Estimation of Value at Risk (VaR) in the Context of the Global Financial Crisis of 2007-08 : Application on Selected Sectors in India

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Abstract

The most-recent global financial meltdown of 2007-08 has generated concerns among the risk professionals and researchers regarding the effectiveness of alternative risk assessment methodologies. The turbulence caused by the global financial crisis, especially in the stock markets, has greatly challenged risk management. This study undertook empirical estimation of Value-at-Risk, the widely used risk assessment methodology for assessing market risk. The single number, Value-at-Risk, indicates the maximum loss that may be incurred for a given portfolio for a specified time horizon and a confidence level. The study focused on the performance of some major Indian sectors listed on the National Stock Exchange, on which most of the trades are conducted. A hypothetical portfolio, composed with the selected sectoral indices, was also constructed and its performance was examined. The general techniques commonly used to estimate Value-at-Risk are parametric method (Delta Normal method) and non parametric method (Historical Simulation method and Monte Carlo Simulation method). The crucial period addressed in the study refers to the period from 2007-08 and Value-at-Risk was estimated on the selected sectors. The results based on three Value-at-Risk methods were then compared and analyzed. The results revealed that among the estimated Value-at-Risk based on alternative methodologies, Monte Carlo Simulation method yielded the best possible results in all the key elements of Value-at-Risk analysis. Even for the adequately diversified portfolio, the study reflected the way in which the dominant sectors in the market responded to the crisis phase and how they worked upon the hypothetical portfolio.

Keywords: **financial crisis, Indian Stock market, Value-at-Risk**

JEL Classification: C22, C41, G01, G11, G32

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The Global Financial Crisis or the "Great Recession" of 2007-08 is often considered to be the worst financial crisis since the Great Depression of the 1930s. The magnum episode of the 2007-08 financial crisis in the U.S. had a profound and significant effect on the country's stock market in the form of a major crash that was completely different from the pre crisis period. The event resulted in the collapse of major reputed financial institutions, with a massive impact on the real economy. In the globalized scenario, the financial crisis has had a significant impact across countries.

In India, the impact of the global financial turmoil was felt primarily in its equity market. The NSE S & P CNX Nifty increased significantly from a level of 3634 points during the beginning of April 2007 to its peak of 6288 points on January 8, 2008 in the presence of heavy portfolio flows corresponding to the high growth performance of the Indian corporate sector. The Index fell from its closing peak of 6288 points on January 8, 2008 to less than 4000 points by October 27, 2008 (2524 points), in line with similar large declines in other major stock markets. The market crash was felt across sectors, and had a destabilizing impact on the economy.

While liberalization of the markets with the associated benefits is welcome, the consequent possibility of

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disturbances and excess volatility with its risk features needs to be taken as a matter of concern. An important dimension of the issue is the assessment of risk so that proactive measures can be taken, and suitable business strategies may be framed in the given scenario. While research studies on stock market risk assessment methods and their empirical applications abound in literature, it appears important to look into the relevance of these methods in the context of a financial crisis, given the increasing integration among national financial markets and the corresponding risk exposures thereof. The efficacy of the alternative risk assessment methodologies in terms of capturing the market behaviour and predicting forthcoming risk episodes, if any, needs to be revisited in the contemporary context. This paper undertakes a study on Value-at-Risk (VaR) methodology of risk assessment for the major Indian sectors during the recent crisis period.

Related Literature on VaR

Value-at-Risk (VaR) methodology basically is a measure to assess the upcoming financial risk of losses on the basis of which business entities may estimate their capital holdings as a buffer. VaR is defined as the maximum potential loss to any portfolio or a security with a given probability over a certain time horizon. Several research studies have been conducted both on the methodological up gradation as well as empirical validation of the methods. Most of these studies are in the context of the developed countries. The first indirect reference to VaR was found in the New York Stock Exchange in 1922, which has been documented by Holton (2014), and there was an indication to its member firms to hold capital 10% of their assets. The widespread adoption of VaR was made after 1994 since J. P. Morgan introduced Risk Metrics system on the Internet. Jorion (1996) showed that VaR serves as a standard measurement to estimate unexpected losses for all risk categories.

In order to estimate the VaR, both parametric and non parametric methods may be used. Under the non parametric method, the historical simulation approach and Monte Carlo simulation are used ; while, under the parametric approach, the delta normal method approach is used. The distinction between the delta normal method approach and the historical simulation approach was first focused upon by Crnkovic and Drachman (1997). Beder (1995) applied eight common VaR methodologies to three hypothetical portfolios and found subsequent differences among these methods. Hendricks (1996) focused on VaR models ; Jamshidian and Zhu (1996) established the proficiency of the Monte Carlo Simulation method over standard Delta Normal method approach by using nonlinear positions (such as options).

Lopez (1999) developed an alternative evaluation method based on loss functions to estimate VaR. Under the assumption of normal distribution, the comparative functioning of historical simulation and delta normal method approaches were investigated by Allen (1994). A stronger analysis was conducted by Billio and Pelizzon (2000), who used a multivariate switching regime model to calculate VaR for 10 Italian stocks. Zangari (1996) and Schinassi (1999) studied VaR models which were based on historical relationship between price movements in many markets, and they tended to breakdown during stress time and turbulence when there were structural breaks in relationships across the market.

Basak and Shapiro (2001) proposed an alternative methodology which generated losses which were lower than those of the VaR. Brooks and Persand (2003) considered the asymmetric VaR framework and proved that this asymmetric framework did not lead to underestimate the VaR in unconditional return distribution or in the volatility specification. Lin, Chang, and Ching (2005) compared three revised historical simulation methods - the hybrid method, filtered historical simulation method, and Hull and White's method for estimating Value-at-Risk. The database were based on 11 years of 5 daily stock prices and 5 foreign exchange rates, and the empirical results exhibited that Hull & White's method was a significant improvement for three confidence levels, based on analysis of conservative, accuracy, and efficiency.

Lamantia, Ortobelli, and Rachev (2006) compared and looked into the forecasting power and the performance of associated aggregation rules of different VaR models. Empirical results demonstrated that stable Paretian models, and the Student's t-copula have well forecasting ability, and some stable parametric models present better performance for smaller percentiles and for large portfolios. Dockery and Efentakis (2008) compared and also estimated the model-based Value-at-Risk (VaR) models by using daily data from the London Stock Exchange covering the period from January 1992 to December 2002. The empirical results indicated the degree of accuracy of the various methods as well as address to proper model selection. The equally weighted moving average (EWMA) model caters more accurate estimated VaR than the GARCH methods, including the popular historical simulation (HS) approach, by altering the estimation horizon.

The research analysis of VaR has also expanded in the context of financial crisis. Bao, Lee, and Saltoglu (2004) analyzed the performance of parametric and nonparametric VaR models before, during, and after the Asian Financial Crisis. They demonstrated that most VaR models behaved similarly before and after the crisis, but differently in the crisis period. Zikovic and Aktan (2009) investigated the relative performance of VaR models on Turkey and Croatia's stock market prior to and during the global financial crisis and indicated that during the crisis period, the advanced VaR models such as EVT (extreme value theory) and HHS (hybrid historical simulation) methods adequately measured the equity risk on Turkish and Croatian equity markets in times of crisis.

McAleer, Martin, and Amaral (2009) assessed the effects of the Basel II Accord on risk management and illustrated how risk management strategies executed during the 2008-09 financial crisis worked on the daily data of the Standard and Poor's 500 Composite Index (S&P500) and the Dow Jones Industrial Average (DJIA) for the period from 3/1/1928 - 1/7/2009. Basically, an aggressive risk management strategy and GARCH type models have been chosen to forecast Value-at-Risk (VaR) using a single risk model. Totic, Bulajic, and Vlastelica (2011) conducted a comparative analysis and predictive functioning of eight VaR models, that is, simple analytical VaR, historical VaR, VaR based on EWMA volatility model, VaR based on GARCH (1,1) volatility model, unconditional GPD VaR, conditional GPD VaR model covering the sample of daily returns of FTSE100 index from March 25, 1997 to March 22, 2011. Statistically, backtesting enables testing for accuracy among all the VaR models, and the empirical results in this study established that EVT based VaR generated most accurate VaR estimates.

Mutu, Balogh, and Moldovan (2011) considered five stock market indices form Central and Eastern Europe: BET (Romania), PX50 (Czech Republic), BUX (Hungary), SOFIX (Bulgary), and WIG20 (Poland) for the time span 30.09.2004 to 30.09.2010, and analyzed the performance of Value at Risk models through Historical Simulation, EWMA, GARCH, and EVT models. The results support advanced VaR models such as extreme value theory or GARCH models to adequately measure the risk of the capital markets. Uppal (2013) evaluated the performance of various Value-at-Risk (VaR) measures during the Global Financial Crisis period in five developed and five emerging markets. The dynamic EVT-VaR model both in the pre-crisis and the crisis period performed better than the other competing models.

Koima, Mwita, and Nassiuma (2013), in order to consider extreme rare events that caused enormous losses, selected data from Nairobi Stock Exchange's (NSE) specific equities from Barclays Bank. The results justified that the EVT-VaR model captured the rare events which made it the most robust method of estimating VaR. Grace, Mwita, and Kihoro (2014) considered daily average share prices of Kakuzi and BAT stocks of Nairobi Stock Exchange as a sample for the period from January 2003 to December 2013. They observed that VaR is used to evaluate riskiness of stocks and volatility was studied by applying GARCH family models. Backtesting of VaR was also applied to examine the accuracy of the results.

In the Indian context, one of the leading research studies by Sarma, Thomas, and Shah (2000) on the performance of alternative VaR models considered India's Nifty stock market index and adopted a statistical model based on a loss function. Varma (1999) examined VaR for the Indian stock market with emphasis on EWMA model and GARCH-GED specifications. Nath and Reddy (2003) studied the Indian foreign exchange market and used the Rupee-Dollar exchange rates to specify the best suited VaR methods for the Indian system. Samanta and Nath (2003) studied three categories of VaR methods, that is, the delta normal method, including the risk-metrics ; historical simulation ; and tail - index based approach, and found that VaR models under the delta normal method approach underestimated VaR numbers.

Raina and Mukhopadhyay (2004), by using simulated annealing framework, optimized portfolio components of equities, equity futures, and equity European options by minimizing Value at Risk. Samanta and Thakur (2006) assessed the accuracy of VaR estimates incurred through the application of tail index based on the data obtained from BSE Sensex and BSE 100 from the time horizon from 1999 to 2005. Empirical results established the fact that tail index based methods provide relatively more accurate VaR estimates.

Tripathi and Gupta (2008) empirically evaluated the accuracy of parametric and non-parametric VaR models by applying the chi square test statistic. The data comprised of 30 securities selected from the BSE Sensex and NSE Nifty for the period from January 2006 to February 2007. The results pointed out that VaR overestimated the loss in 24 securities out of 30 securities, and also, VaR estimates did not accurately measure the risk in equity investments in India.

The study of Jadhav and Ramanathan (2009) was based upon two types of comparison procedure of VaR models. The procedures used in-sample (to examine the estimated method's goodness-of-fit ability) and out-of-sample (to evaluate the forecasting quality of the estimated model), and the VaR models were traditional parametric and non-parametric along with nine new nonparametric VaR models based on stock price return data from India and New York stock markets. Their results supported the new non parametric VaR models. Virdi (2011) computed the conventional VaR models for Nifty Fifty securities for the period from 2007-08. Backtesting was also applied on those models to examine the accuracy of the results. Sahi, Pahuja, and Dogra (2013) evaluated VaR estimation on 20 schemes of top 10 Indian mutual fund houses.

A completely different area of application approach of parametric and nonparametric VaR was found in a study by Malhotra (2014). The basic aim of the paper was to estimate portfolio risk capital by using temperature series from the year 1996 to 2013 on a monthly basis of three different cities, that is, Delhi, Mumbai, and Chennai. Further volatilities were linked with VaR estimation. The results concluded a risk assessment of weather related investment in the agricultural industry.

Despite the plethora of studies in this area, there appears to be a lacuna in the literature in estimating VaR addressing the recent global financial crisis with reference to the major dominating sectors in the Indian stock market. The importance of this study lies in the fact that the industrial sectors do not always respond in the similar manner, particularly under a stressful scenario. The variation in the sectoral response to a crisis situation is attributable to the sectoral features and their sensitivity to the market. This has not been addressed in the earlier literature in terms of the risk analysis in the Indian context for the chosen time period. Furthermore, the implication of the differences in methodological approaches on VaR has also been investigated for the selected sectors, which the relevant literature does not provide.

Research Objectives and Methodology

➢ **Research Objectives:** The main objective of this paper is to evaluate the performance of the alternative VaR models applied on the selected Indian sectors. The alternative VaR models are delta normal, historical simulation, and Monte Carlo simulation techniques. This study considers only the recent financial crisis period. A hypothetical portfolio is constructed with the selected sectoral indices, the stocks of which are mostly traded, and therefore, are the dominant ones in the market. Individual sectors as well as the hypothetical portfolio are dealt with for the analysis.

The study hypothesizes that :

➔ Value- at- Risk (VaR) estimates of the individual sectors reflect the respective sectoral performance features.

➔ Sensitivity of the sectors to the market in terms of VaR Beta is passed through in the VaR estimates of the sectors.

➔ The differences in VaR estimation methodologies contribute the sectoral VaRs.

➔ A hypothetical portfolio with diversified composition of sectoral indices also features to be affected during the crisis period.

The research objectives in the study are the following :

(1) To estimate VaR for the individual sectors,

(2) To estimate market sensitivity of selected sectors,

(3) To compare the alternative methodologies of VaR results derived from the study.

➯ **VaR Computation:** There are three key elements of VaR - a specified level of loss, a fixed time period over which risk is accessed, and a confidence level. With these elements, VaR is estimated as follows:

$$\text{VaR} = \alpha * \text{time factor} * \text{volatility} \qquad (1)$$

where,
α is the critical value that determines the one tailed confidence level of standard normal distribution Time factor is defined as $\sqrt{t}$, where t is the time horizon in measuring the VaR, and volatility is represented by standard deviation of the stock measured in currency units over one year.

For a portfolio comprised of individual stocks :

Individual Stock VaR (VaR_i) $= \text{Total invest} * \omega_i * \sigma_i * \alpha * \sqrt{\text{days}}$ (2)
where, ω_i = weight of the i^{th} stock, σ_i = standard deviation of i^{th} stock, and α = confidence level

Portfolio VaR (VaR_P) $= \text{Total invest} * \sigma_p * \alpha * \sqrt{\text{days}}$ (3)
where, α = confidence level and σ_p = portfolio standard deviation

To get standard deviation of the portfolio, we premultiply and postmultiply the variance - covariance matrix of stocks' return by weight of individual asset in the portfolio.

The expression of σ_p is given by $\sigma_p = \sqrt{(\omega^T \Omega \omega)}$, where ω is N X 1 matrix of portfolio equal weights vector, pre and post multiplying variance covariance matrix Ω.

VaR Beta: This estimation shows the contribution of an individual stock to the portfolio risk. The method of determining beta (the systematic risk) of a stock within a particular portfolio is given by :

$$\text{VaR Beta} = \frac{\Omega \omega}{\omega^T \Omega \omega} \qquad (4)$$

Ω = Variance Covariance matrix of stocks' return, ω = weight of the stocks, $\omega^T \Omega \omega$ = Portfolio variance

Component VaR: Component VaR is the contribution of a specific stock to the entire portfolio VaR. If a particular stock is removed, then the portfolio VaR would change by the component VaR of that stock. The component VaR is a product of weightof the i^{th} asset, its corresponding VaR Beta, and the portfolio VaR.

$$\text{Component VaR} = \omega_i * \text{VaR Beta}_i * \text{VaR}_P \qquad (5)$$

where, ω_i = weight of the i^{th} stock, VaR Beta_i = VaR Beta of the i^{th} stock, and VaR_P = portfolio VaR

VaR can be calculated using the following alternative methods:

(1) Delta Normal Method
(2) Historical Simulation Method
(3) Monte Carlo Simulation Method

➯ **Delta Normal Method :** This method assumes that asset returns are multivariate normally distributed with mean return zero as well as portfolio return is linearly dependent on all asset returns. Historical data on stock returns are used to estimate mean, standard deviation, and correlation among the stock returns. Individual stock VaR as well as VaR of a portfolio under this method are estimated as stated in equation (2) and (3), respectively. Further, the other risk characters, VaR Beta and Component VaR have been analyzed by the equations (4) and (5), respectively.

The advantages of this method lie in its simplicity in terms of matrix multiplication calculation and VaR computation utilizing standard mathematical properties of normal distribution. The assumption of normality in return distribution generates a tendency to overlook the non- normality features and ,therefore, the fat tail in the distribution may not also be recognized. Further for instruments such as future, options whose returns are non linear functions of risk factors, VaR loses its applicability.

➯ **Historical Simulation Method :** It is the method of predicting the future return depending directly upon the past empirical returns. The underlying assumption of this method is that, future asset return of a particular stock follows the same distribution as that of the historical price of that stock. The initial step of the method is to prepare profit and loss of the current portfolio which is affected by market factors for each of the last N days, that is, N sets of hypothetical market factors are generated using their current values and the changes in the last periods for N days. N hypothetical mark to market portfolio values as well as the corresponding profits and losses on the portfolio are calculated on the basis of the market factors.

Calculation of VaR at α confidence level is done in the historical simulation method by generating a profit and loss scenario, which is sorted out by denoting $\Delta V(1), \Delta V(2), \ldots\ldots \Delta V(m)$ in descending order. The VaR can be calculated as follows:

VaR = $-\Delta V(k)$ where, $k = m\,\alpha$ i.e. $k = \alpha$ percentile of scenario m. Generally α, the confidence level can be considered as 95% or 99%.

Under this methodology also we use the same formulation as in equations (2), (3), (4), and (5).

Its advantages lie in its simplicity as this method does not indulge any assumption regarding the distribution of parent population as well as the estimation of volatilities. Fat tail of the return distribution is also revealed under this method. But being based on sufficiently large historical price data, the estimation method carries the features of the past in predicting the future values. This method does not reckon distributional pattern while calculating future scenarios which are completely based on historical data sample.

➯ **Monte Carlo Simulation Method :** It is the most sophisticated and powerful approach to estimate the VaR model. This method has two steps. In the first step, the financial variables are specified by the stochastic process. In the second step, 'price paths' for all financial variables are simulated. This 'pseudo' actualization is used to compute the return distribution.

In this type of method, one can randomly generate many scenarios and calculate the VaR of the portfolio. It is almost similar to the historical simulation method except that, here, simulation is done on many scenarios using a forward looking estimation of volatilities rather than the historical volatilities over a period of time. It involves a random number generator to produce tens of thousands of hypothetical changes in the market. These are then used to construct thousands of hypothetical profits and losses on the current portfolio, ordering the changes in portfolio value from worst to best. The 99% VaR, for example, is computed as the loss such that 1% of the profits or losses are below it, and 99% are above it. The variance-covariance matrix of asset returns generated by the Monte Carlo simulation method is then given as:

$$\Omega_{\text{MonteCarlo}} = \begin{bmatrix} \sigma_{11} & \sigma_{12} & \sigma_{13} \\ \sigma_{21} & \sigma_{22} & \sigma_{23} \\ \sigma_{31} & \sigma_{32} & \sigma_{33} \end{bmatrix}$$

Monte Carlo VaR= (0.01 percentile of scenario $'m'$) *(total invest) *($\sqrt{}$days)

Under this methodology also, we use the same formulation of VaR as in equations (2), (3), (4), and (5) .

The major advantage of this method is that it incorporates nonlinear positions in the calculation of VaR and is also flexible in using any probability distributions. The disadvantages of the method lie in its computation as it involves a lot of time in calculating large scenarios. If the assumption of the pricing model and the underlying stochastic process are not specified properly, the VaR estimation becomes disrupted.

All the alternative VaR methods, as discussed above, in terms of individual stocks are applied on the Indian stock market, taking the returns of the selected sectoral indices.

Data Sources and Description

The data set used for the stock market is S & P CNX Nifty as available from NSE India website. Returns are calculated as logarithmic differences in daily sector indices:

$$R_t = log\,(P_t / P_{t-1}) \qquad (6)$$

Where R_t is the return for day t and P_t is the index level at the end of day t.

➯ **Data Set :** This study considers the period from January 3, 2005 to December 30, 2011. Structural break test was carried out to identify the breakpoints, that is, the crisis period. The period of crisis in the Indian Stock market is demarcated from 02.06.2008 - 29.05.2009. A plot of the log returns of CNX Nifty displays volatility-clustering phenomenon, large and small swings tend to cluster (Figure 1). The clustering feature is seen to be very prominent during the peak crisis period. Further spikes are sharply observed for the years 2008 and 2009.

The most significant features are reflected in skewness and kurtosis. Kurtosis in Crisis period (5.8276) exceeds 3 and exhibits leptokurtic distribution. The distribution is also positively skewed (0.4865). The highly significant

Figure 1. Plot of Log Return of CNX Nifty

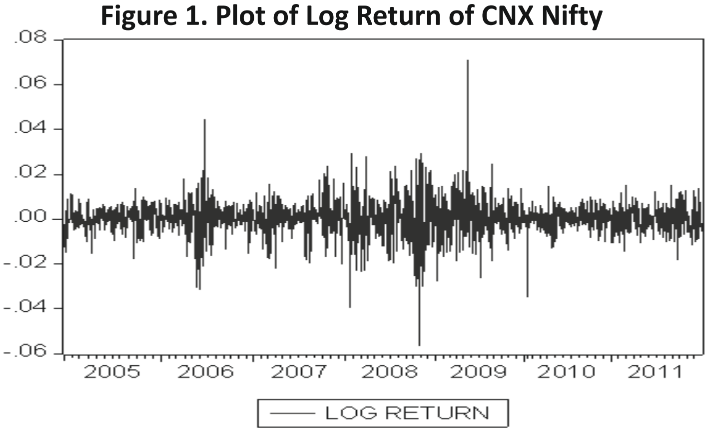

Table 1. Descriptive Statistics for the Chosen Crisis Period

Mean	Median	S.D	Kurtosis	Skewness	Minimum	Maximum	JB Statistic	Probability
-2.20485E-05	0.0004992	0.02546	5.827689328	0.48654739	-0.122029	0.177440	684.056	0.000

values of Jarque-Bera test statistic leads to rejection of the normality assumption of the distribution. The Figure 2 also indicates the same and the distribution is shown to have fat tail. The concave departure from the linearity of the QQ-plot (Figure 2) is an indication of fat-tail and sharp peak. Further stationarity of the CNX Nifty series is examined through ADF test. The highly significant Augmented Dickey-Fuller test statistic value (-39.81665) shows that the CNX Nifty return series is stationary. Also Durbin-Watson test statistic value (1.996937) shows that there is no serial correlation in residuals.

This study considers sectoral index of the selected sectors which are dominant in the Indian stock market. The sectors selected are (a) Auto Sector, (b) Energy Sector, (c) IT Sector, (d) MNC Sector, (e) PSU Bank Sector, (f) Bank Sector, (g) Realty Sector, (h) Metal Sector, (i) Pharma Sector, (j) PSE Sector, (k) Service Sector, (l) FMCG Sector. Returns on the sectoral indices are estimated using equation (6) .

The log returns of the above sectors were calculated for each sector to examine whether volatility clustering exists or not, and their plots are shown in the Appendix-Chart 1. Again, a descriptive statistics of the above sectors were also presented separately during the crisis period so as to understand how these sectors behaved during this period. The results are shown in Appendix- Table 2. Furthermore, a study was also made to observe to what extent these sectors responded during the crisis period, that is, to estimate the existence of fat tail and for that, QQ plots of those sectors were plotted, which are shown in the Appendix-Chart 2.

Construction of Hypothetical Portfolio

The hypothetical portfolio constructed for VaR estimation has considered the following criteria :

Figure 2. Theoretical Quantile-Quantile

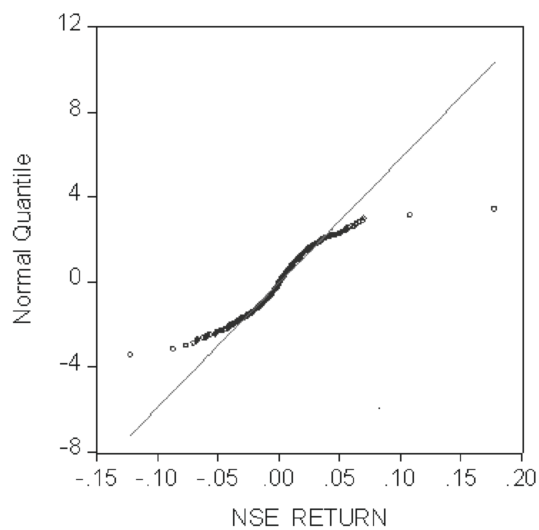

Table 2. Beta Sensitivities of Individual Sectors with Respect to the Market

Sectors	CNX AUTO	CNX BANK	CNX FMCG	CNX ENERGY	CNX IT	CNX METAL	CNX MNC	CNX PHARMA	CNX PSE	CNX PSU BANK	CNX REALTY	CNX SERVICE
Beta Values	0.6983	1.1199	0.5378	0.9827	0.8324	1.1966	0.703	0.5073	0.8791	0.99049	1.5633	1.00685

Table 3. Individual Sector VaR under Alternative VaR Methods

INDIVIDUAL SECTOR (NSE CNX)	DELTA NORMAL METHOD	HISTORICAL SIMULATION METHOD	MONTE CARLO SIMULATION METHOD
AUTO SECTOR	3982.97408	9562.68398	2470.45548
BANK SECTOR	5927.96180	14417.27852	3866.04153
ENERGY SECTOR	4891.78102	9689.30237	3035.35274
IT SECTOR	5000.23858	12843.76406	3093.43022
METAL SECTOR	6436.30737	11627.63026	4436.05858
MNC SECTOR	3724.44926	15310.44724	2317.72343
PHARMA SECTOR	3310.02704	9865.972368	2061.91047
PSE SECTOR	4530.53549	9822.352639	2573.65538
PSU BANK SECTOR	5669.40152	10968.13578	2951.67653
REALTY SECTOR	5562.07921	14573.56159	5904.48948
FMCG SECTOR	3443.22786	21938.37937	2136.62163
SERVICE SECTOR	4863.64556	12070.54623	3067.46644

↳ **Portfolio Risk:** This refers to volatility in portfolio returns over a period of time; volatility of each sector included in the portfolio is estimated through Beta measure, which represents the sector's sensitivity to the swings in the market.

↳ **Portfolio Diversification:** Considering the age old principle that diversification entails lower risk, the hypothetical portfolio in this study is constructed with diversified sectors having less correlation among their returns. The results are shown in the Appendix-Table 1. The diversified portfolio covers sectors like Health, Energy, Banking, Realty, IT, and so forth.

Next, as sectors are also the dominant ones having the stocks on which most of the trades are conducted, market sensitivities of the sectors appear important. Thus, beta sensitivities of individual sectors with respect to the market have been estimated by regressing market returns (S & P CNX NIFTY) on individual sector's returns.

From the Table 2, it is observed that the most aggressive sectors are Realty sector followed by Metal sector, Bank sector with their beta values greater than 1. Service sector with Beta value being almost 1 appears to move more or less in tandem with the market, and the rest of the sectors behave in a defensive manner.

Empirical Analysis and Results

Empirical analysis initially estimates individual sector VaR. Then VaR Beta of the individual sectors comprising the hypothetical portfolio is estimated. Construction of portfolio VaR follows next. Finally, contribution of the individual sector in portfolio VaR is examined through the estimation of component VaR.

↳ **Individual Sector VaR:** Assuming our portfolio position as ₹ 1000,000 invested with the equal weights assigned to each sector, time horizon as 5 days and 1% significance level, we make a comparative study on individual sector VaRs over the crucial period with respect to the alternative VaR methodologies. The Table 3 exhibits individual sector VaRs for the crisis period.

The Table 3 reveals that under the delta normal method, the Metal sector, Banking sector, and Realty sector assume high values as compared to others. Under the historical simulation method, Realty sector and Banking sector also assume higher values but now preceded by sectors like FMCG and MNC. Under Monte Carlo Simulation method Realty sector followed by Metal sector and Banking sector exhibit higher VaRs among others. Thus across the alternative VaR methods Realty sector consistently assume prominence with high VaRs reflecting the sub-prime contagion effect of the financial crisis featured with Realty disaster. Bank sector, which mostly comprises private banks along with other banks having efficient national network and international outreach, also surfaces in having high VaRs both under all the alternative VaR methods. Some discussion on the features of the selected sectors appears relevant at this juncture.

➪ **Realty Sector:** Since the crisis originated in this sector in US and the effect spread across the world, the relatively high VaR is well expected and this is reflected very clearly in the Monte Carlo estimate and also in other estimates.

➪ **Banking Sector:** It can be observed that though the Banking sector in general exhibit high VaR estimates compared to the other sectors, the PSU banks, in all the VaR estimations, assume less value than that of the other banks. This may be attributed to the state ownership feature of the former category of banks. One may also recollect that Indian banks had earlier been wholly owned by the government which changed to a mixed model of public and private ownership after liberalization of the 1990s. During 2008, weakness of the Indian private sector banks has surfaced vis-a vis the relative strength of the public sector banks. This in addition to the fact that the public sector banks have, as their back up, government bail out provision, explain relatively lower VaR compared to other banks. The VaR estimation in the non-parametric methods of Historical Simulation and Monte Carlo Simulation assume much lower values as compared to their parametric counterpart.

➪ **Pharmaceutical Sector:** Indian Pharmaceutical market has experienced a dramatic change during the early years of the preceding decade. The Pharma companies gradually proved their ability to provide facilities for a complete range of services for drug development at less cost than many developed markets. This might have provided some resilience to this sector during the crisis resulting in low VaR compared to other sectors.

➪ **Automobile Sector:** There has been a differential impact of the global financial crisis on Global North and Global South countries with motor vehicle sales much less affected in the developing areas which includes India. Thus VaR estimations for this industry during the selected period are relatively much lower.

➪ **FMCG Sector:** The FMCG sector during the decade of 2000 has adopted a new strategy of revamping their distribution outreach to even the rural areas, upgrading the existing consumers with value added products thus exploiting their potential growth prospects and develop a strong local market base. This has kept their VaR estimate low for Delta Normal and Monte Carlo Simulation methods. But the crisis build up pressure captured in Historical Simulation seems to be reflected in FMCG VaR.

➪ **IT Sector:** The IT industry having large global exposure does have VaR estimations on the higher side among the VaR estimations of other selected sectors, in all the three methods as quite expected. However, the sector also seems to depict some resilience and tenacity in countering the unpredictable conditions. The successful establishment of software companies in India with low cost and wide range of service offerings has somewhat softened the impact of global blow of financial crisis.

➪ **Metal Sector :** The financial crisis having originated from the Realty sector, the effect on the metal industry had been quite severe. The steel industry, in particular had been hard hit. The high VaR estimations in Delta Normal and Monte Carlo simulation methods reflect this phenomenon. However, a relatively lower value among other sectors in Historical Simulation method can be explained by the lagged effect on this industry with metal being used as an input in the housing sector.

➷ **MNC Sector:** The MNC sector having largest exposure to the global environment among others is found to have captured the crisis build up pressure much earlier which is strongly built-in in the Historical Simulation method in having high VaR. However, in two other VaR methods which do not entail past reflections MNC VaRs rank lower.

➷ **Service Sector:** The service sector in India is known for its variety of multi-level services at affordable cost. This feature has provided some support to the sector though the service opportunities somewhat slumped during the period. Thus the relative VaR estimations have remained somewhere in the middle of the extremes of other sectoral estimations. The VaR estimations of the selected sectors, as presented in Table 3, are found to be consistent with the reality thus confirming the hypothesis that the VaR estimations reflect the real sectoral features.

Coming to the comparison of alternative methods, it is revealed, in general, that Monte Carlo Simulation method generates lowest VaR for all the sectors considered under study. In this method, VaR is based on random number generation of future scenarios and therefore free from historical bias as well as distributional assumption associated with Historical Simulation method and Delta Normal method respectively. Historical Simulation method, being based on historical data, automatically captures the significant features of the pre assigned periods. Thus the crisis build up pressure in the pre crisis period is captured in the Historical Simulation VaR, it yields more than double value than that of the Delta Normal VaR and even further higher than that of the Monte Carlo VaRs in all the chosen sectors. Again Delta Normal method imposing the assumption of normal distribution eventually underestimates the true VaR.

➷ **Individual Sector VaR Beta:** Table 4 below shows the VaR Beta values of the sectors under the alternative methodologies. VaR Beta of a sector in a portfolio implicates the risk contribution of that sector to the portfolio risk.

From the Table 4, we find that irrespective of the VaR methods, the Realty Sector, the Banking sector have high VaR Beta values (values greater than 1) as compared to most of the other sectors. This may be due to the fact that the Global Financial crisis generated from the subprime mortgage crisis in USA is seen to have worked upon

Table 4. VaR Beta of the Individual Sector Under Alternative Methods

INDIVIDUAL SECTOR (NSE CNX)	DELTA NORMAL METHOD	HISTORICAL SIMULATION METHOD	MONTE CARLO SIMULATION METHOD
AUTO SECTOR	0.777297899	0.779076879	0.236564732
BANK SECTOR	1.227443384	1.234047463	1.316441722
ENERGY SECTOR	1.018724341	0.598827642	1.077274234
IT SECTOR	0.878689015	1.016756065	0.965351296
METAL SECTOR	1.291788999	0.883354447	1.304817712
MNC SECTOR	0.773620056	1.288654559	0.905340261
PHARMA SECTOR	0.561999219	0.771096204	0.673724099
PSE SECTOR	0.941383535	0.560846262	0.949110551
PSUBANK SECTOR	1.115511697	0.942192972	1.182708914
REALTY SECTOR	1.753905294	1.321719144	1.759471336
FMCG SECTOR	0.599482958	1.739281192	0.531140955
SERVICE SECTOR	1.064955531	1.068949097	1.102856109

heavily on Realty and Bank sector. This is here to note that Banking sector working as intermediary of national and international transactions had to bear the global pressure of crisis.

But at the same time it is also to be highlighted here that VaR Betas of PSU Bank sector are less than the VaR Betas of the Bank sector, which includes private banks, under all the three methods. The justification of this result follows from the explanation given on the respective VaR estimates (Table 3) above on these two Banking sectors. VaR Beta of FMCG also indicates the same pattern as that in Table 3 where the past build up pressure of the crisis is captured heavily in the Historical Simulation VaR Beta whereas in the other two methods VaR betas of this sector ranks very low. MNC has also come up with high VaR Betas under Historical Simulation method as this sector has the opportunity to process world wide information much earlier. But similar to Table 3 results, VaR Betas of this sector as estimated in the other two methods, rank low relative to the other sectors. The Metal sector, reflects high sensitivity in terms of VaR Betas, as compared to the other sectors, under Delta Normal and Monta Carlo Simulation methods which is also reflected in high VaR estimations under these methods in Table 3.

Metal VaR Beta estimate of Historical Simulation ranks low as this is a follow up sector of the Realty sector as explained above. Overall, the Tables 3 and 4 reveal similar pattern in the estimations reflecting pass through of the sectoral risk, reflected by Beta sensitivity of the sector to the VaR estimate of the sector itself. This confirms our second hypothesis that market sensitivity of the sectors is passed through in the sectoral VaR estimates. Also our discussions on Table 3 and Table 4 comparing the results of VaR estimates and also VaR Beta estimates under different methodological approaches confirm our third hypothesis that differences in estimation approaches would be reflected in sectoral VaR and sectoral VaR Betas.

➪ **Portfolio VaR:** The portfolio VaR results (Table 5) for the crisis period under study shows that the Value-at-Risk more than doubled from the Delta Normal method to the Historical Simulation method. This may be explained by the fact that the underlying crisis factors start operating much earlier heading towards a full blown

Table 5. Portfolio VaR

DELTA NORMAL METHOD	HISTORICAL SIMULATION METHOD	MONTE CARLO SIMULATION METHOD
52969.80627	130941.7859	24201.52982

Table 6. Component VaR Under Alternative VaR Methods

INDIVIDUAL SECTOR (NSE CNX)	DELTA NORMAL METHOD	HISTORICAL SIMULATION METHOD	MONTE CARLO SIMULATION METHOD
AUTO SECTOR	3429.73748	8497.74269	476.91152
BANK SECTOR	5415.95260	13460.31194	2653.92989
ENERGY SECTOR	4495.00385	6531.68309	2171.77115
IT SECTOR	3877.11410	11090.21672	1946.13604
METAL SECTOR	5699.87022	9635.14514	2630.49650
MNC SECTOR	3413.50942	14055.93616	1825.15456
PHARMA SECTOR	2479.75684	8410.69387	1358.21929
PSE SECTOR	4153.74645	6117.40299	1913.39495
PSU BANK SECTOR	4922.06692	10276.92343	2384.32627
REALTY SECTOR	7738.90515	12235.09634	3547.072047
FMCG SECTOR	2645.14952	18971.12397	1070.77347
SERVICE SECTOR	4698.99366	11659.50964	2223.34409

crisis and this is captured in the Historical Simulation method being based on past data. Monte Carlo Simulation VaR method, on the other hand, yields less portfolio VaR value being based on random number generated simulation. It has neither parametric limitations nor historical data bias.

↳ **Component VaR:** VaR Betas of the sectors along with their respective weights in the portfolio comprise the sectoral component in the portfolio VaR (Table 6). These sectoral components are disjoined and mutually exhaustive to build portfolio VaR and therefore add up to portfolio VaR. In our paper the sectors have equal weights. Still, Realty sector consistently assumes very high component VaR relative to the other sectors under all the methods. Notably, this sector has high Beta with respect to market as well as portfolio risk.

Research Implications

This study focuses on the analysis of the Value at Risk of the dominant Indian sectors during the financial crisis of 2007-2008. The implication of VaR results highlights the probability of expected loss and this is dependent on the market sensitivity of the variable concerned. The current research, therefore, clearly unleashes the response of the chosen sectors to a crisis situation of this sort. This would create awareness among the investors that even the leading sectors may be hit by a stress event and thus help them to frame their investment strategy with the perception of the nature of response the sectors would have during a crisis situation. In the construction of portfolio, reflection of VaR Beta, the sensitivity of the sectors would also provide a guideline to the investors.

Concluding Observations

The paper contributes to the literature by conducting a VaR assessment through alternative methodologies on the selected individual sectors as well as on a hypothetical portfolio addressing the financial crisis of 2007-08 in the Indian context. The hypothetical portfolio is constructed on the basis of the sectors prominent in the market.

Among the different methods of VaR applied on the chosen data set, it is revealed that Monte Carlo Simulation method generates lowest VaR than that generated under the Historical Simulation method and Delta Normal method .The Monte Carlo Simulation method is widely considered as the relatively better theoretical approach to simulation of risk because its chief advantage is that it provides a more comprehensive picture of potential risks embedded in the "tail" of the distribution. This method based on random number generation of future scenarios, is seen to allow for the highest flexibility in choosing distributions for returns. Under Historical Simulation method the portfolio returns assigned by an equal probability weight of $1/N$ to each day's return by which the risk factors, and the historically simulated returns are independently and identically distributed (i.i.d) through time. But this is somewhat unrealistic as the volatility of asset returns depend on the time periods. Delta Normal method, on the other hand, can underestimate risk in tail of distribution. Return series do not always follow normal distribution, especially in crisis show significant amount of kurtosis which leads to fatter tails and extreme outcomes occurring much more frequently than would be predicted by the normal distribution assumption.

The study reflects the way in which the dominant sectors in the market responded to the crisis phase and how they have worked upon the hypothetical portfolio. Among the selected sectors, VaR of the Realty sector, the Banking Sector have the values much higher than that of the other sectors. Therefore, in the VaR Beta analysis these sectors surface as the ones contributing more to the portfolio VaR. The results of the study throw light on the fact that financial crisis of this stature can make even the most relied upon and well performing sectors highly risky and therefore can shake the confidence of the investor community at large in an economy.

It is, however, to be noted that our chosen period refers to the situation of Global Financial Crisis only. The overall risk characters of the selected sectors and the portfolio are revealed through their behaviour during the turmoil period. From the investors' viewpoint this study gives an idea of the risk resilience of the contemporary frontline sectors and their suitability as a candidate in investors' portfolio. As a future agenda for research the analysis can be extended for the pre and post crisis periods and the results can be compared for all the three periods as well which has not been done here and therefore stands as a limitation of this study.

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Appendix Tables and Charts

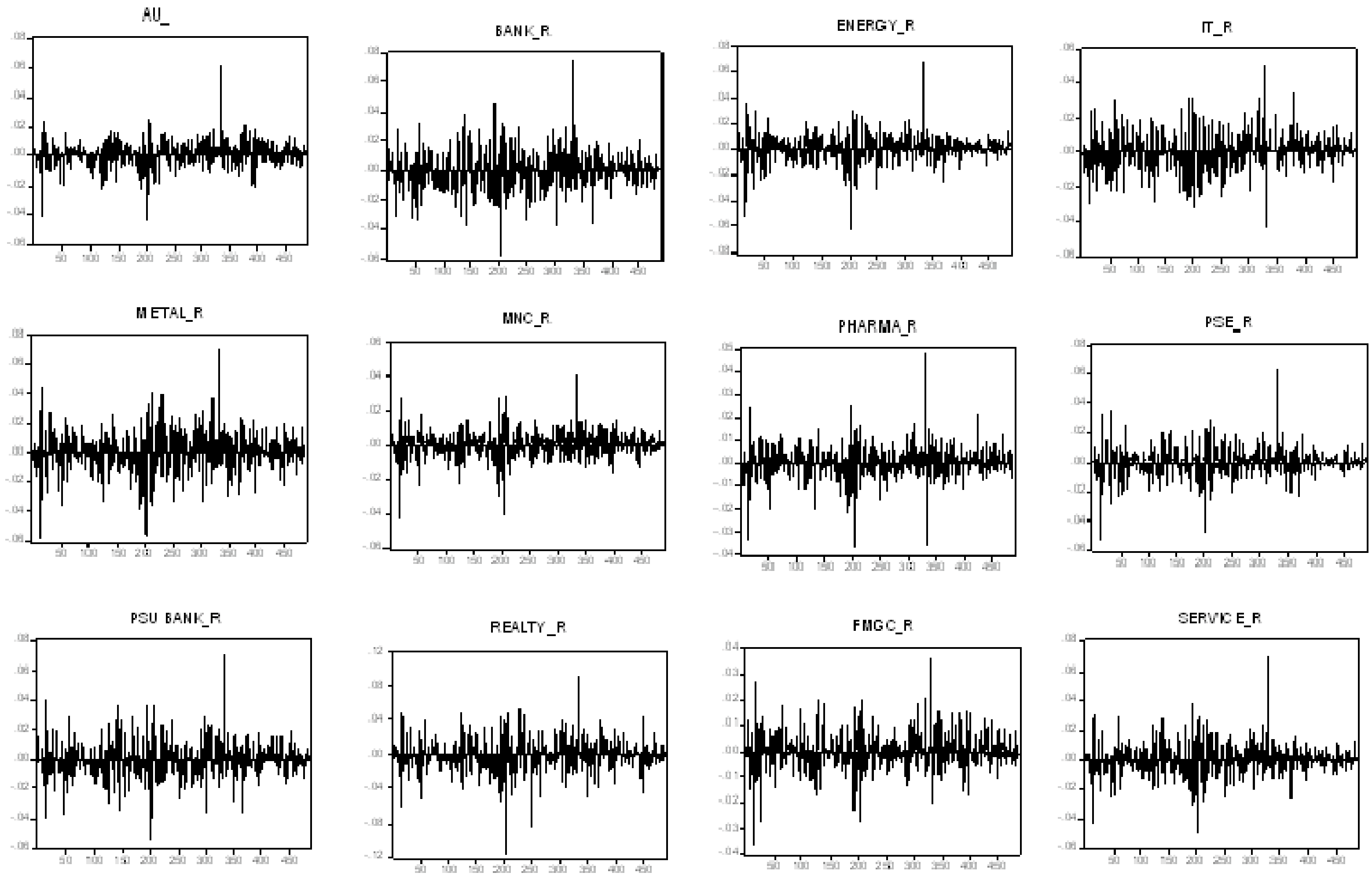
Appendix Table 1. Correlation Matrix of Sector Returns During the Crisis Period

CNX Sectors	AUTO	BANK	ENERGY	IT	METAL	MNC	PHARMA	PSE	PSU BANK	REALTY	FMGC	SERVICE
AUTO	1											
BANK	0.750307	1										
ENERGY	0.757007	0.794932	1									
IT	0.649059	0.650914	0.694515	1								
METAL	0.760654	0.757596	0.821829	0.647567	1							
MNC	0.846188	0.780894	0.827909	0.708764	0.809623	1						
PHARMA	0.660034	0.600537	0.678393	0.631724	0.624586	0.721963	1					
PSE	0.760604	0.796776	0.937807	0.652982	0.816297	0.831754	0.68281541	1				
PSU BANK	0.714852	0.943191	0.745868	0.576076	0.710547	0.738906	0.547746	0.763742	1			
REALTY	0.721734	0.793872	0.769179	0.578905	0.769441	0.768074	0.58120197	0.774196	0.748834241	1		
FMCG	0.678763	0.64348	0.683651	0.598731	0.61468	0.797948	0.66465438	0.694832	0.610922609	0.5920717	1	
SERVICE	0.795814	0.911298	0.903156	0.820538	0.827431	0.863709	0.70701369	0.886225	0.840440632	0.8098816	0.715086	1

Appendix Table 2. Descriptive Statistics of the Sector Returns During the Crisis Period

	CNX AUTO	CNX BANK	CNX ENERGY	CNX IT	CNX METAL	CNX MNC	CNX PHARMA	CNX PSE	CNX PSU BANK	CNX REALTY	CNX FMCG	CNX SERVICE
Observations	488	488	488	488	488	488	488	488	488	488	488	488
Mean	0.000244	-8.24E-05	-0.00017	0.000181	-0.00013	6.64E-05	0.000152	-9.15E-05	8.94E-06	-0.00111	9.50E-05	-0.00016
Median	0.00062	-7.67E-05	-0.00011	8.76E-05	-4.42E-05	0.000243	0.000261	-0.00016	-6.77E-05	-0.00078	0.00029	-0.00013
Maximum	0.060821	0.07487	0.06707	0.050901	0.070299	0.040428	0.048462	0.062498	0.071017	0.092308	0.036063	0.06943
Minimum	-0.0448	-0.05858	-0.06311	-0.04426	-0.05837	-0.04358	-0.0375	-0.05366	-0.05507	-0.11752	-0.03697	-0.05015
Std. Dev.	0.009203	0.013702	0.011306	0.011556	0.014877	0.008609	0.007649	0.010472	0.013104	0.020375	0.007958	0.011241
Skewness	0.013355	0.198649	-0.18152	0.112555	-0.19823	-0.32495	-0.25813	0.005411	0.20997	-0.31202	-0.18539	0.239365
Kurtosis	8.298111	5.308412	8.360383	4.2474	4.870977	6.469969	9.165996	8.068913	5.509365	6.287087	5.624793	6.993464
Jarque-Bera	570.7707	111.5611	586.9319	32.66916	74.37404	253.4152	778.4826	522.4446	131.623	227.6187	142.8827	328.931
Probability	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00

Appendix Chart 1. Multiple Graphs of Sector Returns for the Crisis Period



Appendix Chart 2. Quantile-Quantile (qq plot) of Sector Returns for the Crisis Period