates the stock price volatility
post 2008 financial crisis in integrated European market where it’s strongly influenced by the global factors and Indian market where the influence is the mixture of global and local factors.

2 LITERATURE REVIEW

Volatility of stock returns in the developed countries has been studied extensively. In the empirical modeling, when dealing with high-frequency financial data, Engle (1982) establishes the ARCH model (autoregressive conditional heteroskedasticity) to solve self-relative and heteroskedasticity problems. Bollerslev (1986) extends it into the GARCH model (generalized ARCH) to describe the phenomenon of volatility clustering of returns. 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 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 (1991) develops the exponential GARCH model (EGARCH) to distinguish this difference. However, positive and negative volatility information is not considered in this analysis, therefore GARCH model is used instead of EGARCH.

There is relatively less empirical research on comparing stock return volatility in emerging markets like India and emerged markets in Europe. 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 across the world. However, we need a more methodical exploration of stock market volatility in Indian stock market, compared to the European counterparts. This paper provides evidence on main features of volatility in the stock markets of India and Germany compared to UK and French stock markets. The rest of the paper is organized as follows. Chapter 3 provides research design used in the study and empirical results are analyzed in Chapter 4.
3 RESEARCH DESIGN

3.1 STUDY PERIOD

The daily closing price French stock market index (CAC 40), German stock market index (DAX 30), UK stock market index (FTSE 100) and Nifty (Nifty 50) of Indian stock market indices from 1st January, 2009 to 31st December, 2016 are collected to analyze the existence of the price volatility post financial crisis in 2008. 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 behavior and the pattern of volatility and therefore it will be instructive to study volatility after the financial crisis.

3.2 SAMPLES

It comprises of daily closing price of 2050 observations for four prominent stock market indices of the emerging economies of Asia namely India and largest economies of Europe namely UK, France and Germany. Euronext Paris is France's securities market, formerly known as the Paris Bourse, which merged with the Amsterdam, Lisbon and Brussels exchanges in September 2000 to form Euronext NV, which is the second largest exchange in Europe behind the UK's London Stock Exchange Group. The index “CAC 40” represents a capitalization-weighted measure of the 40 most significant values among the 100 highest market caps on the Euronext Paris. Frankfurt Stock Exchange (Frankfurter Wertpapierbörse, FWB) is the largest of the seven stock exchanges in Germany and is the world's 10th largest stock exchange by market capitalization. The FWB index “DAX 30” consists of 30 major German companies trading on the Frankfurt Stock Exchange. The London Stock Exchange is a British-based stock exchange founded in 1801 and is the world third largest stock exchange by market capitalization. The “FTSE 100” Index, is a share of the 100 companies listed on the London Stock Exchange with the highest market capitalization. The National Stock Exchange (NSE) is the leading stock exchange of India incorporated in 1992 and is the 12th largest stock exchange in the world. The Nifty index “Nifty 50” consists of 50 stocks listed on two criteria namely market capitalization and liquidity. It is, therefore, insightful to study volatility of both the stock markets of India and Europe.

3.3 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:
\[
\sigma = \sqrt{\frac{1}{n-1} \sum_{i=1}^{n} (R_i - \bar{R})^2}
\]  
(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.

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:

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

\[
\Delta r_t = \gamma r_{t-1} + \sum_{i=1}^{p} \beta_i \Delta r_{t-1} + \epsilon_t
\]  
(3)

Constant, no trend:

\[
\Delta r_t = \alpha + \gamma r_{t-1} + \sum_{i=1}^{p} \beta_i \Delta r_{t-1} + \epsilon_t
\]  
(4)

Constant and trend:

\[
\Delta r_t = \alpha + \gamma r_{t-1} + \lambda_t + \sum_{i=1}^{p} \beta_i \Delta r_{t-1} + \epsilon_t
\]  
(5)
The lag length should be chosen so that the residuals aren’t serially correlated. The null hypothesis is $H_0: \delta = 0$ and $H_1: \delta < 1$. The acceptance of null hypothesis implies non-stationarity and rejection of null hypothesis implies stationarity in the time series.

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 modeling 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:

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

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 $\beta_1$ indicate that shocks to conditional variance takes a long time to die out, so volatility is ‘persistent.’ Large GARCH error coefficient $\alpha_1$ means that volatility reacts quite intensely to market movements and so if $\alpha_1$ is relatively high and $\beta_1$ 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.’

Gretl is a cross-platform software package for econometric analysis, written in the C programming language. It is free, open-source software. One may redistribute it and/or modify it under the terms of the GNU General Public License (GPL) as published by the Free Software Foundation. Gretl R2017a is used to carry out the empirical analysis of the above mentioned method.

4 **EMPIRICAL RESULTS**

Figure 1, shows the daily closing price (a) and log return of daily closing price (b) for CAC 40 and Nifty 50. Figure 2, shows the daily closing price (a) and log return of daily closing price (b) for DAX 30 and Nifty 50. Figure 3, shows the daily closing price (a) and log return of daily closing price (b) for FTSE 100 and Nifty 50.
Stock Price Volatility in European & Indian Capital Market: Post-Finance Crisis

Fig. 1 Comparison of CAC 40 and Nifty 50 between Jan’09 and Dec’16

Fig. 2 Comparison of DAX 30 and Nifty 50 between Jan’09 and Dec’16

Fig. 3 Comparison of FTSE 100 and Nifty 50 between Jan’09 and Dec’16
4.1 DESCRIPTIVE STATISTICS

The descriptive statistics for the return series include mean, median, minimum, maximum, standard deviation, skewness and kurtosis. Table - 1 presents the descriptive statistics of stock markets taken for the study. The mean values of the select markets are positive during the study period from January 2009 to December 2016. The standard deviations of all the companies are positive which are plotted normally from the mean. The mean returns of the select indices are positive and they are the highest (0.000498) for Nifty 50 and the lowest (0.000182) for CAC 40. The Standard Deviation of Returns is the highest (0.01396) for CAC 40 and the lowest (0.01079) for FTSE 100. This indicates the fact that the select indices are relatively volatile; the highest volatile index is CAC 40 followed by DAX 30, Nifty 50 and FTSE 100 during the study period. The Nifty 50 has positive (Right Skewed Distribution) skewness value and it indicates there is high probability of getting positive returns. The remaining selected indices have negative (Left Skewed Distribution) skewness, which means that the select indices are having the higher possibility of getting negative returns and all the indices are positively / negatively deviated from Normal Distribution. Higher kurtosis values indicates unexpected return distributions are not normal.

Table 1. Descriptive Statistics of Daily Returns between 01-Jan-2009 and 31-Dec-2016

<table>
<thead>
<tr>
<th>Statistic</th>
<th>CAC 40</th>
<th>DAX 30</th>
<th>FTSE 100</th>
<th>Nifty 50</th>
</tr>
</thead>
<tbody>
<tr>
<td>Mean</td>
<td>0.000182</td>
<td>0.000410</td>
<td>0.000219</td>
<td>0.000498</td>
</tr>
<tr>
<td>Median</td>
<td>0.000418</td>
<td>0.000905</td>
<td>0.000568</td>
<td>0.000237</td>
</tr>
<tr>
<td>Minimum</td>
<td>-0.083844</td>
<td>-0.070673</td>
<td>-0.054816</td>
<td>-0.063802</td>
</tr>
<tr>
<td>Maximum</td>
<td>0.092208</td>
<td>0.058951</td>
<td>0.050323</td>
<td>0.16334</td>
</tr>
<tr>
<td>Standard Deviation</td>
<td>0.01396</td>
<td>0.01370</td>
<td>0.01079</td>
<td>0.01231</td>
</tr>
<tr>
<td>Skewness</td>
<td>-0.12547</td>
<td>-0.22545</td>
<td>-0.16730</td>
<td>1.0068</td>
</tr>
<tr>
<td>Kurtosis</td>
<td>2.9890</td>
<td>2.1315</td>
<td>2.3557</td>
<td>16.693</td>
</tr>
</tbody>
</table>

4.2 TEST OF NORMALITY

Table – 2 indicates that the p-value of Jarque-Bera Test is between 0 and 1. The Jarque-Bera Test used in normality testing shows that the Null Hypothesis, which suggests that the series are normally distributed, is rejected at 1% significance level for the selected stock markets. This shows that the return values are not normally distributed.
Table 2. Normality Testing of Daily Returns between 01-Jan-2009 and 31-Dec-2016

<table>
<thead>
<tr>
<th>Market</th>
<th>Jarque-Bera test</th>
<th>P-Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>CAC 40</td>
<td>768.5</td>
<td>~0.000</td>
</tr>
<tr>
<td>DAX 30</td>
<td>403.9</td>
<td>~0.000</td>
</tr>
<tr>
<td>FTSE 100</td>
<td>476.7</td>
<td>~0.000</td>
</tr>
<tr>
<td>Nifty 50</td>
<td>23452.7</td>
<td>0.000</td>
</tr>
</tbody>
</table>

4.3 UNIT ROOT TEST

Unit root test tests whether a time series variable is non-stationary and possesses a unit root. The null hypothesis is generally defined as the presence of a unit root and the alternative hypothesis is defined as presence of either stationarity or trend stationarity. Table – 3 presents the results Augmented Dickey-Fuller Test of stock market indices taken for the period of the study. 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.

Table 3. Unit Root Testing of Daily Returns using Augmented Dickey-Fuller Test

<table>
<thead>
<tr>
<th>Market</th>
<th>Augmented Dickey Fuller Test</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Model 1 (no constant, no trend)</td>
</tr>
<tr>
<td>CAC 40</td>
<td>-22.2993</td>
</tr>
<tr>
<td>DAX 30</td>
<td>-10.0013</td>
</tr>
<tr>
<td>FTSE 100</td>
<td>-10.1830</td>
</tr>
<tr>
<td>Nifty 50</td>
<td>-9.82373</td>
</tr>
</tbody>
</table>

4.4 NON LINEAR MODEL – GARCH (1, 1)

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 $\beta_1$ are always marked greater than those of $\alpha_1$ 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 0.9772
for French stock market (CAC), 0.9855 for German stock market (DAX), 0.9740 for UK stock market (FTSE) and 0.9875 for Indian stock market (Nifty). These values are less than unity, which indicates that the stationarity condition is not violated. The sum of Coefficient ($\alpha_1 + \beta_1$) in German stock market and Indian Stock market is higher than UK and French stock market, which indicates a long persistence of volatility in Indian and German stock market. As the lag coefficient of conditional variance $\beta_1$ is higher than the error coefficient $\alpha_1$ 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.

Table 4. Coefficients of GARCH (1, 1) Model for Daily Returns between 01-Jan-2009 and 31-Dec-2016

<table>
<thead>
<tr>
<th>Statistic</th>
<th>CAC 40</th>
<th>DAX 30</th>
<th>FTSE 100</th>
<th>Nifty 50</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\alpha_0$</td>
<td>4.70E-06</td>
<td>2.82E-06</td>
<td>3.16E-06</td>
<td>1.77E-06</td>
</tr>
<tr>
<td>$\alpha_1$</td>
<td>0.0997</td>
<td>0.0845</td>
<td>0.1208</td>
<td>0.0538</td>
</tr>
<tr>
<td>$\beta_1$</td>
<td>0.8775</td>
<td>0.9010</td>
<td>0.8532</td>
<td>0.9337</td>
</tr>
<tr>
<td>$\alpha_1 + \beta_1$</td>
<td>0.9772</td>
<td>0.9855</td>
<td>0.9740</td>
<td>0.9875</td>
</tr>
<tr>
<td>AIC</td>
<td>-12031</td>
<td>-12110</td>
<td>-12985</td>
<td>-12242</td>
</tr>
<tr>
<td>Log-likelihood</td>
<td>6020.8</td>
<td>6060.2</td>
<td>6497.6</td>
<td>6126.0</td>
</tr>
</tbody>
</table>

5 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 volatility in the Indian and European stock markets exhibits the persistence of volatility. The study used daily data on CAC, DAX, FTSE and Nifty between 2009 and 2016 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 this post financial crisis study of the stock volatility in three Major European and Indian stock market indicates that German stock market in Europe and Indian stock market has more volatility when compared to London or French stock market.
6 Bibliography


