DIFFERENCE IN FRAGILITY PATTERN IN INDIAN & US STOCK MARKE DURING SUB-PRIME CRISIS

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Abstract The present paper proposes to analyze the fragility pattern in U.S. and Indian stock market. The descriptive statistics for both countries indices have been calculated individually. The returns from the Indian Stock market with reference to the previous day's return of the US stock market shows lot of feedback effect from US to India. Volatility Models such as ARCH (1), GARCH (1, 1) and EGARCH (1, 1) has been applied on major indices ndexes and on selected sectoral indices. Some pre-tests, for example, the unit root test and the ARCH LM test to check whether there was ARCH impact or not are utilized. The result shows that there was difference in the fragility pattern of U.S. and Indian Stock market. U.S. market was more volatile than Indian market.

Key words: stock markets, subprime crisis, fragility, volatility

Introduction

Global financial situation was triggered by the subprime mortgage crisis in the United States, which became apparent from mid-2007. Financial crises are characterized by the sudden and simultaneous materialization of risks that, during normal times, seemed independent. As a result, risk lowering opportunities are considerably reduced just when the need for them is greater, which causes significant threats to the global financial system. As capital market connections intensified, their trends have become more and more correlated and, in general, the world's large stock markets post similar evolutions. Thus, during the growth stage of the economic cycle, stock markets register positive evolutions, but as a crisis occurs, their falls become strongly correlated as well.

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The first clues that signaled the recent financial crisis emerged in the summer of 2007 when two hedging funds managed by investment bank Bear Stearns entered difficulty. The funds had invested in instruments based on high risk mortgage loans. That was the beginning. Gradually, the crisis spread internationally and the fall of the financial sector stirred chaos across the entire economy. The situation of financial markets worsened starting September 2008, with the bankruptcy of American investment bank Lehman Brothers. Financial market confidence dropped considerably and risk premiums rose to extremely high levels. After an initial recovery period, the crisis reached emerging countries.

In the last quarter of 2008, many emerging economies faced problems with their local currencies and stock markets. Currency exchange rates were under pressure in all regions, causing a combination between currency depreciation and lowering of foreign reserves. When crisis affects the real activities, it affects the stock market, as profit expectation on financial investments would be lower. If financial investment would be affected, its impact would be felt on the real investment, as real investment would not increase. Once the real sector activity lessens, that would affect the entire economy. Thus, it is mainly the expectation of the investors mainly works affecting both the financial and real investment in the economy. This paper describes the methodology and testing results to examine the fragility pattern between Indian and US stock market.

Literature review

Literature describes the volatility pattern between Indian and US stock market during sub-prime crisis. Chakrabarti and Roll (2002) conducted comparative study between the East Asian stock markets and European markets volatility during the crisis period. The study found that volatility level increased during the crisis in both the regions. Volatility was highest in East Asia region. Investment declined during the crisis period in East Asia which was the main reason of increase in volatility. Raju and Ghosh (2004) studied the global market returns on varying time basis. Among developing countries India generated low volatility with high return. U.S. returns were positive while France, U.K, Germany and Australia depicted high volatility with low returns pattern. The returns of developing countries were normally distributed. Mun (2005) analyzed the linkage between return and volatility after the 9/11 attacks in America. GARCH model was applied to measure the volatility. Study found that the spillover of volatility affected the returns. In short there was negative relationship between returns and volatility.

Rasmussen (2006) examined the stock returns performance using time series and cross –sectional data. Main objective of study was to reduce pricing error in CAPM model. Different measure was selected to examine the forecasting ability for stock returns. Results showed that traditional dividend ratio performance was well among other new forecasting variables. Leeves (2007) studied the volatility of Jakarta Stock Exchange during the global financial crisis. EGARCH model was applied on daily return from the period 1997 to 2006. Findings indicated that bad news impacted returns more in comparison to good news due to leverage effect in returns. After 1999 the return followed the symmetric trend. Gustavson and Staffan (2008) discussed the origin of sub-prime crisis and reasons behind it. Collateralized debt obligation (CDOs) were introduced to attract more investors. Complex models and bad prediction on historical data, Failure of Risk Management Systems, Excessive Leverage and Relaxed Regulation of Leverage were the most discussed reasons of Subprime Crisis.

Koulakiotis et al (2009) examined the spillover effect of bad and good news on portfolios of three European regions. Multivariate GARCH-BEKK model was applied on returns. Results indicated that Fi Finnish and Danish portfolios were the source of volatility spillover to the Swedish and Norwegian portfolios and Paris, Amsterdam and Brussels stock exchanges affected the volatility of Milan and Madrid stock exchanges. Cripps et al. (2011) examined the growth of global economies through simplified stock-flow analytical framework. The objective was to find out the proportion of speed of growth in developed and developing countries. Results indicated that some countries were below the credit line and other countries were over borrowed. Global imbalance was due to increased trade deficit in developing countries. Negative trade deficit of U.S. also affect other economies negatively because these countries were interrelated to U.S. for trading of goods and services.

Sen (2011) contributed literature on sub-prime crisis. Study described that sub-prime crisis has spillover effects on financial and real economical area in developed and developing economies. Policies framed by bad evaluated model together with deregulation of financial system, global imbalance, easy credit rating and excess leverage in market leads to shortage of finance in the economy. Corrective measures taken by the financial authorities in U.S. have also been not effective to heal unemployment, low growth, the loss in financial sectors in developing countries and grief in Europe. SJ and Kalavathy (2012) analyzed the impact of the Global Financial Crisis on the Indian Stock market through T-test and Binary regression test and Non –parametric test Kruskal - Wallis H –test. These tests examined the short run and long run effects on the stock returns. In additional Parkinson Model and Garman and Klass model were also applied. Results indicated that there was no short term and long term negative impact on stock returns and financial crisis news affected the Indian stock market not in deep sense. Manurung et al. (2013) analyzed relationship between Jakarta Composite Index and macroeconomic indicators, global stock market, and commodities prices with the help of VECM model. Results of model indicated co-movement between the selected variables and Jakarta composite Index was affected by Dow Jones Index, Oil prices and gold prices for long run1. Kosapattarapim (2013) examined the performance of volatility forecasting models in Asian stock market. Best fit model was selected on the basis of AIC and SC criteria. Results of Simulation model revealed that performance of volatility model can be improved by applying Univariate GRACH model. Further non-normal error distribution methods like student-t test enhanced the performance of volatility forecasting.

Objective

This paper attempts to analyze the fragility pattern of US stock market and Indian stock market and have considered it opportune to perform volatility models to analyze the fragility pattern of these markets.

Research methodology

To analyze the fragility pattern the representative indexes of Indian stock market (NSE) and for US stock market (NYSE) have been considered. Daily returns series data have been analyzed starting from1st April, 2005- 30th June, 2013. Descriptive statistics have been utilized to measure the variability. Volatility Models such as ARCH (1), GARCH (1, 1) and EGARCH (1, 1) has been applied. Some pre-tests, for example, the unit root test and the ARCH LM test to check whether there was ARCH impact or not are utilized.

The purpose of modeling is to estimate the coefficients associated to stock market indexes playing the role of exogenous variables to determine their influence on stock market. Further to test the normality of data Descriptive Statistics (mean, standard deviation, variance, maximum, minimum, skewness and kurtosis) have been considered.

Analysis and interpretation

Descriptive Statistics Analysis:

Table 1.1: Descriptive Statistics of US Indices:

INDEX	Mean	S.D	Variance	Skewness	Kurtosis
NYSE	0.02282	0.445817	0.198753	16.38079	340.7068
NYSE ENERGY	-0.00075	0.016396	0.000269	0.301306	12.99690
NYSE FINANCE	0.000923	0.022425	0.000503	1.111191	16.06063
NYSE FMCG	-0.00941	0.198014	0.03921	-20.3309	419.0142
NYSE PHARMA	-0.00011	0.011214	0.000124	0.026290	13.87311

Table 1.1 shows that the mean value of Energy, FMCG and Pharma sector comes in negative. So, among all sector these sectors have minimum mean. Standard deviation of NYSE index is 0.445 and the variance is 0.1987 which is higher among other sectors. The Energy sector has minimum variance. Kurtosis values of all the sectors were above 3 and skewness was also above 0, it means data does not show the sign of normality.

Table 1.2: Descriptive Statistics of Indian Indices:

INDEX	Mean	S.D	Variance	Skewness	Kurtosis
NSE (Nifty 50)	0.00071	0.017582	0.000309	0.302446	13.07028
CNX ENERGY	-0.00056	0.018235	0.000333	0.066214	12.53622
CNX FINANCE	-0.00089	0.021979	0.000483	-0.25342	9.581906
CNX FMCG	-0.00104	0.014478	0.00021	0.229206	6.604049
CNX PHARMA	-0.00078	0.013261	0.000176	0.193915	11.51408

Table 1.2 indicates that all the sectoral indices have negative sign in mean returns which is not a good sign. Kurtosis for all the indices was above 3 which indicate that data was not normal. The finance sector has a maximum standard deviation (0.021979) and variance (0.000483) among all sectors. Skewness shows that all indices have figure above 0. It means returns were not normal.

From the results of table 1.1 and 1.2, it can be concluded that U.S. indices were more volatile on the basis of variance, skewness and kurtosis statistics from the Indian Indices. As shown in the tables U.S. Indices have larger values of variance, Skewness and kurtosis in comparison to Indian Indices.

Unit Root Testing (ADF Test): Before applying the ARCH model, It is required to check that whether the data is stationary or not. For this purpose unit root test (ADF) test has been applied. Following is the hypothesis to the test:

Ho: Series has a unit root i.e. series is non- stationary.

Table 1.3: ADF level for US Indices:

Null Hypothesis	P-Value	H0	Result
NYSE has a unit root	0.0000	Reject	Series do not have a unit root
NYSE ENERGY has a unit root	0.0000	Reject	Series do not have a unit root
NYSE FINANCE has a unit root	0.0000	Reject	Series do not have a unit root
NYSE FMCG has a unit root	0.0000	Reject	Series do not have a unit root
NYSE PHARMA has a unit root	0.0000	Reject	Series do not have a unit root

Results of table 1.3 indicates that all the series of U.S. found Stationary for ADF test as all the probability values were less than 5%. So, the null hypothesis that the data is non-stationary has been rejected.

Table 1.4: ADF level for Indian Indices:

Null Hypothesis	P-Value	H0	Result
NSE nifty 50 has a unit root	0.0000	Reject	Series do not have unit root
CNX ENERGY has a unit root	0.0000	Reject	Series do not have a unit root
CNX FINANCE has a unit root	0.0000	Reject	Series do not have a unit root
CNX FMCG has a unit root	0.0000	Reject	Series do not have a unit root
CNX PHARMA has a unit root	0.0000	Reject	Series do not have a unit root

Output of table 1.4 shows that all the series were found stationary at level. All the p-values for the series were less than 5%. So, the alternative hypothesis that the data has not a unit root has been accepted and rejects the null hypothesis that data has a unit root.

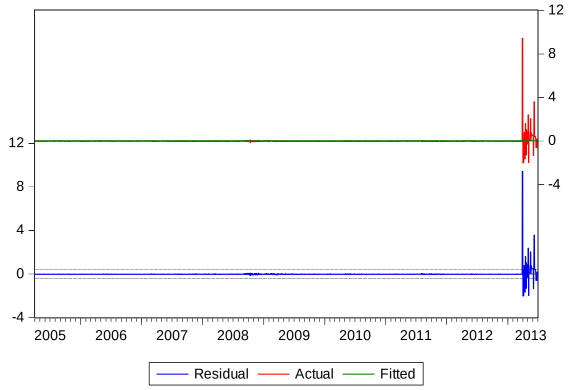
Volatility Clustering Graphs

After verifying the stationarity of the series next condition for applying the ARCH model is there should be Clustering Volatility in time series. Following graphs shows the volatility picture for every sector series.

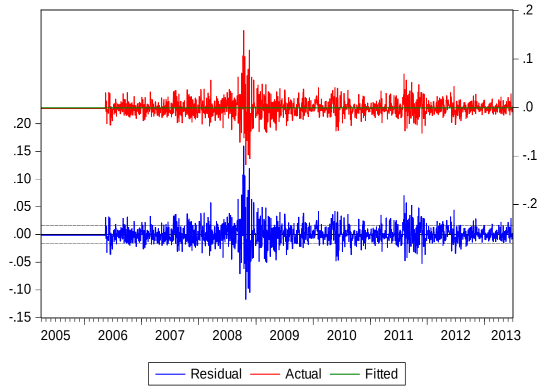
Figure 1.1 Volatility Clustering in U.S. Sectors:

Following Graphs show volatility picture of U.S. Sectors Indices. The blue line represents the residuals while red line shows actual values of returns.

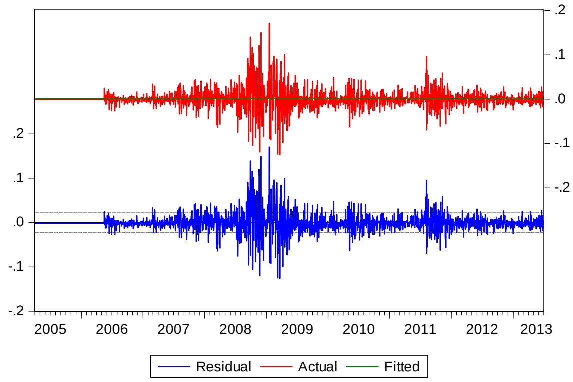
NYSE Index



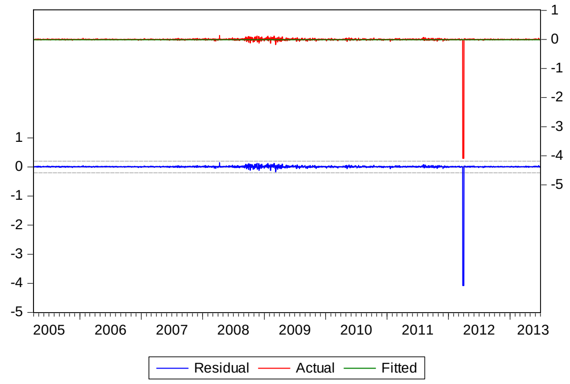
NYSE Energy



NYSE Finance



NYSE FMCG



NYSE Pharma

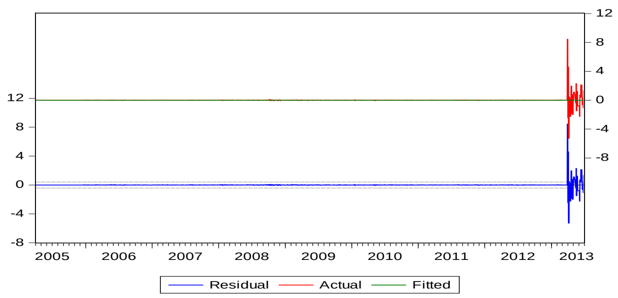
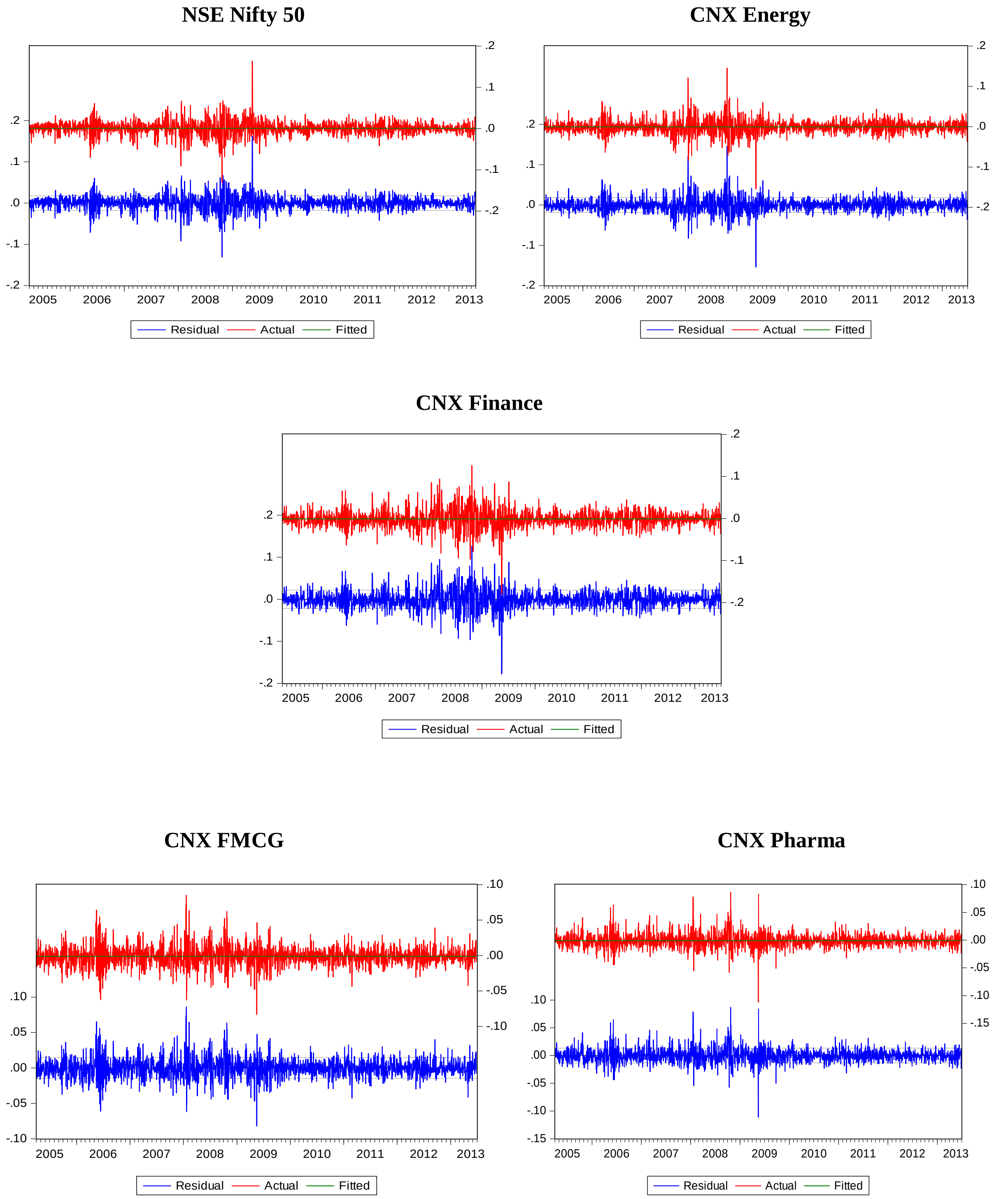


Figure 1.1 shows that the NYSE index follows the constant trend of return for a long time and then it goes high and low for short time. Energy sector shows that it follows the low returns fluctuation and goes high in the middle for a short time and again went to low fluctuations. Pharma sector also follows the same trend as Energy sector. FMCG and Pharma sector shows a negative trend after long time periods.

Figure 1.2 Volatility Clustering In Indian Sectors



Above figure shows that all the sector indices have clustering volatility during the study period. The blue line represents the residuals which are the external factors that affect the returns. Pattern of return follow some time low fluctuation and some time high fluctuations in returns. So, NSE Nifty 50, ENERGY, Finance, FMCG and Pharma have volatility in their returns.

Both Figures depicts the clustering of volatility in U.S. and Indian Indices. It is clear from the graphs that variations were high in U.S. Indices. So, Impact of crisis was more on U.S. Stock market as compared to Indian Stock market.

Normality Test

Jarque-Bera statistics reveal the normality position of time series data, i.e. whether the data is normal or not.

Ho: Data is normally distributed.

Following tables describes the normality position of the data of U.S. and Indian Indices:

Table 1.5 Jarque Bera Statistics of U.S. Indices:

INDEX	Jarque Bera Statistics
NYSE	144522.56 (P=0.0000)
NYSE ENERGY	12591.78 (P=0.0000)
NYSE FINANCE	22034.95 (P=0.0000)
NYSE FMCG	21934.79 (P=0.0000)
NYSE PHARMA	62878.48 (P=0.0000)

Table 1.6 Jarque Bera Statistics of Indian Indices:

INDEX	Jarque Bera Statistics
NSE Nifty 50	12777.19 (P=0.0000)
CNX ENERGY	11418.91 5470.9
CNX FINANCE	1241.794 (P=0.0000)
CNX FMCG	1657.064 (P=0.0000)
CNX PHARMA	9919.338 (P=0.0000)

***Figure in parenthesis indicate P-values**

Table 1.5 describes the Jarque Bera Statistics of U.S. Indices and Table 1.6 of Indian Indices. As all the p-values corresponding to the Jarque Bera statistics are less than 5% which means significant at 5% level in both the tables for all Indices, indicate that the null hypothesis has been rejected i.e. data is normally distributed and accept the alternative hypothesis that the data is not normally distributed.

ARCH LM Test:

After finding out about the non-normality of data, ARCH LM test was applied on time series data. This test is based on best fit mean model ARMA (1, 1) equation which was calculated using stock indices data individually as the dependent variable with constant term. ARCH

LM test verifies that whether the ARCH effect exists or not. Following is the null hypothesis to test:

Ho: There is no ARCH effect.

Following tables shows the results of the test:

Table 1.7 ARCH LM Test for U.S. Indices:

INDEX	Obs*R-squared	Prob. Chi-Square
NYSE	22.72151	0
NYSE ENERGY	639.8468	0
NYSE FINANCE	624.2645	0
NYSE FMCG	1.309725	0
NYSE PHARMA	568.537	0

Table 1.8 ARCH LM Test for Indian Indices:

INDEX	Obs*R-squared	Prob. Chi-Square
NSE Nifty 50	359.3306	0
CNX ENERGY	308.4303	0
CNX FINANCE	288.9685	0
CNX FMCG	522.8985	0
CNX PHARMA	385.5651	0

Table 1.7 shows that for ARCH LM test the p-values of the chi-square corresponding to the observed R squared of all the indices of U.S. stock market were less than 5% meaning that the null hypothesis that there is no arch effect has been rejected and the alternative hypothesis has been accepted that there is ARCH effect. Likewise table 1.8 shows the P-values for the Indian indices, which were also less than 5%, indicate the rejection of null hypothesis that there is no ARCH effect.

Estimates from Volatility Models (ARCH (1), GARCH (1, 1) & EGARCH (1, 1) :

After verifying the ARCH effects, Volatility Models were applied on U.S. and Indian Indices. The results of which are given below in the tables.

Here ω = Constant α = ARCH term

β = GARCH term y =Leverage Effect

Table 1.9 Estimates of Volatility models of U.S. Indices

Part-1. Result of ARCH (1) Model					
Index	**NYSE**	**NYSE Energy**	**NYSE Finance**	**NYSE FMCG**	**NYSE Pharma**
Mean Equation					
c	-0.000551	2.92E-07	-2.85E-07	0.000168	-0.000221
	(0.0000)	(0.0000)	(0.0000)	(0.0496)	(0.0212)
Variance Equation					
Ώ	0.000087	7.24E-14	3.52E-13	0.000126	4.70E-05
	(0.0000)	(0.0079)	(0.0329)	(0.0000)	(0.0000)
Α	0.942183	0.96241	1.039931	1.915149	0.867163
	(0.0000)	(0.0506)	(0.0000)	(0.0000)	(0.0000)
Part-2. Result of GARCH (1,1) Model					
Index	**NYSE**	**NYSE Energy**	**NYSE Finance**	**NYSE FMCG**	**NYSE Pharma**
Mean Equation					
c	0.002181	2.35E-07	2.84E-07	0.038252	-0.000326
	(0.0000)	(0.2966)	(0.0000)	(0.0000)	(0.0633)
Variance Equation					
Ώ	0.001589	9.56E-15	3.70E-15	0.01382	3.63E-06
	(0.0000)	(0.7428)	(0.6008)	(0.0000)	(0.0000)
Α	1.204882	0.294518	0.315748	0.326124	0.176227
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
β	-0.006272	0.748185	0.73587	-0.016743	0.793859
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Part-3. Result of EGARCH (1,1) Model					
Index	**NYSE**	**NYSE Energy**	**NYSE Finance**	**NYSE FMCG**	**NYSE Pharma**
Mean Equation					
c	-0.000636	3.70E-07	-5.58E-07	0.000471	-0.000252
	(0.0246)	(0.0643)	(0.0000)	(0.1174)	(0.1515)
Variance Equation					
Ώ	-0.109833	-1.500432	-0.090492	-0.39937	-0.560021
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Α	0.104316	1.821617	0.153176	0.197212	0.287756
	(0.0000)	(0.0491)	(0.0000)	(0.0000)	(0.0000)
Υ	-0.092465	-0.274833	0.141506	0.17054	0.043929
	(0.0000)	(0.0582)	(0.0000)	(0.0181)	(0.0105)
β	0.995094	0.886977	1.00418	0.968673	0.96402
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)

***Figure in parenthesis indicate P-values**

Table 1.9 shows the output of volatility models into three parts. **Part1** described the results from ARCH (1) model. Results describe the two equations (mean and variance). Coefficients of mean equation of all the indices were significant at 5% level of significance. In variance equation Coefficients of constant term (ω) were also significant at 5% level of significance as all the p-values were less than 5%. The symmetric effect (**α**) coefficients shows the sensitivity to market events which were significant at 5% level of significance for all the selected indices. So, coefficients of ARCH (**α**) term shows highest volatility in Finance and FMCG sector then Energy, NYSE and at last Pharma sector has lowest volatility position among all the Indices.

Part 2 described the results from GARCH (1, 1) model. Results describe the Coefficients of mean equation were insignificant at 5% level of significance of Energy and Pharma sector but significant of other three Indices as the p-values were less than 5%. In variance equation Coefficients of constant term (ω) were insignificant at 5% level of significance of Energy and Finance sector but significant of other three Indices as the p-values were less than 5%. All the ARCH and GARCH coefficients were significant at 5% level of significance. The sum of ARCH and GARCH Coefficients (**α** + **β**) was (1) of NYSE, (1) of NYSE Energy, (1) of NYSE Finance, (0.30) of NYSE FMCG and (0.97) of NYSE Pharma which indicates that shocks to volatility have a persistent effect on the conditional variance. These shocks have a permanent effect if the sum of the ARCH and GARCH coefficients equals unity and the sum of NYSE; Energy and finance sectors coefficients were equal to 1. This means that volatility in NYSE, Energy and finance sectors then in Pharma sector prevails for a long term period during the crisis period. FMCG sector was less volatile among all the indices.

Part 3 described the results from EGARCH (1, 1) model. Results describe the Coefficients of mean equation of NYSE Energy and Finance was significant at 5% level of significance and other three Indices were Insignificant. Coefficients of (**α**) were significant at 5% level of significance for all the selected indices. The parameter β measures the persistence in conditional volatility irrespective of anything happening in the market. The β coefficients were positive of all the indices and all were statistically significant at 5% level of significance. The coefficient on the asymmetry term (**Y**) of NYSE and NYSE Energy were negative and statistically significant at 5% level of significance. This means leverage effect was present in these Indices and good news generates less volatility than bad news on NYSE and on NYSE Energy. Coefficients of (**Y**) term of other three Indices were positive & significant at 5% level indicating rejection of leverage effect.

Table 1.10 Estimates of Volatility models of Indian Indices

Part-1. Result of ARCH (1) Model					
Index	**NSE(Nifty50)**	**CNX Energy**	**CNX Finance**	**CNX FMCG**	**CNX Pharma**
Mean Equation					
c	0.001084	-0.000817	-0.001117	-0.001188	-0.001297
	(0.0005)	(0.0116)	(0.0190)	(0.0000)	(0.0000)
Variance Equation					
ώ	0.000102	0.000115	0.000199	0.000075	0.000063
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
α	0.81507	0.859562	1.029556	0.873266	0.778397
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Part-2. Result of GARCH (1,1) Model					
Index	**NSE(Nifty 50)**	**CNX Energy**	**CNX Finance**	**CNX FMCG**	**CNX Pharma**
Mean Equation					
c	0.001332	-0.000757	-0.001426	-0.001314	-0.00129
	(0.0000)	(0.0224)	(0.0021)	(0.0000)	(0.0000)
Variance Equation					
ώ	4.85E-06	6.68E-06	6.82E-06	2.80E-05	4.45E-05
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
α	0.164902	0.165554	0.131714	0.459717	0.638889
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
β	0.82691	0.816648	0.860046	0.456882	0.189585
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Part-3. Result of EGARCH (1,1) Model					
Index	**NSE(Nifty 50)**	**CNX Energy**	**CNX Finance**	**CNX FMCG**	**CNX Pharma**
Mean Equation					
c	0.000658	-0.000452	-0.000953	-0.001041	-0.001268
	(0.0392)	(0.0187)	(0.0391)	(0.0001)	(0.0000)
Variance Equation					
ώ	-0.478964	-0.507313	-0.358756	-1.919257	-2.834203
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
α	0.27572	0.285213	0.225881	0.580335	0.657732
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Υ	-0.115757	0.059341	0.09229	0.069775	0.037467
	(0.0000)	(0.0007)	(0.0000)	(0.0181)	(0.0280)
β	0.968872	0.966237	0.976644	0.832385	0.740251
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)

*** Figure in parenthesis indicate P-values**

Table 1.10 shows the output of volatility models into three parts. **Part1** described the results from ARCH (1) model. Results describe the two equations (mean and variance). Coefficients of mean equation of all the indices were significant at 5% level of significance. In variance equation Coefficients of constant term (ω) were also significant at 5% level of significance as all the p-values were less than 5%. The symmetric effect (**α**) coefficients shows the sensitivity to market events which were significant at 5% level of significance for all the selected indices. So, coefficients of ARCH (**α)** term shows highest volatility in Finance and FMCG sector then Energy, NSE (Nifty 50) and at last Pharma sector has lowest volatility position among all the Indices.

Part 2 described the results from GARCH (1, 1) model. Results describe that the Coefficients of mean equation of all the indices were significant at 5% level of significance. In variance equation Coefficients of constant term (ω) were also significant at 5% level of significance as all the p-values were less than 5%. The ARCH (**α)** and GARCH (β) coefficients were significant at 5% level of significance. The sum of ARCH and GARCH Coefficients (**α** + **β**) was (0.99) of NSE (Nifty 50), (0.98) of CNX Energy, (0.99) of CNX Finance, (0.91) of CNX FMCG and (0.82) of CNX Pharma which indicates that shocks to volatility have a persistent effect on the conditional variance. These shocks have a permanent effect if the sum of the ARCH and GARCH coefficients equals to unity.

Part 3 described the results from EGARCH (1, 1) model. Results describe the Coefficients of mean equation of all the indices were significant at 5% level of significance. The symmetric effect (**α**) coefficients shows the sensitivity to market events which were significant at 5% level of significance for all the indices. The parameter β measures the persistence in conditional volatility irrespective of anything happening in the market. The β coefficients were positive of all the indices and all were statistically significant at 5% level of significance. The coefficient on the asymmetry term (**Ƴ**) of NSE (Nifty 50) was negative and statistically significant at 5% level of significance. This means leverage effect was present in NSE (Nifty 50) Index and good news generates less volatility than bad news on NSE (Nifty 50) Index. Other four Indices were found significant at 5% level but the positive signs of these indices of asymmetry term (**Ƴ**) indicate the non presence of leverage effect.

As it is clear from the output of table 1.9 and 1.10 that all the three model measures the volatility in U.S. and Indian Indices and volatility coefficients from these models were high in U.S. Indices. So, Impact of sub-prime crisis was more on U.S. indices.

Conclusion

As the Objective was to analyze the fragility pattern in U.S. and Indian stock market, the descriptive statistics for both countries indices have been calculated individually. Next ADF test has been applied for stationarity which confirm that all the series of U.S. and India were stationary. Clustering volatility charts shows that there was high volatility persistence in U.S. stock market Indices in comparison to Indian market indices. Jarque –Bera statistics indicates that all the p-values were less than 5% for both countries indices which means data was not normally distributed.

Then ARCH LM test was applied to check the ARCH effect. All the indices of both countries clear the ARCH effect test as all the chi- square p-values were less than 5%. Then the ARCH (1), GARCH (1, 1) and EGARCH (1, 1) model were applied on all the series with dependent variable and constant with ARMA (1, 1) regressor which describes the volatility values. All the volatility coefficients reported by **α** and β of U.S. Indices were higher than Indian Indices which means variations were high in the U.S. Indices returns as compared to Indian Indices. So, there was difference in the fragility pattern of US and Indian stock market.

References

Chakrabarti, R & Roll, R (2002). East Asia and Europe during the 1997 Asian Collapse: A Clinical Study of a Financial Crisis. *Journal of Financial Markets*, vol. 5, no. 1, pp. 1-30.

Raju, M.T. and Ghosh, Anirban (2004). Stock Market Volatility-An International Comparison. Securities and Exchange Board of India.

Mun. C. Kyung-Chun (2005). Contagion and impulse response of international stock markets around the 9-11 terrorist attacks. Global Finance Journal, 16 (1), 48-68.

Rasmussen, Anne-Sofie Reng (2006). How well do financial and macroeconomic variables predict stock returns: Time-series and cross-sectional evidence. *Available Online at papers.ssrn.com/sol3/papers.cfm?abstract_id=941187.*

Leeves, G (2007). Asymmetric Volatility of Stock Returns during the Asian Crisis: Evidence from Indonesia. *International Review of Economics and Finance*, vol. 16, no. 2, pp. 272-286.

Gustavson, Anna & Unge, Staffan (2008). Unfolding the Subprime Crisis A Study on the Origin of a Global Crisis. Master Thesis in Accounting and Financial Management.

Koulakiotis. A, Dasilas. A and Papasyriopoulos, N. (2009). Volatility and error transmission Spillover effects: Evidence from three European financial regions. *The Quarterly Review of Economics and Finance*, volume 49(3), pp. 858-869.

Cripps, Francis., Izurieta, Alex & Singh, Ajit (2011). Global Imbalances, Under-consumption and Over-borrowing: The State of the World Economy and Future Policies, Development and Change. *International Institute of Social Studies, 42(1): 228–261*.

SJ, Albert William & Kalavathy, S. Titus (2012). The Impact Of Global Financial Crisis On Indian Stock Markets. *International Journal of Research in Commerce & Management, Volume No. 3 (2012), Issue no. 2 (February).*

Manurung, Adler., Pardede, Josua & Sitorus, Romora (2013). Dynamic Interrelationships between Macroeconomic Indicators, Global Stock Market", and Commodities Prices and Jakarta Composite Index (JCI). *Available Online at http://www.academia.edu/3630232/.*

Kosapattarapim, Chaiwat (2013). Improving Volatility forecasting of GARCH models: application to daily returns in emerging stock markets. Doctor of Philosophy thesis, School of Mathematics and Applied Statistics, University of Wollongong.