Market Risk Assessment for Equity, Forex and Derivative Markets in India

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By

JITENDER

(Registration No: 14SEPH03)

Supervisor

Professor Naresh Kumar Sharma

School of Economics,

University of Hyderabad

Hyderabad: 500046 (India)

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DECLARATION

I, **JITENDER**, hereby declare that the research embodied in the present dissertation entitled, "***Market Risk Assessment for Equity, Forex and Derivative Markets in India***" is an original research work carried out by me under the guidance and supervision of Prof. Naresh Kumar Sharma, School of Economics for the award of Doctor of Philosophy from the University of Hyderabad.

I hereby also declare to the best of my knowledge that no part of this dissertation has been submitted previously in full or partial fulfilment for the award of any degree or diploma to this or any other University or Institution.

Date: 7th December 2021 **Jitender**

Place: Hyderabad (Registration No: 14SEPH03)

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Jitender

CERTIFICATE

This is to certify that this thesis entitled **'Market Risk Assessment for Equity, Forex and Derivative Markets in India'**, submitted by Mr. Jitender, in partial fulfilment of requirements for the award of the Doctor of Philosophy in the School of Economics, is a bonafide work carried out by him under my supervision and guidance.

This thesis is free from plagiarism and has not been previously submitted, in part or full, for the award of any other degree or diploma of this or any other university or institution.

Further, the student has the following publication before submission of the thesis:

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Further, the student has passed the following courses towards the fulfilment of coursework requirement for Ph.D./was exempted from doing coursework on the basis of the following courses passed during his M. Phil. Programme and the M. Phil. Degree was awarded.

S.No.	Course Code	Course Title	Credits	Results
1	EC701	Advanced Economic Theory	4	Pass
2	EC702	Social Accounting and Data Base	4	Pass
3	EC703	Research Methodology	4	Pass
4	EC751	Study Area	4	Pass
5	EC752	Dissertation	16	Pass

Prof. Naresh Kumar Sharma
(Supervisor)

Prof. R.V. Ramana Murthy
(Dean School of Economics)

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CHAPTER - 1

INTRODUCTION, BACKGROUND AND OBJECTIVES OF THE STUDY

1.1 Introduction

Since the emergence of globalization, there have been rapid integration of financial markets of different countries all over the world. No country's financial system is fully independent from financial developments and financial disasters happening in different other countries across the world. Different countries' financial markets have been more and more integrating with each other mainly over the last three decades. There have been many phases of financial development in both developed and developing nations in the world and these developments have in turn steered the creation of new and complex financial products like derivatives. The overall volatility observed in financial markets have been increasing day by day and the profession of 'Financial Risk Management' is gaining importance. The value at risk (VaR) method has been developed in the financial risk management domain and has over time became a benchmark for measuring overall 'Market risk' of any financial institution. It measures financial risk with the help of a probabilistic measure. It is also able to capture the risk arising from various market factors like Interest Rate Risk, Equity Price Risk and Foreign Exchange Risk of a financial institution in just one single number which is easily understood by anyone. Due to its accuracy and simplicity, the usage of VaR is extending to calculate different risks like credit and operational risk.

1.2 Background of the Study

1.2.1 Meaning of Risk and Risk Management

Risk is defined mainly in terms of business risk and financial risk. VaR is basically concerned with measuring financial risks facing an organization. Risk in a broader sense means uncertainty of losses that is usually measured by the variability of asset returns. Variability here implies fluctuations in the return of assets. The financial risk is defined mainly in terms of negative returns on financial assets as they are unfavorable to the holder. The financial risk management has become very important in the last three decades due to manifold developments in the financial markets all over the world and mainly due to ‘Global financial crisis of 2008’ which is mainly perceived as a lack of adequate financial risk management system in place. Risk management as a discipline mainly includes identification of financial risks, analyzing exposures of different positions, measurement and finally having a robust risk management system in place.

1.2.2 Development of Risk Management

The area of risk management gained importance due to the fact that the values of financial assets are determined by market using the demand and supply forces. For example, the downfall of the “Bretton Woods system of fixed exchange rate” led to a system of floating exchange rates. In Indian case, particularly after 1991, Liberalization and Globalization has led to increasing integration with the global markets and thus increased impact of external events.

Since 1980, there has been huge development of derivative instruments across the world. Over time, these developments have been taking place in emerging financial markets like India. These derivatives are now traded on mainly all kinds of real and financial assets. Illiquid assets are now also the basis of these products. Custom tailored financial products are being constructed on illiquid assets making them tradable in the market. According to NSE “In India, derivative markets have been functioning since the 19th century, with organized trading in cotton through the establishment of Cotton Trade Association in 1875. Derivatives, as exchange traded financial products were introduced in India in 2000.”

1.2.3 Origin and Development of Value-at-Risk

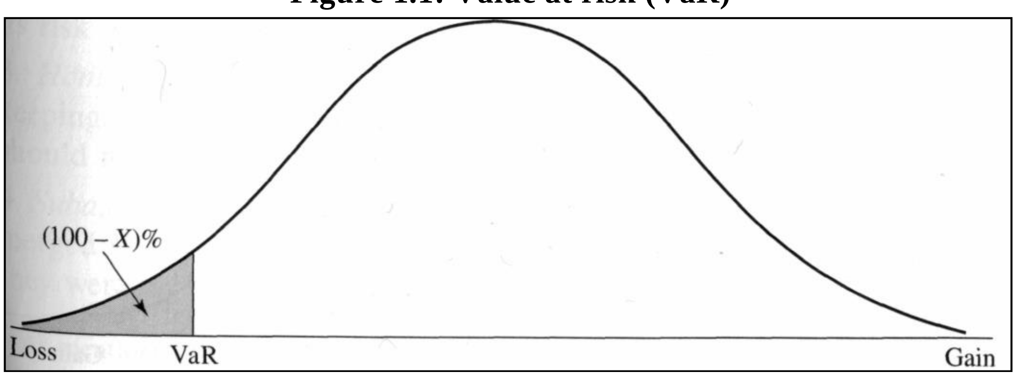
Although widespread use of VaR begins from 1990 onwards, its underlying idea can be traced way back to Markowitz’s “portfolio mean variance framework (1952).” The idea of higher risk for higher return, and the benefits of diversification were the main theories behind it. What is new to VaR is the systematic approach that it follows for risk measurement for the entire portfolio taking the effects from each individual instrument. VaR developed mainly from the shift of accrual-based accounting to mark to market-based accounting where returns on an asset are valued at their current market price on a continuous / daily basis and not on the returns generated based on historical cost.

From 1980s, J P Morgan started developing a risk system to calculate the firm wide risk. This system was used to measure risks of instruments which are traded in markets and have regular price history available. Starting 1990's, J P Morgan staff used to report total risks over one day with 95% level of confidence at 4.15 pm each day. This report was famously known as "4.15 report". According to Risk metrics document " In 1995, J P Morgan provided public access to data on variances and co-variances of various securities and asset classes that it has used internationally for almost a decade to manage risk and allowed software makers to develop software to measure risk. It titled the service as "Risk Metrics" and used the term VaR to describe the risk measure that emerged from the data." Since then many commercial banks, investment banks and regulatory authorities have readily accepted the VaR measure. Over time, VaR has become the established measure of market risk exposure of financial instruments and has become a benchmark for measuring market risk for financial service firms and is also gaining acceptance in non-financial service firms.

1.2.4 Definition of Value-at-Risk

Value at risk (VaR) is a statistically calculated numerical number or percentage that is used to calculate the market risk of a financial instrument. It is the maximum loss that an organization can be confident of incurring on a portfolio of assets with a given level of confidence due to normal market movements over a given time period. Losses greater than VaR are expected to occur with a predetermined probability, which is known in statistics as the "level of significance" or "Type I error." Value at Risk is defined as " a statistical measure to determine the expected loss that an institution can suffer within a given time interval under normal market conditions and at a predefined confidence level". It assesses this risk by using statistical probabilistic measures designed to capture the volatility of asset's returns.

Figure 1.1: Value at risk (VaR)



Source: https://www.bmeclearing.es/ing/Risk-Management/IM-Calculation-model-HVaR

Figure 1.1 shows, when we plot gain/loss distribution, the VaR is calculated from only the left tail as we are only concerned about expected losses (and not potential gains). If we assume the confidence level to be *x*% (*x* in above figure), then the (100-*x*) % VaR will be calculated from deducting the percentile value from left tail of the distribution.

Although VaR was originally intended to measure market risk, its applications have now expanded to include credit risk and operational risk as well. This is justified because banks must assess the riskiness of loans at the time they are made, rather than waiting until the loans default and realizing the true risk they took.

1.2.5 Features of VaR

a) It is a summary measure, as it provides a single value of market risk of a financial instrument. This makes it suitable for all the stakeholders, senior management and other interested parties in the institution that want to know how much risk the financial instrument carries and what can be the potential loss.

b) VaR requires that it is possible to express future expected returns of a financial instrument in probabilistic terms.

c) VaR depends on the time horizon considered. Since for longer periods, it is generally expected that returns will be more dispersed than for shorter horizons, it is natural to assume that VaR increases with the time horizon. If we make an assumption that daily continuously compounded returns are independently and Identically Distributed (IID), then we get the result that VaR is proportional to the square root of time. It means that 10-day VaR is simply 1-day VaR multiplied by square root of 10($\sqrt{10}$).

d) The time horizon selected must be at least the time period required for an orderly portfolio liquidation. If it is less than that then the liquidity risk may arise and should be independently included in the model. Financial theory provides very little guidance on the choice of the time horizon. This choice is mainly subjective and related to the business of the institution and the kind of portfolio under analysis. For a bank trading portfolio invested in highly liquid assets, the choice of one-day time horizon is probably the best one. For a pension fund with a quarterly portfolio rebalancing and reporting, a 90-day time horizon is more appropriate. As Banks and financial institutions generally perform portfolio re-balancing on a daily basis, VaR should be computed on a daily basis as well. The time horizon in any case should not be less than the time over which the institution calculates its P&L statement.

e) VaR depends on the probability level chosen (confidence interval) for our forecasted figure. If we want the VaR to better capture the large losses that could occur unexpectedly in the market, then we have to take a higher confidence level. Higher confidence level would imply that losses greater than the forecasted VaR value will occur with a low probability. This comes at a cost that the VaR figure gets increased as it now measures losses in the extreme tails of the distribution. This will then require financial institutions to have higher capital requirement to cover expected losses on a financial position.

f) It should be noted that VaR captures only normal market risks and not those events which are perceived by the investors as somewhat abnormal and which generally take place over a very long horizon of time, like “1987 Stock market crash”, “Asian financial crisis of 1997” and the more recently “Global Financial crisis’ of 2008.” The VaR approach is flexible because it can be adapted to the needs of different financial institutions simply by choosing the time horizon and probability level as found appropriate by the management of that institution based on the financial product or service that it is trading in. For example, for pension funds, it may be desirable to calculate VaR for a longer horizon than compared to a brokerage or trading firm.

g) One of the most important aspects is that the concept of VaR does not require any specific theoretical assumptions about financial market behaviour. As a result, implementing VaR-based risk management systems necessitates a high level of judgement, skill, and subjectivity. The use of different models to describe market behaviour results in results that can be, and frequently are, dramatically different from one another.

1.3 Objectives of the Study

Since the emergence of VaR, manifold developments have taken place within this measure. Many new methods have been developed and different variants from the original methods have been suggested which are aiming to capture volatility of a financial instrument as accurately as possible. VaR is also being used for performance evaluation for financial institutions. The numerous factors of increased global competition for Indian banks by foreign banks, increased deregulation, introduction of advanced products, and innovation in delivery methods have underlined the necessity for Indian banks to stand prepared in terms of adequately monitoring market risk.

In India, the Reserve Bank of India (RBI) guidelines are calling banks to adopt VaR as a preferred methodology for measuring market risk. Indian banks are exploring to make advancements in terms of technology, quality and stability so as to expand and diversify at a much faster rate and match with their foreign counterparts. However, this expansion is increasing the market risk for Indian banks given that the increasing competition due to globalization and liberalization. In banks and other financial institutions, financial risk has now started playing a major part in the earnings of a bank. This has started giving a significant challenge to Indian banking system in terms of required manpower with appropriate skills that can understand the sources of market risk and learn the techniques which can be used to measure and manage it appropriately. A financial institution is exposed to market risk due to adverse movements in equity, forex and derivative markets. Hence, the present study is trying to find the best VaR model for various Indian financial markets.

The present study aims at the following 3 objectives:

I. The study aims at finding the most appropriate VaR model for Indian equity market.
II. The study aims at finding the most appropriate VaR model for Indian currency market.
III. The study aims at finding the most appropriate VaR model for Indian futures (derivatives) market.

1.4 Methodology of the Study

The Indian equity, forex and derivative markets consists of various banks, companies and other financial and non-financial institutions. All of these players have the potential to influence the overall market as per their respective market share. Since each of the individual market player cannot be studied in one single study, the study is based on the benchmark market indices which represent different financial markets. An index is a statistical measure comprising the overall market players and tracks the movement of overall market. The study has taken three different indices representing Indian equity, forex and derivative markets.

For the first objective, BSE Sensex is taken as a benchmark to measure risk arising from Indian equity market as it is considered the barometer of Indian equity market. Sensex is a composite index of 30 most actively traded stocks in India. It is calculated using "free-float methodology. Free-float methodology market capitalization is calculated by taking the current market share price and multiplying it by the number of shares available in the market for trading." For the second objective, Indian rupee/ US dollar (₹/$) exchange rate is taken as a benchmark to measure risk arising from Indian currency market as most of international transactions related to foreign direct investment and foreign portfolio investment are routed through US $. For the third objective, Nifty futures are taken as a benchmark to measure risk arising out of Indian futures. Nifty is the second national level stock exchange after Sensex and more than 90% of the derivative market trading in Indian Financial Market is accounted by National Stock Exchange (NSE).

In order to examine the different objectives, the study takes daily data on the required variables for the three objectives (BSE Sensex, (₹/$) Exchange rate and Nifty futures) from January 1, 2006 to December 31, 2015 covering a period of 10 years of modelling dataset. This range of 10 years' of data allows the study to draw meaningful insights and conclusions from actual return distribution as the period is sufficiently long enough to study the behavior of any financial market. As per the required mandate for stress-testing framework from many regulatory bodies across the world (e.g. "Comprehensive Capital Analysis and Review (CCAR) and Dodd Frank Annual Stress Testing (DFAST) in USA and International Financial Reporting Standard (IFRS 9))," at least one macroeconomic slowdown period must be included in the modelling period. The study's time frame includes the global financial crisis of 2008-09. As a result, the modelling framework includes a macroeconomic stress period, and the final model is appropriate for both baseline and stress projections for future time periods.

The study will first examine the different characteristics of Indian financial markets such as skewness, presence of tail behavior in return distribution, normality, presence of volatility clustering, asymmetry in volatility, stationarity etc. Next the study will try to find the best VaR method for market risk estimation for different Indian financial markets (Equity, forex and derivative).

For the first, second and third objectives, the data is obtained from the official website of BSE, RBI and NSE respectively. The data treatment and VaR calculation follows similar steps for all the three objectives. Firstly, the return series has been generated taking the logarithmic difference between closing prices of successive days. Continuously compounded returns are generated for the series as $\boldsymbol{R_t = ln\,(I_t / I_{t-1})}$**,** where, R_t is the return at time t, I_t is the index value at time t and I_{t-1} is the index value at time $t-1$. '***ln***' indicates the natural logarithm to base 'e'. The positive return ($\boldsymbol{R_t}$) indicates a rising index value and is favorable, whereas the negative return ($\boldsymbol{R_t}$) indicates a loss and is unfavorable for the financial asset holder. The research has employed continuously compounded returns.

Then using the return series, descriptive statistics have been analyzed to examine the basic characteristics of the return distribution. In order to check whether the daily returns are normally distributed or not, Jarque Bera, Lilliefors and Anderson-Darling tests are used. The study has also used the Quantile-Quantile (QQ) plot graphical test to get a better picture about the tails of the return distribution. The study tests the normality of the return distribution as normality is a crucial assumption for time series forecasting. The study uses Lung Box Q-statistics (LBQ Statistic) of squared return, Generalized Autoregressive Conditional Heteroscedasticity (GARCH) tests to examine volatility clustering. Heavy tails or fat tails behavior is checked for all the returns' series and alternative distributional assumptions are suggested if the assumed theoretical distribution fails to capture heavy tails. Asymmetric response to volatility is observed by using Exponential Generalized Autoregressive Conditional Heteroscedasticity (EGARCH) method. Then value-at-risk for BSE Sensex, (₹/$) exchange rate and Nifty futures are calculated using "variance covariance (VcV), Exponentially Weighted Moving Average (EWMA), Generalized Auto-Regressive Conditional Heteroscedasticity (GARCH), Historical Simulation (HS) and Monte Carlo Simulation (MCS)" methods for 1-day time horizon at 99% level of confidence. The study finally uses various back-testing procedures to assess the predictive accuracy of different VaR models employed for the study and finally selects the best VaR method for various Indian financial markets.

1.5 Justification of the Study

For a long time, research on financial risk management in India has primarily focused on credit risk. The extent of risk posed by market risk instruments in the Indian financial market has not been thoroughly studied. In comparison to credit risk, there are fewer studies dealing with market risk. This is largely due to the fact that the Indian financial market has from a long time been dominated by credit products related to retail, auto, housing, and personal finance. Commercial banks in India have traditionally focused on lending, which primarily generates credit risk. As the world's financial flows become more integrated, and the Indian financial market becomes more open to foreign portfolio investments, there is a need for a systematic study to quantify market risk from equity, forex, and derivative markets, and to develop the best predictable statistical model that can be leveraged for forecasting purposes.

The present study attempts to close this gap by examining the predictive accuracy of various VaR models for Indian equity, forex, and derivative markets. This research can assist market participants, traders, risk managers, and researchers who are interested in conducting a systematic and quantitative study of the Indian financial market. As the financial world have seen failures of risk management across many banks (such as Barings Bank, Metallgesellschaft, Orange Country etc.), there is a strong requirement for appropriate quantification of financial risks which is appropriately provided by the VaR technique. The VaR concept is becoming a global standard for the measurement and management of market risks faced by banks arising from equity, debt, forex and derivative markets. It is now extensively used by many financial and non-financial institutions. The use of VaR has also been recommended by the "Basel committee on Banking and Supervision" for the measurement of regulatory requirements. As Indian financial markets are becoming more and more competitive and complex, appropriate risk measurement tool is essential in India also. The VaR has been recommended by Reserve Bank of India (RBI) also for market risk measurement. But the usage of VaR is very limited in India. This is due to very limited market trading activity by most of our commercial banks. The capital market in India have experienced a state of high volatility as value of the indices in Indian capital market are increasingly influenced by financial developments and disasters happening across the world's financial markets. Furthermore, the number of studies on Value at Risk in the Indian context is limited. As a result, this study makes an attempt to investigate the application of various VaR models for the Indian Financial Markets, which include equity, forex, and derivative markets.

1.6 Scope and Limitations of the Study

Although VaR was initially proposed as a tool for market risk measurement, over time its application have been extended towards the measurement of credit risk and operational risk. The present study, however, limits its scope to the measurement of market risk variables only. In addition, the study only considers a one-day time horizon when assessing market risk. Further research can be undertaken on the suitability of VaR as a tool for measuring and managing credit and operational risks of a financial institution with different time horizons. Future research can also be carried out on some illiquid portfolios which needs longer period to liquidate and thus needs to be reviewed for a longer horizon of time.

1.7 Organization of the Study

The study is organized into six chapters. The first chapter includes the introduction and background which discusses the meaning of risk management, origins and development of VaR and risk management, objectives of the study, justification of the study and scope and limitations of the study. The second chapter makes a review of some of the relevant literatures which are dealt with development of new methods and their performance evaluation, selection of best method among various models of VaR calculation. The third chapter deals with the conceptual framework around VaR. The fourth chapter makes a theoretical review of different VaR models such as parametric and non-parametric by considering the theoretical structures of models. The fifth chapter presents the empirical estimation and VaR forecast for Indian equity, forex and derivative markets and evaluate the performance of different VaR models by using various methods of backtesting. Finally, the sixth chapter concludes the study.

CHAPTER - 2

REVIEW OF LITERATURE

2.1 Introduction

The value at risk (VaR) method has been developed in the financial risk management domain and has over time became a benchmark for measuring overall 'Market risk' of any financial institution. Although the development of its idea can be drawn back to the age of Markowitz (mean variance portfolio optimization, 1952) but its systematic use started from 1994 onwards. After the development of Risk Metric as a standard methodology by J. P. Morgan in 1994 and free availability of data base (volatilities and correlations across products and markets), the application of VaR has increased. Since then many international financial institutions, academicians and researchers have shown interest in the development and implementation of VaR. As a result, many new methods and techniques within the VaR framework have been developed. In the present chapter, an attempt is made to bring out a review of the relevant literatures which are dealt with development of VaR and its variants. Regulators of financial institutions worldwide recognized that VaR is able to adequately capture the market risk so they also adopted VaR as a benchmark for setting capital requirements for banks and financial institutions to prevent them from collapsing in the case of a slowdown or systemic failure of the entire financial system. It also captures adequately whether a position is working as a hedging instrument or not, if by including it in the overall portfolio the VaR figure is decreased, then the instrument can be taken as a hedge instrument.

2.2 Review of Literature

Beder (1995) applied three hypothetical portfolios to eight common VaR methodologies. Portfolio one consisted solely of US treasury strips, portfolio two of outright and positions on the S&P 500 equity index contract, and portfolio three of a combination of portfolios one and two to investigate differences in the forecast values of VaR figures. She discovered that the expected capital at risk is affected by the VaR methodology as well as the assumptions underlying the specific correlation matrices. The outcomes of eight different VaR methodologies were discovered to be significantly different. As a result, it demonstrates that VaR estimated using different methods can differ significantly.

Many empirical studies have found that using the normal distribution of asset returns is inappropriate. Venkatraman (1997) proposed a mixture of different distributions as an alternative to the normal distribution. He investigated the parameters of the mixture of normal distributions using three methods: traditional maximum likelihood, quasi-Bayesian maximum likelihood, and Zangari's Bayesian approach (1996). He investigated the performance of this method using foreign exchange data for eight currencies from 1978 to 1996. At high confidence intervals, he discovered that the mixture of normal distributions produces smaller errors than the normal approach. He also discovered that the normal distribution approach underestimates VaR at very high levels of confidence and overestimates it at lower levels of confidence.

In the VaR framework for the Indian stock market, Varma (1999) provided empirical tests of various risk management models. He discovered that risk management models are heavily reliant on estimates of underlying price volatility. He discovered that EWMA models perform well at higher risk levels, such as 10% or 5%, but fail at 1%.

Tian and Zhan (2000) investigated the theory and algorithm for estimating VaR using Extreme Value Theory (EVT) and described the procedure and a programme for calculating critical statistics and related parameters using the two-step subsample bootstrap method.

Danielsson et al. (2000) estimated VaR using the Extreme Value Theory (EVT) method and compared the results to traditional methods. The standardised residuals were discovered to be non-normally distributed. They came to the conclusion that the VaR calculated by EVT is significantly higher than the corresponding figure obtained by other traditional methods.

In the context of bank solvency supervision, Coronado (2000) compared the results of historical simulation, variance-covariance methods, and the Monte Carlo simulation method as a measurement of market risk for actual nonlinear portfolios. She discovered that the VaR estimates differ significantly across methods, and the difference is even greater if the confidence level is higher. According to her, industry experts have suggested that a horizon of more than ten days may be required for regulatory capital purposes. It was also suggested that combining the liquidity horizon of individual positions with a constant level of risk might be a good strategy.

Sawant (2001) used principal component analysis to calculate the VaR for government securities portfolios (PCA). He employed the three primary components, which are referred to as the factors causing the parallel shifts, changes in slope, and changes in curvatures observed in the yield curve dynamics. Based on the actual analyses, he discovered that three factors account for 85 percent of the changes in the yield curve. As a result, he discovered that principal component analyses produce a lower VaR value than risk metrics.

Zhou. (2002) computed VaR using a method developed and based on extreme value theory (EVT). He discovered an asymmetric return distribution with fat tails, negative skewness, and a large kurtosis, indicating the presence of a non-normal distribution.

VaR numbers and capital charges for two portfolios were determined by Nath and Samanta (2003) using different VaR models such as variance co-variance approach, historical simulation, and tail-based approach. They discovered that using a variance covariance technique in the form of a risk metrics database undervalues VaR numbers, but using a historical simulation approach yields more accurate VaR estimates.

Semi-parametric approaches for estimating scaled residual values were proposed by Fan and Gu. (2003) on eight stock indices, they used four VaR methods: risk metrics, non-parametric, semi-parametric risk estimators, and adaptive risk estimators. Adaptive risk estimators were shown to be the best method among the four VaR estimators in the study.

Angelidis et al. (2004) built a number of volatility models based on three alternative distributional assumptions: normal distribution, generalised error distribution, and generalised error distribution of returns. They used five broad market stock indices to create five highly diversified portfolios. Volatility clustering and non-normality of return distribution were discovered in their dataset. They employed conditional coverage and unconditional coverage as back-testing procedures to verify the out of sample forecasting performance. As a result, they discovered that using the normalcy assumption to estimate yields very poor results.

Aktham I. & Haitham, (2006) has compared the performance of various VaR models for seven Middle East and North Africa (MENA) countries. The results demonstrate that Extreme Value Theory approach provide accurate VaR estimates as it is able to capture the fat tails behaviour of returns adequately, this implies that the MENA markets returns are characterized by fat tails.

In the context of high volatility and heavy tails, Kisacik (2006) investigated the performance of VaR techniques. He divided VaR methods into two categories: traditional and alternative approaches, the latter of which includes the extreme value theory approach. He discovered that non-normal distributions occur. He discovered that the generalised pareto distribution works effectively in the tails of the distribution, that is, where the quantile is 99 percent or greater, based on an empirical comparison of VaR approaches. In lower quantiles (less than 99 percent), traditional approaches produced good results. As a consequence, EVT outperformed existing methods for investigating tail events in the setting of high volatility and heavy tails.

Dutta and Bhattacharya (2008) show that bootstrapped historical simulation VaR is a better strategy than traditional historical simulation VaR because it maintains the genuine distributional property while also addressing the scarcity of suitable data points. They use the historical simulation approach and bootstrapped historical simulation method to calculate VaR and projected shortfall using S&P CNX Nifty data from April 1, 2000 to March 31, 2007. With a five-day time horizon, they employ a 95 percent confidence interval. They demonstrate that the assumption of normal distribution is inappropriate for the return distribution using a graphical plot of profit and loss of index return and a Quantile-Quantile (QQ) plot. They discover that the bootstrapped historical simulation VaR figure is lower than the standard historical simulation estimate in their VaR estimation.

Sollis (2009) evaluates various VaR approaches under Basel II regulatory framework. The author mentions that there are flaws in the VaR models which failed to predict the global financial crisis of 2008. The author criticizes the variance covariance model developed by Risk metrics. He mentions that variance covariance is used by many financial institutions because of its simplicity in understanding and calculation. Variance covariance model assumes that asset returns are normally distributed. The author observes that assets' returns does not follow the normal distribution. As such, the VaR estimates based on variance covariance approach will underestimate the true VaR.

Financial risks are underestimated when VaR models with underlying Gaussian distribution are used, according to Taamouti (2009). Volatility clustering and heavy tails are not captured by Gaussian models. The large fluctuations in the market returns during market stress periods are not accounted for in the Gaussian based VaR models. In order to overcome these drawbacks, the author suggests the use of regime-switching VaR models to capture financial return volatility.

Samanta et al (2010) measure the market risk of selected government bonds using VaR models in India. The authors employ distributions based on non-normal assumption about asset returns like Historical Simulation and Extreme Value Theory. The authors say that government securities market in India is not as vibrant and developed as found in developed economies financial markets. The empirical results showed that historical simulation method is able to provide accurate VaR numbers for the Indian Bond Market.

Dimitrakopoulos (2010) measured the market risk in developed and emerging equity markets portfolio. A relative analysis of the performance of various VaR models in developed and developing markets is made during normal, crisis and post-crisis periods. The results showed that for the markets characterized with fat tailed returns which are found most often in emerging market equity portfolios, traditional VaR models give better VaR estimates. While the traditional VaR models are under estimated in case of developed markets. The VaR modelling becomes difficult during the crisis period particularly in case of emerging markets. Due to the presence of exceptional events in the estimated sample, the performance of parametric VaR models improves while non-parametric models deteriorates during post-crisis periods.

Baixauli et al. (2011) demonstrated the algorithm's potential utility in generating efficient portfolios when the risk measure prevents the calculation of an optimal solution. Their findings showed that VaR-efficient portfolios are reliable in both bullish and bearish markets, and that they outperform Markowitz efficient portfolios in the VaR-return area. As the portfolio's risk level rises, the improvement declines.

The prediction ability of different VaR models was compared and ranked by Şener and Mengütürk (2012). They suggest that the credit crisis period (2007-09) provides a unique opportunity to examine the effectiveness of various VaR models in both emerging and industrialized countries. They offer a VaR ranking model that aims to reduce residual autocorrelation difficulties while minimizing the magnitude of errors between anticipated and actual losses. The results show that EGARCH provides more accurate VaR estimates. Their findings also show that the performance of different VaR models is mostly determined by how well they represent asymmetric behaviour, rather than whether they are parametric, non-parametric, semi-parametric, or hybrid models.

The accuracy of Value-at-Risk (VaR) calculation in the Thai Stock Exchange was investigated by Sethapramote et al (2014). They used GARCH and the GARCH paradigm in conjunction with a long-memory process (FIGARCH). The Lo's R|S statistics demonstrate that there is considerable evidence of a long memory process in volatility but not in the mean of the SET50 index returns.

Chowdhury & Bhattacharya (2015) studied the appropriate VaR method post the global financial crisis by focusing on major Indian sectors listed on National Stock Exchange. They created the hypothetical portfolio with selected sectorial indices and used VaR to estimate the portfolio risk. They conclude that Monte Carlo Simulation method provide the most appropriate results.

Poornima and Reddy (2017) used the VaR-CoVaR (Variance-Covariance) model to compare the market risk of a local and foreign hypothetical portfolio. For developing a hypothetical domestic portfolio, they used daily closing prices of Nifty Spot (NSR), Nifty Future (NFR), INRUSD currency pair Spot (USR), and INRUSD currency pair Future (UFR) from 2000 to 2014. For the construction of an international portfolio, data from BRICS countries, as well as US and UK equity market indices, is used from January 2000 to December 2014. They discovered that the VaR-CoVaR model produces accurate results at 95% and 90% confidence intervals.

2.3 Conclusion

This chapter has provided some of the important empirical studies related to VaR. The empirical research has shown that financial asset returns are very often non-normally distributed and it need to be incorporated by using appropriate statistical distributions which can incorporate this non-normality.The next two chapters will provide basic concepts related to VaR, various calculation methods as well as its place in Basel regulatory regime for market risk measurement and management. The next chapters will try to find whether Indian financial markets are also categorized by empirically observed non-normally distributions and which alternative distributions best describes the various Indian financial market like equity, forex and derivative.

CHAPTER - 3

BASIC CONCEPTS OF VALUE-AT-RISK

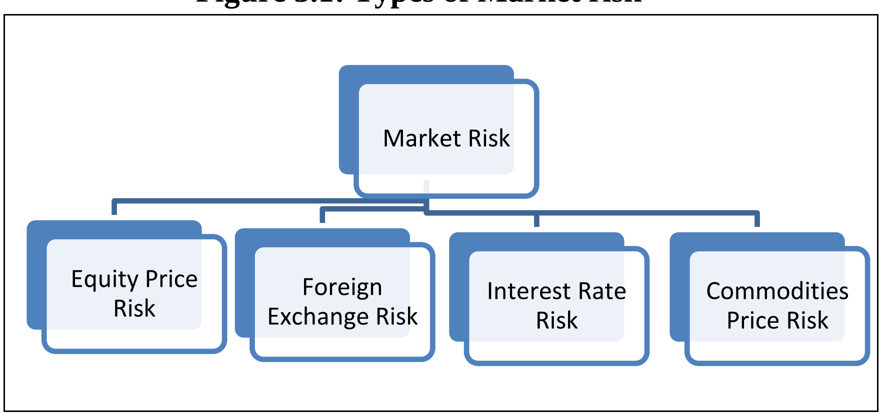
3.1 Introduction

In the financial markets there exists different types of risk such as market risk, credit risk, liquidity risk, operational risk and legal risk. It is to measure market risk for which VaR was originally proposed but over time it has also been tested to measure other types of risks like credit and operational risk. This chapter presents a discussion on different concepts related to VaR such as different types of risk (Market, credit, operational etc.) that exists in the financial markets and the traditional risk measurement methods that were used before the development of VaR. This chapter also discusses the place of VaR in Basel regulatory framework and in Basel back-testing procedure. The next section provides brief overview of various kinds of financial risks. All these risk categories are not independent from each other and one risk can create other risk or vice versa.

3.2 Types of Risks

3.2.1 Market Risk

Figure 3.1: Types of Market risk



Source: Hull (2013)

Overall financial risk can be divided into systematic and unsystematic risk. Systematic risk affects all the financial institutions equally and it has to be faced by every financial institution. It is an undiversifiable risk and can't be avoided through diversification across financial products; e.g. Global financial crisis of 2008, macro-economic slowdown affecting the whole industry. Unsystematic risk on the other hand, is a firm specific risk and arises due to internal matters pertaining to the individual firm. This risk can be avoided by appropriate diversification across financial products. Market risk is a systematic, undiversifiable risk affecting the whole industry. It arises from unfavourable movements in the values of the market variables which are continuously used to determine the price of a traded financial instrument. It arises from changes in the values or volatilities of equity stock, market determined interest rates, and foreign exchange rates and commodities prices. Market risk can arise from four different sources as mentioned below,

a) Equity price risk: This risk arises from the volatility observed in stock prices.
b) Foreign exchange risk: This risk arises due to fluctuations in the market determined currency exchange rates.
c) Interest rate risk : It arises due to the expectation that the value of a security might fall due to adverse movements in interest rates.
d) Commodity Price Risk:It arises due to unexpected changes in commodity prices, such as the price of crude oil.

Market risk arises whenever any financial instrument valuation is traded in the market. The main tool suggested for Market risk measurement and management is VaR. Other adhoc measures include limits on financial exposures and independent supervision by risk experts. The present study aims at examining the best VaR method for different financial markets in India: equity, forex and derivative markets.

3.2.2 Credit Risk

When counterparties are unable or unwilling to fulfil their contractual obligations, credit risk arises. This risk is not independent from market risk as generally whenever a counterparty defaults, the market value of the firm's assets reduces and it adversely impacts its profitability. Credit risk is defined as the potential loss in mark-to-market value that may occur as a result of a credit event. A credit event occurs when the counterparty's ability to perform its obligations reduces. Thus, changes in market value of debt owing to changes in market perception of default is also a way of creating credit risk. This risk is mitigated by credit restrictions on notional, existing, and potential exposures, as well as credit enhancement elements such as demanding security as a proportion of the loaned-out amount, are used to keep credit risk under control. Credit risk can be found in loans, bonds, and debentures. Credit risk also involves sovereign risk, which happens when a country imposes a foreign exchange control that prevents counterparties from fulfilling their obligations.

3.2.3 Liquidity Risk

There are two types of liquidity risk: asset liquidity risk and funding liquidity risk. Asset liquidity risk is also known as market/product liquidity risk. This risk primarily occurs when a transaction is not completed at current market prices due to the position's size in relation to the normal trading position. Funding liquidity risk arises when the bank cannot meet the creditors demand as they fall due. It means that bank cannot meet the demand of customers wishing to withdraw their deposits on time. VaR models have not reached a well-established and accepted stage to measure this kind of risk. In extreme cases where the market crashes, traders generally close out their positions. In that situation, over the counter derivatives (OTC) or tailored derivatives are very difficult to close out in the market. Liquidity risk is difficult to measure and if someone has discovered losses on a position, he can expect those losses to increase if he tries to close his position at a time when the markets are illiquid.

3.2.4 Operational Risk

This kind of risk arises from manmade and technical errors or accidents. This includes frauds wherein traders intentionally provide falsify information, or doing certain kinds of trades that may reduce the individual trading desk’s risk but may subject the overall risk to a higher-level. Also, management failures, inadequate procedures and controls and technical problems create this risk. Technical errors can occur as a result of a failure in information processing, settlement systems, or, more broadly, any difficulty in back office operations that deal with transaction recording and individual trader reconciliation with the firm's aggregate holdings. Model risk, which arises when the particular mathematical or statistical model used to derive value of financial instruments is flawed. The parameters that go into the calculation of complex financial derivatives must be given a very careful analyses before being implemented in the institution. For that, out of sample forecasting is a must for all the models. Also, sometimes the model is perfectly calibrated but the manpower is not in a position to correctly apply and understand that model.

3.2.5 Interest-rate Risk

Interest rate risk arises due to unfavourable movements in market interest rates by which the market value of the firm's assets may decline and value of its liabilities may increase. It impacts only those instruments that are sensitive to market interest rate movements particularly bonds and interest-rate derivatives. In the mark to market accounting, it significantly impacts the daily changes in the value of the portfolio and needs to be taken care of by using appropriate hedging methods.

3.2.6 Gap Risk

This risk emerges when market participants anticipate a rapid and significant drop in the stock's price. Such moves usually occur in response to negative news, which can cause a stock's price to drop significantly from the previous day's closing price.

3.2.7 Basis Risk

Basis Risk equals the difference between the spot price of the hedged asset and the contract's futures price. It occurs when the price of the asset to be hedged differs from the price of the asset that serves as the hedge. The spot and futures prices of the asset do not converge on the futures contract's expiration date under certain situations. The difference between the two amounts is known as the basis risk.

Basel Accord and Value-at-Risk

Following the Bank for International Settlements (BIS) recommendations to commercial banks to use VaR for determining economic capital requirements, value-at-risk (VaR) gained widespread recognition. The Basel Accord's regulatory capital requirement is one of the most important international capital requirements. It has taken the lead in standardizing bank regulations across borders. During the 1990s, the Accord was accepted as a global standard, with well over 100 countries using the Basel framework to determine regulatory capital requirements for their banking systems.

The Basel Committee's initiatives are intended to: define standards for regulators in cross-jurisdictional situations and to ensure that international banks or bank holding companies are not exempted from comprehensive regulation by their own local regulatory authority. This accord also aims at promoting uniform capital requirements for all member countries in order to make different banks incorporated in different countries comparable in terms of capital requirement. The first Basel Accord (1988) focused primarily on banking in terms of deposit taking and lending. As a result, its primary focus was on credit risk.

3.3 Basel 1

Before the Basel regulation came in place, the regulatory framework was very much different in different countries. Prior to it, balance sheet activities like interest rate swaps, currency swaps and options were growing. These off-balance sheet activities did not affect the total assets and thus didn’t affect the amount of capital the bank was obligatory to hold. In 1988, regulators from a group of 10 countries met to design an international system for supervisory regulation. This committee became known as Basel accord, and its main objective was to design a system which protected the financial systems of individual countries from collapsing. This agreement reached a common measure to be adopted worldwide which can be taken as a benchmark to judge whether a bank is able to face financial losses or not. This came in terms of defining a capital adequacy ratio. Basel 1 required assets to capital ratio of less than 20 (e.g. assets/capital <20) or capital assets ratio to be at least 5%. This accord primarily aimed at identifying the level of credit risk that banks were exposed to. If the exposure was higher then, it implied greater capital adequacy requirement. The overall aim of capital adequacy rules was to protect the depositors.

3.3.1 Credit Risk Measurement

The Basel 1 system examined each individual category of asset and then assigned a weighting system which was based on the level of credit risk inherent in that asset. Under this, rates of 0% were allocated to those assets that were considered to be totally credit risk free like government securities in the form of government bonds and treasury bills, cash in hand and stock of physical gold with the bank. At the other extreme, weightings of 100%

were imposed on assets such as equity, corporate bonds and government debt from less developed countries.

3.3.2 Weaknesses of the Basel I Accord

a) Market Risk: The Basel I accord focused almost entirely on credit risk, and its overly simplified procedure failed to account for market risk adequately. For example, if interest rates rise, the value of the bonds in the bank's portfolio falls, and customers with current account deposits may suffer. The issue of market risk becomes even more pressing with the introduction of derivatives. Futures and options can exhibit extremely volatile swings in response to relatively minor changes in the underlying asset.

b) Portfolio Credit Risk: This accord failed in giving incentives to banks which reduced their credit risk by diversifying their assets across various segments. And thus, it overestimated capital requirements to some extent for those banks which were taking prudent measures to manage their credit risk. It acted as a disincentive for banks and called them to invest in risky assets with very adverse consequences. Following the failure of the Basel 1and with International Organization of Securities Commissions (IOSCO) initiative, the Basel Committee issued a package of proposed new amendments to the 1988 accord in April 1993, which included the minimum capital requirements for banks for market risk. Banks were required to identify a trading book and hold sufficient capital for trading book market risk. The Basel Committee issued a revised proposal in 1996.

3.3.3 1996 Proposals of the Basel Committee

1996 amendment aimed at measuring market risk associated with trading activities and maintain capital to back those risks. It proposed two methods for market risk a.) Standardized measurement approach and b). Internal model-based approach.

a) Standardized measurement approach: There are capital charges separately to each of the items in trading book. It ignores correlation between assets and thus there is no consideration of diversification benefits. Banks with less sophisticated risk management systems preferred this method.

b) Internal model-based approach: Well defined Mathematical formulas are used here to calculate VaR and then the value is converted into a capital requirement figure. Capital charges are generally lower as it considers correlation between assets and diversification benefits are thus considered. This approach is usually used by banks with advanced risk management risk functions.

3.3.4 Issues with Diversification

Regulators consideration of correlation between assets has both pros and cons. In case the correlation between the assets is low or negative, then there is a possibility of diversification benefits that could be reaped by allocating funds such that the overall risk of the portfolio is reduced. Regulators however, sometimes are reluctant to incorporate diversification into their rules for capital adequacy calculations. This stems from the fact that during extreme market crashes almost all the assets fall in value together irrespective of the correlation coefficient between them. This happens because most of the holders of the assets try to liquidate their positions as early as possible and this causes fall in the value of all of the assets together. Correlation across all assets tends to move closer to unity. A risk system that rewards diversification in such circumstances would tend to underestimate the loss figure that could occur. Since risk management is more concerned with extreme as opposed to normal circumstances, the view of regulators to not consider diversification may look to be over-prudent but certainly can help the financial system in the long run. It is also suggested that both diversified and undiversified VaR should be provided for analysis and decision making. Diversified VaR can be used to examine resource allocation to generate maximum portfolio returns at least possible risk, whereas undiversified VaR will provide information regarding what can happen under extreme market moves and may provide a red signal about the loss if diversification benefits do not occur.

Overall, under the Basel-I accord, capital requirements on a credit exposure were same irrespective of the borrower's credit rating that whether it was triple-A or triple-C. In this regard, it was seen as a very inefficient system and called banks to lend to very risky businesses in the hope of generating very high returns at no additional cost as the capital requirement was indifferent to the borrower's credit rating. Also, Basel-I accord was found to be static and not easily acceptable to new banking activities and risk management techniques.

Because of these constraints, the Basel Committee proposed a new accord known as the Basel-II accord, which was implemented in 2004. Basel- II aimed at encouraging better and more systematic risk management practices, mainly in the area of credit risk, and also aim to provide improved measures of capital adequacy for the benefit of supervisors and the market in general.

3.4 Basel II

The new Basel agreement established a three-pillar approach to capital adequacy that includes "(1) minimum capital requirements, (2) supervisory review of internal bank capital requirements relative to risk, and (3) increased public disclosure of risk and capital information sufficient to provide meaningful market information." The following section goes into greater detail about these three Basel II pillars.

3.4.1 The First Pillar: Minimum Capital Requirement

The first pillar sets out minimum capital requirements. The framework requires a minimum ratio of 8% of capital to risk weighted assets. Risk weights are calculated based on the riskiness of the financial instrument. For example, investment in government bonds constitute 0% risk while in highly risky corporate bonds of low rating will constitute 100% of risk weight. For credit risk, three different ways were provided: "Standardized approach, Foundation internal rating-based approach (IRB) and Advanced internal rating-based approach (AIRB)." For the first time, the Basel-II framework proposed a measure for operational risk. There were three approaches to operational risk: "the Basic Indicator approach, the Standardized approach, and the Internal Measurement approach." According to the 1996 amendment, the market risk measurement framework remained unchanged, and VaR was the metric to be relied on.

3.4.2 The Second Pillar: Supervisory Review Process

This pillar requires that supervisors must ensure that each individual bank falling in their jurisdiction has its own adequate internal risk management system in place to access the adequacy of capital requirement. This framework stresses the need to have an internal capital assessment process relating to particular risk profile of each individual bank. This internal process would then be subjected to supervisory review and intervention by regulatory bodies wherever appropriate.

3.4.3 The Third Pillar: Market Discipline

This pillar aims to supplement the minimum capital requirements and supervisory review process by developing a set of disclosure requirements that will allow market participants to determine an institution's capital adequacy. This framework establishes disclosure requirements and recommendations in a variety of areas, including how a bank calculates capital adequacy and risk assessment methods.

Overall, Basel-II provided a major support to the calculation of market risk using VaR metric. In order to satisfy these pillars, banks need to calculate their risk by the most accurate methods of VaR in order to pass the Basel norms.

3.5 Basel III Accord

Basel I and II were primarily concerned with the required level of reserves that banks must hold for various classes of loans, as well as other assets and investments that the bank has made. Basel III, on the other hand, was created in response to the flaws in the financial regulatory landscape revealed by the 2008 financial crisis. This is primarily related to the risks of a "run on the bank" by requiring varying levels of reserves for various types of bank deposits and other borrowings. The Third Basel Agreement is a “global, voluntary regulatory standard governing bank capital adequacy, stress testing, and market liquidity risk. This new accord aims at strengthening the capital requirements by increasing liquidity and decreasing the leverage of the bank”.

Regulators all over the world have been very much concerned about the reliability of the financial risk models. In this regard, supervisory risk management framework for model risk management by Federal Reserve Bank (*Supervisory Guidance on Model Risk Management, SR 11-7*) has been used as a benchmark across the world by major Financial Institutions. This Framework has defined that there should be a 3-tier setup for effective financial risk management. These 3 tiers are as follows:

1) First line of Defense: This consists of model developers and sponsors who take the first initiative for building any statistical or financial model. This process comprises of many steps

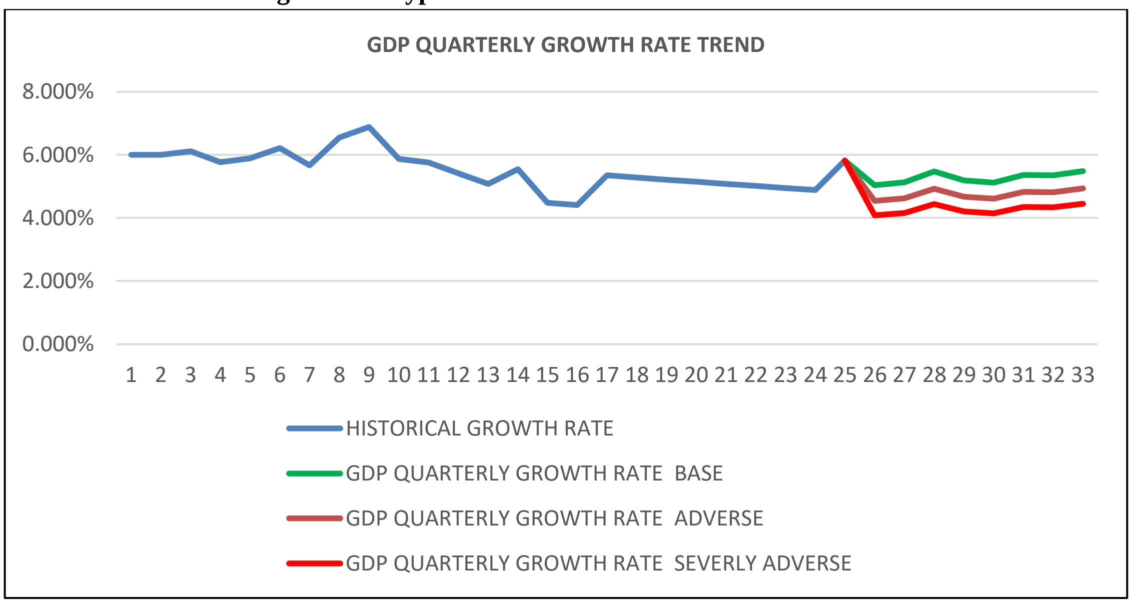
like data collection, sampling, segmentation, defining important independent variables based on business intuition, model development iterations with different variables (forward, backward and stepwise) and then finally comparing the performance of the different models developed by model evaluation criteria which comes under the broad category of model validation techniques. After that a final model is selected which is also called a champion model and other (at least one) second best model is kept as a challenger model. The challenger model will be used in case the champion model cannot be used in the form it was designed by the model developers. There might be cases that there is a regulatory restriction on certain variables or data sources which are input to the champion model but regulatory authorities do not permit their use and new model needs to be in place. As there is a time lag between a new model development and its final implementation, a challenger model will be used to derive business decisions till that time.

2) Second Line of Defense: As per this framework, there would be an independent risk management team in a financial institution which would check the accuracy of all the models developed by the first line of defense. This team needs to be independent from the first line of defense and should provide independent judgement over the appropriateness of the model developed by the first line. This team performs independent validation of the models which comprises data quality checks, performance evaluation, sensitivity and scenario analysis, stress testing, backtesting and benchmarking analysis.

3) Third line of Defense: This consists of internal auditors who would from time to time check the accuracy of the models as well as supervise both the first and second lines of defense. This team works as an internal supervisor for model development and validation teams within a financial institution and this line is allowed to communicate directly with the external regulators.

After the global financial crisis of 2007-08, there has been growing emphasis on how the financial system would respond if there are macroeconomic or financial shocks happen in any economy. In this regard, many developed financial markets have established certain systems whereby the accuracy of the financial risk management system is checked by stress testing the financial or statistical models used by any financial institution. In USA, Comprehensive Capital Analysis and Review (CCAR) is mandated to be used by Financial Institutions as per the guidelines by Federal Reserve Bank (FRB). The aim of this analysis is to check whether the Financial Institutions are adequately capitalized that they can face the macroeconomic stress arising in the economy. In this regard, all the financial models used by a financial institution needs to ascertain that what can be the probable loss over future 9 quarters in 3 different macroeconomic scenarios (base, adverse and severely adverse). These scenarios are provided by regulatory institutions in terms of their future expectations for the economy. A bank would need to assess how sensitive the model is as per the three scenarios and whether it is adequately capitalized to face the risk which might occur if any of the unfavorable scenario (adverse or severely adverse) takes place. These hypothetical stress scenarios (as an example) for macroeconomic variable Gross Domestic Product (GDP) growth rate are shown in figure 3.2 below:

Figure 3.2: Hypothetical stress scenarios



Source: Author's Generation as an illustration

The above figure presents a hypothetical history of GDP growth rate for 25 quarters (1-25) and post that presents the 3 different hypothetical scenarios (base, adverse and severely adverse) of expected GDP growth rate for next future nine quarters (25-33).

Base Scenario (Green curve): Here it is assumed that the economy will continue to behave mostly similar to what it has been in the past. Past is taken as a perfect predictor of what is going to happen in the future and depending on the current prevailing macro-economic conditions, future is expected to behave in a similar fashion.

Adverse scenario (Magenta curve): Macro Economic downturn is expected by decrease in GDP growth rate. The potential causes can be increase in unemployment rate, increase in inflation, financial or economic crisis etc. The regulatory authorities will provide different values for different macroeconomic and financial variables as per their expectation for the future 9 quarters.

Severely adverse scenario (Red curve): This scenario assumes that very adverse situation will happen to the economy and the GDP growth rate will fall even further and can possibly turn out to be negative and the economy could be under recession. The potential causes can be similar to adverse scenario but with a higher severity.

For Indian financial market, as of now there is no annual stress testing exercise followed by Indian banks and financial institutions that could see the impact of different macroeconomic and financial shocks on the overall capital requirement. Though Basel II capital requirement is followed by Indian banks and it provides an overall assessment regarding whether banks are adequately capitalized or not, the study however, suggests that similar to CCAR there should be some form of annual stress testing mechanism that can foresee the probable downturn/crisis that may take place in future and regulatory bodies may thus plan accordingly to face the adverse outcomes which might arise in the future.

3.6 Basel in India

In India, Basel I framework was put as a regulatory mechanism from 1992-93 and was extended for three subsequent years. Basel II implementation framework for Commercial banks in India started from March 31, 2007 and by the end of Dec 31, 2018, most of the Indian banks are following Basel II guidelines for determining capital requirements. For Basel III, the RBI set March 2019 as the initial deadline for banks to meet capital requirements under the Basel III norms. It was later postponed to March 2020. Due to the ongoing Covid-19 pandemic, the RBI has further decided to defer the implementation of Basel III norms. Presently, most of the Indian banks need significant amount of additional capital and time for becoming Basel III complaint.

3.7 An Overview of Traditional Risk Measures

The study now provides a brief overview of traditional risk measures that have been in use for a very long time. Depending on the implied risk perception, the various risk measures fall into one of two distinct groups. Risk is measured in the first group in terms of the probability weighted deviation of returns from some reference point. Both negative and positive deviations from the benchmark target have an impact on these risk measures. In the case of symmetrical distributions, this method makes sense. However, in the economic sense, since positive returns are favorable to asset holder, positive returns should not be considered as a source of market risk. In the calculation of VaR, risk is measured only by some variation on the lower side of the assumed level of confidence. Below, the study provides the most common risk measures.

3.7.1 Dispersion Measures: Standard Deviation Risk Measure

This is the most frequently used metric for measuring risk associated with a financial asset. It is also one of the inputs for most of other advanced sophisticated risk models used in financial risk management discipline. The basic idea behind the standard deviation as a risk measure is that it is a measure of volatility, i.e. the greater the difference between a stock's return and its average return, the more volatile the stock. The standard deviation is the average of squared deviations from the mean. And the square of standard deviation is variance. For a continuous series the standard deviation is calculated as (Equation 3.1):

$$\sigma_x = \sqrt{\int_{-\infty}^{\infty} f(x)\ (x-\mu_x)^2 dx} \qquad \text{....} \qquad (3.1)$$

Where, x is a random variable, σ_x is the standard deviation of x, $f(x)$ is the density function of x, μ_x is the mean of the density function. The standard deviation is one of the important measures of risk. It gives equal treatment to upside and downside variations from the mean value. The higher the deviation from the mean value, higher is the contribution to standard deviation from each individual deviation. It is a good measure in case of symmetrical distributions, but when tails are very asymmetrical, the use of standard deviation for risk measurement may provide misleading results.

3.7.2 The Coefficient of variation Risk Measure

The "coefficient of variation" is calculated by dividing the standard deviation by the mean of the return series. The standard deviation is an absolute risk measure, whereas the coefficient of variation is a relative risk measure. It is employed when the goal is to compare the variability of two or more series. The series with the highest "coefficient of variation" is said to be less consistent, less uniform, less stable, or less homogeneous.

3.7.3 The Mean Absolute Deviation Risk Measure

The "mean absolute deviation (MAD)" is the arithmetic mean of all the distances of individual observations from their mean or predefined target. This dispersion measure is given by (Equation 3.2):

$$MAD = \int_{-\infty}^{\infty} f(x) \ |x - \mu_x| dx \quad \text{.... (3.2)}$$

The mean-standard deviation model's main advantages are its linearity and the ability to solve the optimization problem using a linear programme.

The study has discussed above some of the traditional measures of VaR, now the study presents the various parameters involved in the calculation of VaR.

3.8 Parameters in the Calculation of Value-at-Risk

The next chapter will discuss various VaR calculation methods. All VaR methods, however involve selection of certain basic parameters. These parameters are given below,

1. choice of Time Horizon
2. choice of the confidence level
3. window length
4. choice of the theoretical probability distribution function.

3.8.1 The Choice of Time Horizon

The time horizon is primarily subjective and is related to the underlying business of the bank/financial institution as well as the type of financial instrument under consideration. In practice, the holding period can last anywhere from a single trading day to several years. A one-day time horizon is probably the best choice for a bank trading portfolio invested in highly liquid assets because the assets can be liquidated at very short notice. A 90-day horizon is more appropriate for an investment manager who focuses on quarterly portfolio rebalancing and reporting. The time horizon should ideally correspond to the length of time required for an orderly portfolio liquidation. The appropriate holding period is determined by the asset class (equity versus bonds), the industry (equity versus insurance), the internal position, and whether the risk is measured from an internal risk management or a regulatory requirement perspective.

Trading activity and asset liquidity (i.e. the time and ability to convert a given position to cash) also have an effect on the appropriate holding period. If the time horizon is shorter than what is required for an orderly portfolio liquidation, the liquidity risk must be explicitly modelled. Given the volume of daily trading and the importance of financial assets in their balance sheets, banks and financial institutions typically use a 1-day time horizon to effectively mark-to-market their asset portfolio. For official reporting, the Basel Committee requires a 10-day holding period. They still allow for a shorter holding period and VaR scaling to correspond to a 10-day holding period.

Time horizon consideration is very important when comparing VaR measures of two different portfolios as it becomes inconsistent to compare the VaR on a 10-day time horizon with the VaR on 1-day time horizon. The former is, ceteris paribus, larger than the latter. Statistically, there is no need to calculate different VaR measures for different time horizons. Because under a set of restrictive but commonly accepted assumption that daily returns are assumed to follow independent and identically distributed (i.i.d), the VaR at ten-day time horizon is approximately $\sqrt{t}$ times the VaR computed using 1-day time horizon. It makes an assumption that the weights of different instruments in a portfolio remains the same over the holding period. The present study is using one day time horizon for calculating VaR.

3.8.2 The Choice of the Confidence Level

In financial theory, there is no recommended guidance for determining the magnitude of the confidence level. The confidence level chosen is primarily determined by the purpose of the VaR estimation. When the primary goal is to meet imposed constraints, such as central bank requirements, there isn't much choice available. The Basel requirement, which allows for a choice between a “standardized approach and an internal model-based approach”, has been adopted by the vast majority of central banks. The “standardized approach” is simple to implement, but it does not take into account correlations between financial instruments. In most cases, it results in a “significant overestimation of risk”.

Asset correlation is incorporated into the "internal model-based approach." This method takes longer, but it is much more flexible and produces more realistic risk estimates. The internal approach calls for a level of confidence of 99 percent (1 percent for worst-case scenarios) and a time horizon of 10 days. This, however, yields a very conservative estimate. An exception (a loss that exceeds the predicted level) is expected once every 100 days, which is extremely rare. When the primary goal is to develop an effective internal risk management model, it is best to use parameters that produce observable and empirically verifiable results. Firms can typically use a confidence level of 95 percent or 99 percent and a short time horizon, such as one day. In this case, losses greater than the predicted level are likely to occur once every 20 days. The current study computes VaR with a 95% confidence level.

3.8.3 Window Length

The length of the data sample (the observation period) is referred to as the window length or historical observation period of sample data in VaR calculations. Sampling and database availability define the length of the window. The volatility of the risk factors is determined by the duration of the historical observation period, hence this observation time relates VaR to the history of market risk factors. In practice, the regulatory requirement stipulates that the historical observation period be at least one year long, but it can be anything from a month to many years.. The current study evaluates various VaR models for Indian financial markets over a 10-year historical observation period.

3.8.4 The Choice of the Probability Function

This parameter might not be required in all methods of VaR estimations because in non-parametric methods, no assumption is made regarding any probability distribution or cumulative distribution function for the returns. But the parametric methods of VaR estimations require that the probability density functions of expected returns are known or can be estimated with a well-known distribution. The most commonly used distribution is the normal distribution. The assumption of normality significantly simplifies the computational burden required for calculating VaR and provides the researcher with an enormous statistical toolkit. Reliance on normality is enhanced because almost all known inferential statistical methods start with the assumption of normality which is theoretically justified based on central limit theorem. A significant part of empirical studies on assets' returns however, do not support the assumption of normality and empirical distribution of asset returns are found to have higher peaks around the mean value and heavier and fatter tails than the normal distribution (leptokurtic returns distribution). Due to this empirical finding, various non-normal leptokurtic distribution such as t-distribution, logistic distribution, Generalized Error Distribution, x^2- distribution etc. are used in the advanced models of calculating VaR for nonlinear instruments.

3.9 Conclusion

This chapter has provided an overview of different financial risks in a financial institution and regulatory framework (Basel guidelines) around those risk types. Even though VaR was initially developed for market risk measurement but overtime its application are now being extended for credit and operational risks and credit VaR and operational VaR are also becoming a promising area for further research as well. The chapter has also well elaborated the various parameters required for VaR calculation and how these parameters can be selected based on the given financial product. The next chapter will discuss the different methods of VaR calculation namely, parametric and non-parametric methods based upon the fundamentals presented in the present chapter.

CHAPTER – 4

REVIEW OF VALUE-AT-RISK MODELS

4.1 Introduction

Since the introduction of Risk Metrics VaR approach by J. P. Morgan, it has emerged as a powerful tool to measure market risk. With the adoption of VaR methodology by Basel accord for the determination of minimum capital requirements for market risk, it has attracted the attention of many researchers and practitioners. As a result of intensive research in the market risk management domain and the approach of VaR, many methodologies are developed for the purpose of risk measurement and management. The various methodologies of VaR can be divided into mainly two broad categories. First one is the 'parametric methods' of VaR. These methods mainly involve the estimation of parameters of the assumed theoretical probability distribution function. In this category, major methods are "variance-covariance method (VcV), Exponentially Weighted Moving Average (EWMA) method and Generalized Auto-Regressive Conditional Heteroscedasticity (GARCH) method." The second category is based on simulation methods. In this category two major methods are Historical Simulation (HS) and Monte-Carlo Simulation (MCS) methods. These methods do not involve any estimation of parameters of the distribution. They use simulations to generate return distribution. This chapter provides a review of the various above-mentioned methods of VaR.

4.2 Parametric Value-at-Risk Models

"Variance-covariance (VcV), Exponentially Weighted Moving Average (EWMA) and Generalized Auto-Regressive Conditional Heteroscedasticity (GARCH)" are parametric methods of VaR calculation. The estimation of parameters (volatility) of the postulated theoretical probability distribution function is the major focus of these approaches. All three parametric techniques estimate volatility in various ways, but they all assume that the underlying return distribution is normal. There are several approaches for estimating volatility, the majority of which entail the analysis of historical data. They come under the broad category of moving average (MA) estimates. The MA techniques have been widely used in finance especially for estimating returns and volatility measured over time. Empirical research has shown that it is often better not to use mean deviation of returns, but to use squared returns instead as they are able to capture volatility clustering phenomenon accurately. All the parametric and non-parametric methods use continuous compounding returns. Here, returns are compounded at every possible moment and frequency of compounding tends to infinity. Continuous returns have better statistical properties than either simple or percentage returns. If we want to get a temporal aggregation of returns then we just need to simply add the returns over the relevant past time periods. Therefore, returns computed over multiple days are simple sums of multiple one day period returns. Financial models generally have the implicit assumption that actual returns are approximately normally distributed. This can be a possibility only when we are measuring returns by continuous formula. This happens because the probability distribution function (pdf) of percentage returns cannot be assumed to be symmetrical or bell shaped. This is because of the 'Limited liability principle', by which an investor can lose up to a maximum of the amount invested and not more than that. It is found in most of the organised financial institutions that owners have limited liability (equity shareholders) which means that in the case of collapse of the business their personal assets cannot be used to fully repay the debts. This implies that the expected returns should range from -100% to ∞. If the normal distribution is assumed, then it violates this principle as then returns would range from '- ∞ to ∞'. When log returns are assumed to be normally distributed then prices will follow lognormal distribution. All the prices will turn out to be positive regardless of the initial price and the principle of limited liability will be satisfied because lognormal distribution tends from 0 to ∞. Log returns are also useful when measuring cross-currency exchange rates as it gives a symmetrical picture. Log returns are also necessary if the assumption of normality of cross exchange rates is to be maintained. For example, if percentage returns ₹/$ are supposed to be normally distributed, then $/₹ percentage returns cannot be normally distributed. Percentage returns do not preserve the normality of reciprocal rates since a bias in one of the series is introduced. Log returns for exchange rates have also another appealing property that returns on a given foreign currency can be expressed as the sum of cross rate returns. The present study has thus used log returns for all the empirical estimation of various VaR models.

Different parametric VaR methods are elaborated below.

4.2.1 Variance Covariance method

In this method of calculating VaR, the main focus is on volatility of the underlying asset's return. It is a parametric method that assumes multivariate normally distributed asset returns. This approach considers diversification and we can find diversification benefits if different assets' returns series are negatively correlated with each other. This uses data on volatilities and correlations of various assets and then by applying weights to the positions, calculates VaR. The weights could be the relative contribution to the overall portfolio by the individual assets. Software programs are existing nowadays with inbuilt functions for spreadsheets, and the volatility and correlation data is regularly updated by the proprietary organisations.

4.2.1.2 Steps for VaR Computation

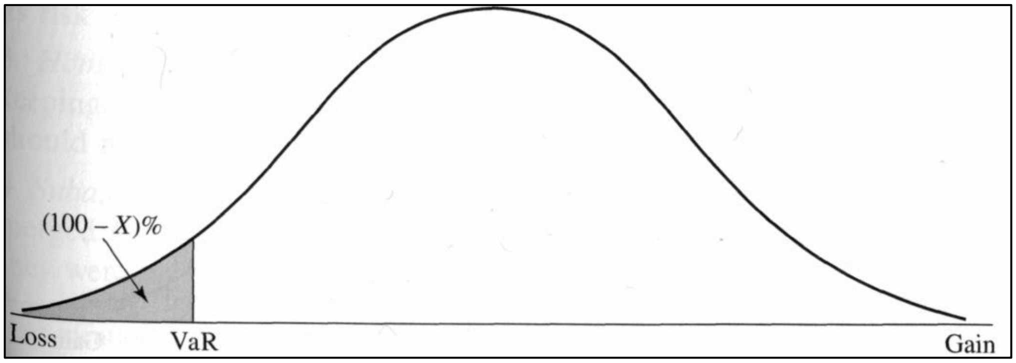
1. Calculate the Mark to market value of the current portfolio: The present market value of the return series needs to be calculated at this stage. Formulas expressing the present value of various positions are obtained from 'inbuilt software' programmes and if ready-made formulas are not available then most updated market value as per recent return observed is calculated and is taken as a benchmark for further analysis. The present study uses the market index values as benchmark which are marked to market.

2. Set the Time Horizon: The appropriate time horizon should be set depending on the composition of the portfolio which the institution has. If most of the assets can be liquidated at short notice or are easily tradable, then a one day or one-week horizon may be set. If most of the positions are illiquid for a short period of time than a longer horizon of one month to three-months can be chosen. The present study uses benchmark indices which are liquid and thus one day time horizon is chosen for estimating VaR from various methods.

3. Set the Confidence Level: How much confidence the researcher wants in the calculated figure is decided at this stage. Here self judgement plays a very important role as there are no set guidelines for choosing the confidence level. For example, if the confidence level is 99% than the risk figure is expected to equal or exceed VaR figure in a 1 out of 100 days. The present study uses 99% confidence level as the tails of the return distribution can be captured adequately.

4. Record the VaR Figure: Following the above steps and using the normal distribution of asset returns we finally arrive at the VaR figure from left tail of the return's distribution (Figure 4.1).

Figure 4.1: VaR calculation



Source: https://www.bmeclearing.es/ing/Risk-Management/IM-Calculation-model-HVaR

This method calculates the 1-day VaR with 99% confidence level as (Equation 4.1)

$$\boldsymbol{VcV\ \ VaR = Amount\ of\ the\ position} * [\boldsymbol{\mu - \ 2.33\sigma_t}] \qquad ..(\mathbf{4.1})$$

Where μ is mean, σ_t is standard deviation and 2.33 refers to the 'z' value of standard normal distribution (corresponding to the 99% confidence interval selected)

And the VaR for k days' period is estimated as (Equation 4.2)

$$\boldsymbol{VaR\ (k) = \sqrt{k}\ \times\ 1\ day\ VaR} \qquad \ldots\ (\mathbf{4.2})$$

This is known as the square root of time rule in VaR calculations. The square root of time rule implicitly assumes that daily returns are independent random variables. When the return distribution under consideration is either normal or very close to normal, the variance-covariance method is appropriate. It is however, unable to capture 'fat tails' behaviour observed in financial return series. This method computes volatility from historical time series data using standard deviation.

4.2.1.3 Limitations of Variance Covariance Approach

a) The method puts heavy reliance on the normal distribution. This distribution assumes complete randomness of returns on financial assets. Its major weakness is that it is not able to capture 'fat tails' behaviour detected in the financial return series. Fat tails are observed because of the 'Herd Behaviour' observed in the financial markets wherein, when the asset price starts falling, people start selling their shares in the expectation that it may further fall into very low extreme values. This actually lowers the price much below the rational optimum price only because of extra sales pressure by market agents.

b) The volatility and the correlation data may not be stable over time as the approach assumes it to be. This is particularly true in certain major events like stock market crashes.

c) It is mainly suitable for instruments which are having a linear payoff function. It assumes that the risk reward relationship is linear. Nonlinear instruments like options are not captured adequately. Options having high gamma risk should not be valued from this method as the underlying assumptions are found not to hold.

4.2.2 Exponentially Weighted Moving Average (EWMA) VaR

Financial research has shown that volatility tends to occur in clusters, which means that periods of high volatility are followed by periods of higher volatility, and periods of low volatility are followed by periods of lower volatility. Here, it is observed that the 'volatility is auto correlated over time'. It is known as the 'volatility clustering' phenomenon in technical terms. This method gives more weight to recent observations, and as the observation moves further back in time, its importance for volatility calculation decreases. This mechanism does an excellent job of capturing volatility clustering. The EWMA variance is calculated as follows: (Equation 4.3):

$$\sigma_t^2 = \lambda \cdot \sigma_{t-1}^2 + (1-\lambda) \cdot \Delta r_t^2 \quad \text{....} \qquad (4.3)$$

- *σ_t^2 = conditional variance*
- *λ = decay factor*
- *r_t^2 = squared returns at time 't'*

The name EWMA comes from the fact that weights to previous observations decrease exponentially rather than linearly, as in the standard deviation calculation. JP Morgan risk metrics (1996) employs this technique when calculating the volatility of financial asset returns. One important parameter here is the value of lambda (λ). It shows how the variance is related to past historical return series. The closer the lambda (λ) is to zero, the more weight is given to recent period squared return and if the return series is highly volatile then conditional variance will be highly volatile as well. High values of lambda may be desirable for those assets whose returns do not fluctuate very rapidly. If actual returns behave in a very random fashion, then lambda (λ) should be chosen much lower than 1 as it will allow the adjustment in volatility of recent returns over time in the forecasted volatility series.

EWMA is used by popular VaR technique given by J.P Morgan called 'Risk metrics'. EWMA is a standard statistical technique for measuring variability but it has some limitations also. For determining the appropriate value of lambda (λ), one has to use his/her own judgement as there does not exist any optimal theoretical approach. Risk metrics forecasts of volatility are calculated using a constant λ equal to 0.94 for daily data, and equal to 0.97 for monthly data. These values are found to better capture the conditional volatility from their empirical research on financial returns series. These values have been chosen by minimalizing the mean squared error (MSE) of the time series of historical returns data. The present study has also used λ equal to 0.94 for calculating EWMA VaR. EWMA VaR is computed in a similar way as VcV VaR, only the volatility is calculated by equation 4.3 above.

The method calculates the 1-day VaR with 99% confidence level as (Equation 4.4),

$$\boldsymbol{EWMA\ \ VaR = Amount\ of\ the\ position} * [\boldsymbol{\mu} - \ \mathbf{2.33}\boldsymbol{\sigma_t}] \qquad \ldots(\mathbf{4.4})$$

Where μ is mean, σ_t is standard deviation and 2.33 is the z value of 'standard normal distribution' (corresponding to the 99% confidence interval selected)

4.2.3 Generalized Auto-Regressive Conditional Heteroscedasticity (GARCH)

Another important method for measuring volatility from previous return series is GARCH, which accurately captures the volatility clustering phenomena. This method posits that long-term volatility has mean reversion,' and that volatility will tend to its long-term equilibrium mean level over a sufficiently long period of time. To find the optimal GARCH model, the study has estimated GARCH with various lags using the overall return series in the next chapter on empirical analysis. A GARCH (p, q) model is specified as,

For a log return series r_t, let $a_t = r_t - \mu_t$ which is the mean corrected log return. Then a_t follows a GARCH (p, q) process if (Equation 4.5),

$$a_t = \sigma_t \varepsilon_t,$$

$$\sigma_t^2 = \alpha_0 + \sum_{i=1}^{p} \alpha_i a_{t-i}^2 + \sum_{j=1}^{q} \beta_j \sigma_{t-j}^2 \quad \cdots \quad (4.5)$$

Where $\{\varepsilon_t\}$ is a sequence of IID variable with zero mean and variance one. Then $\alpha_0 > 0$, $\alpha_i \geq 0$, $\beta_j \geq 0$, and $\sum_{i=1}^{i=p}(\alpha_i) + \sum_{i=1}^{i=q}(\beta_j) < 1$. The constraint on α_i *and* β_j implies that the unconditional variance of a_t is finite, where as its conditional variance σ_t^2 evolves over time.

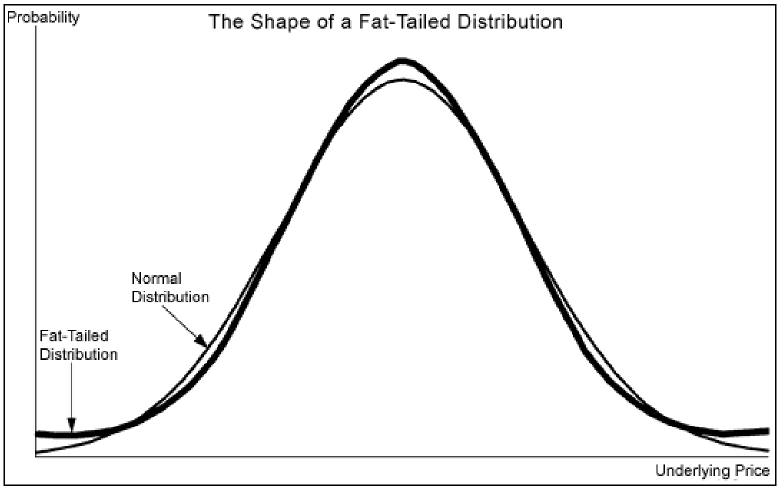
The method calculates the 1-day VaR with 99% confidence level as (Equation 4.6):

$$\boldsymbol{GARCH\ VaR} = \boldsymbol{Amount\ of\ the\ position} * [\boldsymbol{\mu - 2.33\sigma_t}] \quad \ldots (\mathbf{4.6})$$

Where μ is mean, σ_t is GARCH volatility from equation 4.5 above and 2.33 is the z value of 'standard normal distribution' (corresponding to the 99% confidence interval selected)

It is empirically observed that traditional parametric methods based on normality of returns assumption are not able to account for the skewness and the excess kurtosis found normally in financial time series returns data. This phenomenon is very important and forms the basis of alternative methods to calculate VaR. The excess kurtosis is also known as 'fat tails'. It implies that asset returns can move to more extreme values in either side of the mean than what is predicted by the normal distribution curve.

Figure 4.2: Fat tails of financial returns



Source: https://tradersbulletin.co.uk/hard-facts-fat-tail-trading-method/

The actual asset return distribution has small waists and large tails at the extremes, which is known as leptokurtosis. As seen in figure 4.2, using the normal distribution as an approximation understates the likelihood of big extreme shifts on either side of the distribution. Because VaR is concerned with estimating high losses, it's critical that these fat tails are properly represented in the model. Asset returns have also been shown to reach substantially greater values on both sides of the normal distribution, which is not well supported by theory. Historical examples include the Black Monday (1987), Dot-com bubble (1996) and 2008 financial crisis etc. In all these events occurred over a period of last 3 decades, financial returns have reached much extremes (Black Monday was a 23 standard deviation from mean event) which are not well predicted by normal distribution over this period.

This phenomenon is tried to be captured adequately by using theoretical ‘leptokurtic distributions’ which allow for fat tails behaviour like student’s ‘t’, Laplace distribution, logistic distribution etc. However, the problem with many of the leptokurtic distributions is that then the whole computational process would become very difficult to manage and for certain financial products (non-linear derivatives) normal distribution is the only option available to modellers. Even if some alternative is found, it may not be easy for all the banks within a financial system to follow the same methodology. The regulatory framework will become very complicated at the Inter-national level, as many small-scale banks over the world lack specialized expertise and skills to have such kind of robust systems in place.

4.3 Non Parametric Value-at-Risk Model

Non parametric methods makes no assumption that returns follow any particular distribution. The present study now discusses these methods.

4.3.1 Historical simulation method

In this method, VaR is calculated using a non-parametric technique. The use of a thorough valuation technique is a key feature of simulation methodologies. The distribution of returns is not assumed in this method. The actual return distribution is derived from historical data, and VaR is calculated by determining the relevant percentile (e.g. 1st percentile for 99 percent VaR). It is assumed that the past holds all of the necessary information to calculate projected future returns. As a result, data quality becomes critical in this technique. It makes the implicit assumption that the return distribution is constant and steady throughout time.

4.3.1.1 Steps for VaR Calculation

In this method, the return series is generated over the past historical time series data. The data series is then arranged in ascending order having the return data starting from lowest and reaching to the highest in the given period. The VaR is then calculated by finding the required percentile as decided by the researcher.

The length of the past data is critical here because the number of days of past data should be long enough to include the tail of the return distribution. The historical data period should ideally capture economic scenarios that are likely to occur in the near future. Furthermore, if the number of previous days from which market returns are generated is less, then the tale of the distribution may not be captured accurately. Empirical evidence suggests that asset returns have reached to more extreme values on either side of the mean than what the normal distribution curve suggests (Venkatraman (1997) and Robert (2009)). This is known as leptokurtosis, and it occurs when the actual asset return distribution has thin waists and fat tails at the extremes (Figure 4.2 above). The present study has taken historical time series data of 10 years (2006-2015) which also includes global financial crisis period (2007-08). The study is able to draw meaningful conclusions from the return distribution largely owing to this large range of historical time series data. Historical simulation makes no distributional assumptions. It can fully capture the fat tails behaviour of financial returns if they are present in the past data and will display the VaR figure accordingly to reflect the true volatility of the asset under consideration.

4.3.2 Monte Carlo Simulation Method

The basic idea behind Monte-Carlo is to repeatedly simulate a random process for a financial asset that encompasses a wide range of possible outcomes. This method makes no distributional assumptions for the return distribution, nor does it generate the distribution using past data. In this case, a suitable generating mechanism is assumed, and the data is generated by simulations using computer software applications. The designers of the risk measurement system are free to use any distribution they believe best describes potential future changes in market factors. In general, if no significant market change is expected, beliefs about future market behaviour are based on observed past behaviour. So, the system's designers are free to use whichever distribution they believe best describes the previous distribution. When the asset under consideration has non-linear payoff profiles, such as options, this approach is the best and, in most cases, the only option available to a researcher.

4.3.2.1 VaR Estimation Procedure Steps

a) Using algorithms in a spreadsheet, a sequence of random numbers ranging from 0 to 1 is generated. The amount is determined by the number of simulations that must be run. If it is suspected that the algorithm process is not producing true random numbers, the entire sequence of generated random numbers can be divided into various subparts, the average of each subpart taken, and the sequence of these average numbers finally taken to simulate the price path further.

b) A distribution for generating the expected future natural log of asset price is assumed. The study assumes that the price (p_t) follows a 'random walk' process. This process is described as (Equation 4.7):

$$\mathbf{ln}(\boldsymbol{p_t}) = \mathbf{ln}(\boldsymbol{p_{t-1}}) + \boldsymbol{u_t} \qquad \text{....}(\mathbf{4.7})$$

For generating the asset price, the study assumes that prices are continuous variables and the asset price follows "Geometric Brownian Motion (GBM)." This is the continuous counterpart of random walk process, and is described as (Equation 4.8):

$$\boldsymbol{ds = \mu_t s_t dt + \sigma_t s_t dz} \qquad \dots(\mathbf{4.8})$$

Here, μ_t is the expected rate of return on asset at time t, s_t is asset value at time 't' and σ_t is the volatility of the stock price. The *dz* random variable has the mean zero and variance *dt*, which causes price shock randomly to the portfolio value and it has no dependence on the past information. In the above equation, two main parameters are very important to be determined, they are the expected return (μ) and the volatility of the underlying stock (σ_t).

Determination of μ: The study assumes that if the asset is part of a market traded portfolio, it must bear the systematic risk associated with market movements. A rational investor will always expect the return on shares to be at least equal to the risk-free rate available in the market, for which the return on government securities can be used as a proxy, which are supposed to be risk-free in nature. The current study assumes that the expected return is simply the opportunity cost of capital, which is nothing but the market's risk-free rate of interest available elsewhere in the market. In the GBM equation, expected return is proportional to time.

Determination of σ_t: Volatility in the GBM is positively related to the time period over which it is estimated. It grows in proportion to the square root of time. Because expected variations in asset prices are greater over longer time periods, it is reasonable to assume that volatility rises with time. Only when the returns are uncorrelated over time can the square root formula be used to update volatility.

c) The study then obtains another series of observations of "standard normal distribution" with a mean of zero and a variance of one by using the inverse of the cumulative distribution function on the series of random numbers generated. This method is known as the transformation method. This is required for asset price GBM modelling.

d) Following that, asset prices are calculated using the GBM formula and the stochastic terms generated earlier. Finally, different scenarios generated will result in different asset values. The profit and loss distribution can then be constructed, and VaR calculated using the appropriate percentile.

4.3.2.2 Merits of Monte Carlo Simulation Method

The large number of generated scenarios provides a more reliable and comprehensive risk assessment than analytic methods. This method accurately captures the fat tails behaviour of financial markets due to the various scenarios generated. This assumes that prices are log normally distributed, which introduces a significant amount of error when compared to assuming that normal distribution is corrected. It is the only option that can effectively deal with the non-linear payoffs associated with options. When dealing with complex exotic options, Monte Carlo simulations are often the only way to capture their risk, rather than the other two methods mentioned earlier. It can incorporate various types of risks and is thus appropriate for when the portfolio is exposed to multiple risks at the same time. When dealing with a longer time period, it detects the convexity of nonlinear instruments and updates the volatility. It can be used to simulate a variety of alternative hypotheses about return behaviour, such as white noise, autoregressive, and so on.

4.3.2.3 Limitations of Monte Carlo Simulation Method

The issue with this method is the amount of computational effort required. When dealing with a large number of options in a complex portfolio, the researcher will need to run millions of simulation trials. It takes both time and effort. When the stochastic process generating mechanism does not match the actual return generating mechanism, the final conclusions drawn are deceptive. This method also requires assurance that the generated random numbers are truly random. If it is not guaranteed, the only way to proceed is to run simulations across a large number of scenarios.

4.6 Evaluation of Value-at-Risk Methods

Any financial/statistical model can only be relied when it is able to forecast the variable of interest fairly well and the error of prediction is well within limits (significance level). Backtesting is a process by which we see how the model has performed on the past data. This is a model validation exercise. Here, the actual values are compared to what is predicted by the model. Only with model validation, the different Value-at-Risk Methods can be judged based upon their accuracy in prediction.

In the regulatory framework, Market risk capital requirements are directly related to both the estimated level of portfolio risk and the performance of VaR models on back-tests, and a higher capital is required for models which show a poor performance in back-testing results. Since the 1990s, a number of tests that can be used to assess the accuracy of VaR models have been proposed. The current study has also used 3 different tests to check the predictive accuracy of VaR models. These are elaborated in the next chapter on empirical analysis.

The failure rate test is used to derive the Basel rules for back testing. The framework proposed by the committee involves using data from the previous 12 months and comparing it to what the models generate. The committee proposed three outcomes: a green zone, a yellow zone, and a red zone. The green zone label would be given to a model if there were fewer than four exceptions in 250 one-year observations. If the number of exceptions falls between five and nine, the zone is designated as yellow. When models enter the yellow zone, regulators would increase the multiplication factor (k) from the minimum of three to a maximum of six (figure 4.3). The multiplication number (k) is the number by which VaR generated by individual banks need to be multiplied and the figure obtained would be the minimum which every bank is required to hold as minimum regulatory capital for market risk. Finally, if there are 10 or more exceptions, the regulators would consider that a risk model is unreliable. In these cases, they would increase the multiplication factor by an absolute amount of one and carry out further investigations.

Figure 4.3: Basel backtesting rules

Zone	Number of Exceptions	Increase in *k*
Green	0 to 4	0.00
Yellow	5	0.40
	6	0.50
	7	0.65
	8	0.75
	9	0.85
Red	10+	1.00

Source: Basel Committee on Banking Supervision (1996)

The minimum value of multiplication factor was set at three and according to the above table it would change as per the modelling outcomes. This multiplication factor applies on the amount of capital that the financial institution has. This allows financial institutions to use their own risk models as they seem appropriate on the basis of resources and skills that their management has. Once they have adopted a model, the regulators would then provide a minimum multiplication factor of three over and above the capital that the financial institution has, in order to balance any kind of discrepancies in the modelling and this will provide necessary safety to the financial institution in case some market crash happens. It is also seen as a buffer capital to face any economic or financial crisis that may happen in the unforeseen future.

4.6.1 Stress Testing

This is another important technique which can be used as a supplement for model validation exercise. This involves estimating the effect on portfolio when market risk factors are changed to extreme values which were historically observed which can include periods of economic or financial crisis also. Many market moves which happen when there is a market crash or some huge structural change in the economy or a financial system, are not captured by the usual distributional assumptions that are made by risk managers when estimating how much their portfolio could lose. For example, on October 19th, 1987 S&P 500 changed by 22.3 standard deviations. This extreme move is not captured adequately by the distributional assumptions usually employed while modelling risk dynamics. Stress testing takes into account the market movements which are theoretically impossible to happen for the period under consideration but which do happen in the real world. For example, a five standard deviation change will happen once about every 7000 years according to the normal distribution, however, the actual markets show a five standard deviation move much frequently once or twice every ten years in practise.

Prerequisites of a good stress test:

a) It should be applicable to the current situation
b) It should reflect changes in all applicable market factors
c) It should investigate potential regime shifts, as well as whether the current risk parameters will hold or deteriorate.
d) It should consider the lack of liquidity which will happen when the stress scenario will actually take place
e) It should consider the overlapping between ‘market and credit risks’ in a stress scenario.

4.7 Applications of Value-at-Risk

Many advances have been made in the study of VaR. VaR is now recommended by financial market regulators around the world (e.g., Basel) to determine regulatory capital requirements for financial institutions against market risk. Banks which are found to have sound risk management are given the option of calculating their market risk regulatory capital requirement determined by their own internal VaR estimates under the 1996 Amendment to the Basel Agreement. This is known as the internal model-based regulatory capital requirement approach. This method encourages banks to implement sound and efficient risk management systems.

4.8 Limitations of VaR

In spite of the fact that widespread use of VaR is prevalent in the financial industry, the method is far from perfect. It has limitations both as a conceptual approach and in the methods, which are applied to calculate it.

4.8.1 VaR is applicable only for transacted assets and liabilities

Despite the fact that VaR is gaining increasing popularity among financial institutions, it still covers only those risks which are arising from traded financial products. Only market traded instruments have a price history which can be statistically measured and modelled appropriately. For non-traded instruments such as loans and deposits, market price history is not available, so VaR is unable to capture risk associated with non-traded instruments. Of course, securitisation has reduced the proportion of non-traded assets in total portfolio but for many of the financial institutions like commercial banks nontraded assets still form a significant proportion of the balance sheet.

4.8.2 Liquidity risk

VaR does not take into account adequately the liquidity risk. The issue is especially acute for those instruments which are traded in thin markets wherein the buying and selling of relatively small quantities of a single instrument can potentially result in large price fluctuations. Ex-ante losses can be estimated from various VaR methodologies but the actual final loss may turn out to be much higher due to illiquidity in the market. A possible approach would be to use that particular time horizon over which we are easily able to liquidate the financial asset, in the VaR calculation methodologies.

4.8.3 VaR Considers Only Normal Events

VaR cannot be used to calculate the expected loss from changes in extremely unlikely market factors. It is intended to assess risk in the presence of unusual but normal market fluctuations in risk factors. Although a 2 standard deviation event is unusual, it is not rare. Daily returns are expected to exceed two standard deviation moves approximately 7 to 8 times in a year. This is still a normal state in which financial theory and statistical tools function reasonably well. Nonetheless, abnormal market events like a high standard deviation move of about five or higher (e.g. Black Monday (1987) was a 22 standard deviation event) which are seen during market crashes are not captured by the VaR models. In these cases, the well-established rules of financial market simply break down which were observed over an extended period of time. The financial world then behaves in a very random fashion with unstable relationships where the known and established framework does not work well.

4.9 Limitations of VaR methodologies

The study has presented above the limitations of VaR as a conceptual approach. VaR is a statistical measure and is based on certain statistical assumptions and methodologies. If these assumptions are found unrealistic or the methodologies are not able to capture the complexity of real-world financial markets, this is not a limitation of VaR as a conceptual approach for measuring and controlling VaR but a failure of the statistical methods used. Below, some of the limitations of VaR from methodology standpoint are provided.

4.9.1 Valuation models

Valuing exchange traded products is relatively straightforward. As these products are relatively liquid the ‘screen-based price’ can be assumed to be the equilibrium price of the product achieved by demand and supply forces. With OTC options however, traders rely on models such as Black and Scholes as well as Cox, Ross and Rubenstein. All of these models are based upon assumptions, and if these assumptions are found not to hold, then the resulting prices will also be inaccurate. VaR models cannot measure the risk arising as a result of over relying on option valuation models.

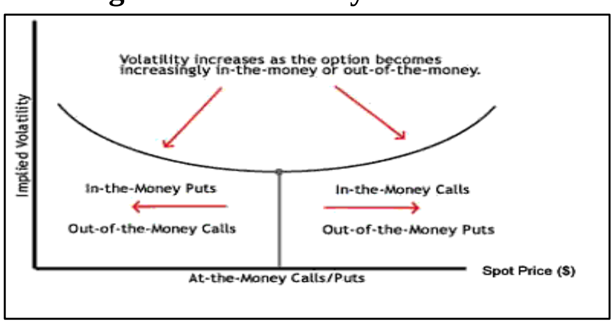
4.9.2 Margining system

Since OTC options are difficult to price, it is not easy to apply a margining system to them. This system works well for exchange traded products as if a trader is making losses on his open positions, he must send the funds to the exchange within 24 hours to cover those losses. Due to this fact, most VaR models cannot cope with OTC options. Although developments in Monte Carlo simulations could improve valuation techniques, different simulation systems could very easily produce different values and in these cases, both counterparties may have difficulty in agreeing on how much margin should be paid.

4.9.3 Volatility smile

Normal distribution of returns based models assume constant volatility, which understates the likelihood that the price will dramatically rise or fall. To counteract this, traders raise the volatility of options that are deeply in the money as well as out of the money. This results in a volatility smile curve.

Figure 4.4: Volatility Smile



Source: https://quantra.quantinsti.com/glossary/Volatility-Smile

Above figure (figure 4.4) displays that ‘implied volatility’ of the market is not independent of the price of the underlying contract. Improved models such as the constant elasticity of variance model have incorporated this into option pricing mechanism.

4.9.4 Standard model and a standard system

Accountants generally prefer to have a standard system of calculation procedures for risk measurement. If it is not in place, banks might use the equivalent of creative accounting tactics. They might be tempted to adopt a system that produces the least VaR and minimise the capital adequacy requirement. A standard model, on the other hand, can encourage all banks to measure risk in the same way, diversify in the same way, and thus hold portfolios that are similar. The difficulty arises here is that if there is a market crash, all banks will act in a similar manner to each other, which will cause considerable instability in the financial system and may create systemic risk.

4.9.5 Normality

The common assumption in most of the VaR methods is that the ‘distribution of log returns’ follows normal distribution or equivalently prices follow “lognormal distribution.” Empirical evidence however, have shown that large events are more likely to occur than what is predicted by the normal distribution. Return distributions are found to have heavier tails than the normal distribution. Mandelbrot and Fama have also remarked that returns follow pareto stable (fractal) distributions which have the feature of having infinite variance. The solution lies in that we choose a different distribution to model financial returns. Efforts have been made to introduce ‘Finite - variance leptokurtic distributions' such as the t-distribution into financial models. The Main problem which arises when the normality assumption is relaxed is that modellers have not been very successful to deal with the non-normal distributions in a widely acceptable and agreed way. This happens because of the fact that manipulation of normally distributed variables is very easy which is done when aggregating the returns or risk on a portfolio basis. Normal distribution is a stable distribution since the sum of normally distributed random variables is itself normally distributed. The central limit theorem suggests that even if we are aggregating over non-normal distributions then as the quantity of these non-normal distributed variables increases, the final aggregated distribution tends to be normal. This simplifies the calculation for the whole portfolio which normally comprises of a large number of financial products and hence can be assumed to be normally distributed. For a normal distribution knowing just the mean and variance of the distribution is enough to fully characterise the whole distribution, no other parameters are needed. Also, if two normally distributed random variables are uncorrelated, they are also statistically independent. These features make the normal distribution a popular choice among the academic community and financial analysts.

4.9.6 Internal valuation problems

Within a financial system, there may be difficulties of reconciling trading and risk measurement information with that of the accounting system. Traders and risk managers tend to value financial instruments differently from accountants. Accountants do not always mark to market the financial instruments. They do not show on the balance sheet, the current market value of the instruments they are dealing with. Accountants rely on the historical cost and this explains why derivative instruments are not shown on the balance sheet, as their actual historical cost at the time of entering into an agreement with a counterparty is very low or negligible that could not change the balance sheet figure by any significant amount. This is in contrast to VaR framework where marked to market is the primary requirement.

4.10 Alternatives to Value at Risk

VaR can also be substituted or better supplemented with other risk measurement methods. Artzner et al. (1999) proposes an organization scheme for risk measures whereby "a risk measure $\rho(\cdot)$ is said to be 'coherent' if it satisfies certain conditions. Let *X* and *Y* be two financial assets. A risk measure $\rho(\cdot)$ is coherent if the following four axioms hold.

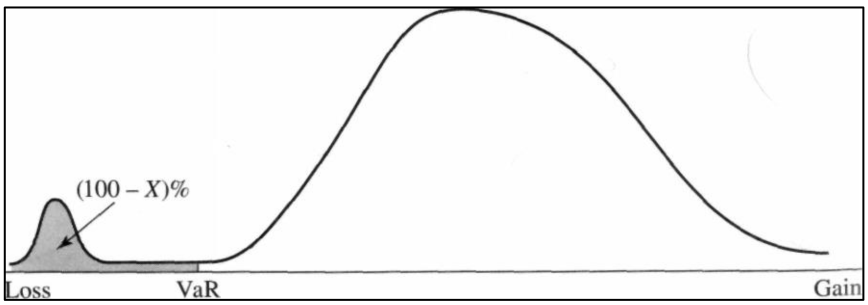
a) Sub-additivity: $\rho(X + Y) < \rho(X) + \rho(Y)$: This requires that if you add two portfolios together the total risk can't get any worse than adding the two risks separately.
b) Homogeneity: For any number $\alpha > 0$, $\rho(\alpha x) = \alpha\rho(X)$, if portfolio is doubled then risk will also double.
c) Monotonicity: If $X < Y$ for each scenario then $\rho(X) > \rho(Y)$. If one portfolio (Y) has better values than other(X) under all scenarios then its risk will be lesser than the other.
d) Risk Free Condition: $\rho(X + k) = \rho(X) - k$ for any constant k. if some amount is added to the portfolio then its risk should be reduced by the amount."

VaR metric satisfy all but sub-additivity. Assuming a normal distribution, however, standard deviation based VaR satisfies sub-additivity property. Sub-additivity is observed to be a very desirable property for all the risk measures as the merger of two assets should not create more risk compared to the addition of the individual risk of the two assets. The study now elaborates some of the alternatives to VaR.

4.10.1 Expected shortfall

When VaR is used to try to limit a trader's risks, it can have unfavourable outcomes. The trader may not cross the VaR figure with the required confidence level, but the expected loss that can occur when the VaR figure is crossed could be exceptionally high.

Figure 4.5: Expected Shortfall



Source: https://www.risk.net/risk-magazine/technical-paper/1506669/var-versus-expected-shortfall

In the above figure 4.5, the loss can be much higher if the VaR figure is breached. Individual traders have the incentives to create these kinds of situations to take on excessive risks but simultaneously not allowing the VaR figure to increase. Expected shortfall is a risk measure that solves the above problem and provides better incentives to traders than VaR. It's also referred to as conditional VaR or tail loss. If the VaR amount is surpassed, it is calculated as the predicted value of loss. It's a risk-adjusted variant of value at risk that's more sensitive to the shape of the loss distribution at the tails of the distribution. Expected shortfall is a function of two parameters: time horizon and confidence level, similar to VaR. It satisfies all four of the above-mentioned desirable properties and outperforms VaR in terms of encouraging diversification. Its disadvantages are that it lacks the simplicity of VaR and is more difficult to comprehend. Back testing with an expected shortfall is also more challenging compared to VaR.

4.11 Conclusion

The present chapter has discussed the various methodologies of VaR calculation (parametric and non-parametric) along with their merits and limitations. The applications and limitations of

VaR are then discussed followed by other alternative approaches that can be considered in place of VaR. The next chapter will provide empirical estimation of different VaR models for various Indian financial markets (equity, derivative and forex). The predictive accuracy of various VaR methods will be estimated to identify the best VaR model for various Indian financial markets.

CHAPTER - 5

ANALYSIS OF VALUE-AT-RISK (VaR) IN INDIA

5.1 Introduction

Market risk is the risk arising from unfavorable movements in market risk factors which are stock prices, exchange rates and interest rates. Market risk factors are the variables which are traded in the financial markets and their values keep changing which in turn affects the "mark to market' value of the portfolio" of any financial institution. These market risk factors affect the entire financial system equally and contributes to 'Systematic Risk' within a financial system. VaR has emerged as the preferred methodology to measure risk arising from these market risk factors. The discussion regarding the various methods of VaR computation has been covered in the previous chapter.

The present chapter aims at examining all the three objectives of the present study which are also mentioned in chapter 1. The three objectives of the present study are:

I. The study aims at finding the most appropriate VaR model for Indian equity market.
II. The study aims at finding the most appropriate VaR model for Indian currency market.
III. The study aims at finding the most appropriate VaR model for Indian futures (derivatives) market.

5.2 Objective 1: Market Risk assessment of Indian equity market

The majority of equity trading in the Indian stock market occurs on the country's two major stock exchanges, the Bombay Stock Exchange (BSE) and the National Stock Exchange (NSE) (NSE). The BSE has been established since 1875. The NSE, on the other hand, was established in 1992 and began trading in 1994. Both exchanges, however, use the same trading mechanism, trading hours, settlement process, and so on. Sensex is considered as the barometer of Indian equity market and it tracks the overall financial and economic health of the economy. The present study has thus used Sensex as the benchmark index representing equity market of India. The sensitivity of each individual stock to Sensex is captured by the Capital Asset Pricing Model (CAPM) 'β'.

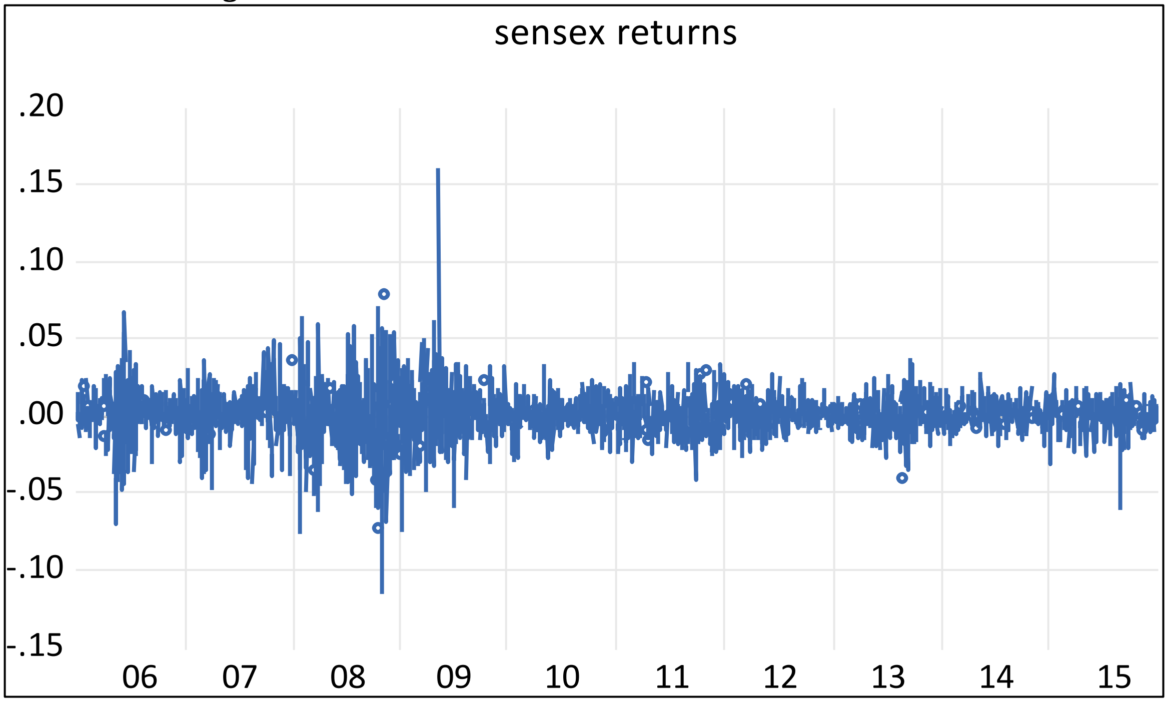
5.2.1 Empirical Analysis and Description of variables and Data Source

The Sensex index of the Bombay Stock Exchange (BSE) is used as the benchmark for the Indian equity market in the present study. It is a composite index of 30 of India's most actively traded stocks. The market value of the index is calculated using the free-float methodology. Market capitalization is calculated using the free-float methodology by taking the equity price and multiplying it by the number of shares available for trading in the market.

Data from the period January 1, 2006 to December 31, 2015 covering a period of 10 years and a total of 2480 observations is obtained from the official website of BSE. This range of data set allows the study to draw meaningful conclusions regarding the statistical behavior of index returns as the period is sufficiently long enough to study the behavior of equity market. Then continuously compounding returns are generated for the index as $\boldsymbol{R_t = \ln (I_t / I_{t-1})}$**,** where, R_t is the return at time t, I_t is the index value at time t, I_{t-1} is the index value at time $t - 1$ and $\ln$ is the natural logarithm. Considering investment in Index funds, the positive return indicates the profit and the negative return indicates the losses.

Figure 5.1 shows the graphical plot of index return. From the figure, it is apparent that the return series is volatile. The level of volatility is relatively even more during the global financial meltdown of 2007- 09. This is supporting the fact that most of the major economies of the world's financial system were influenced by the subprime mortgage crises originated in USA. It is also evident that during the crisis period, asymmetric behavior in volatility is also observed. The volatility is much higher on the positive side (returns are reaching to 15% whereas negative returns are reaching to a minimum of around 11%). The study will formally test whether the returns are showing asymmetric response to volatility by using EGARCH test in the further sections. It's also worth noting that the commonly held assumption for continuous compounded returns is that daily returns are on average 0%, although daily volatility isn't, and is usually found to be significant. This trend is likewise evident, as returns are more or less lingering around zero percent over a ten-year period, but considerable spikes in volatility are noticed.

Figure 5.1: Sensex Return Plot over 2006-2015



Source: Author's generation

The descriptive statistics of Sensex returns are shown in Table 5.1. Returns over this time are positive skewed, as evidenced by the descriptive statistics, with a skewness value of 0.093. Daily mean returns are similarly found to be positive at 0.041%, whereas daily standard deviation is found to be relatively higher than mean returns (1.56%). Mean returns are positive and indicate that on an average, investors have gained over this 10-year period (0.041%).

Table 5.1: Descriptive Statistics of Sensex Return

Metric	Sensex Return Series
Mean	0.041%
Median	0.089%
Maximum	15.99%
Minimum	-11.60%
Std. Dev.	1.56%
Skewness	0.093
Kurtosis	11.24
Total Observations	2479

Source: Author's computation

It has been observed that Subprime Mortgage financial crisis of 2007-08 occurred due to overreliance on faulty financial models used by the mortgage business industry. Regulators all over the world are very much concerned about the financial risk arising from faulty financial/statistical models used by financial industry in general and banking system in particular. The study thus seeks to examine the appropriateness of the financial models by first checking the critical assumptions made under many financial models as, if the assumptions are not satisfied, we may fail to get the appropriate results by VaR. If the assumptions are found not to hold, then the study tries to find what distributional assumptions are best at describing the present data series.

Many financial models rely on the assumption of return normality. Several statistical tests are used below to determine whether the daily returns of the Sensex are normally distributed or not. The analysis of the third and fourth moments around the distribution's mean is the most basic test of normality. Skewness, which measures distribution’s asymmetry and should be zero in the case of a normal distribution, is the third moment around the mean. The mean, median, and mode of a symmetric distribution are all the same. Negative asymmetry indicates that the distribution is skewed to the left, implying that negative returns are more likely than what a normal distribution would predict. In this case, the mean, median, and mode do not coincide. Kurtosis, which measures the peak of the distribution in comparison to normal, should be equal to 3 for a standard normal distribution. If the kurtosis is greater than three, the distribution has fatter tails than the normal distribution, implying that extreme events occur more frequently in the returns data than would be expected under normal distributional assumptions. It is also known as leptokurtosis in financial analysis. It demonstrates that the probability of experiencing extreme large returns on either side of the mean (both positive and negative) is much higher than what a normal distribution suggests. As given in Table: 5.1, “Fat Tailed” behavior in returns series is observed as the kurtosis value is 11.24. It is showing that empirically Sensex returns have reached extreme outliers on both positive and negative sides of the actual distribution much more recurrently than what is projected by a normal distribution.

Statistical tests of normality have also been used to check the normality of the return series of the index. One of these tests is the Jarque-Bera (JB) test. The JB normality test is an asymptotic or large-sample test. This test computes the skewness and kurtosis measures first, then employs the following statistic (Equation 5.1):

$$JB = n \left[\frac{S^2}{6} + \frac{(K-3)^2}{24}\right] \qquad \ldots.(5.1)$$

Where n denotes the sample size, S denotes the skewness coefficient, and K denotes the kurtosis coefficient. Because S = 0 and K = 3 for a normally distributed variable, the JB test of normality is a test of the joint hypothesis that S and K are 0 and 3, respectively. In that case, the JB statistic value is expected to be 0. The null hypothesis states that the data is normally distributed in this case. The JB statistic follows the chi-square distribution with 2 degrees of freedom asymptotically (i.e. in large samples) (dof). We do not reject the null hypothesis and conclude that the returns series is normally distributed if the computed p value of the JB statistics is greater than the level of significance used for the test. However, if the computed p value of the JB statistic is less than the level of significance used for the test, the null hypothesis is rejected, and we conclude that the return series is not normally distributed. Because the number of data points in the current study is quite large, the study has employed the JB statistic.

The JB statistic for Sensex is 7029 (see table 5.2), and the p value for obtaining such a value from a chi-square distribution with two degrees of freedom is 0. This means that the null hypothesis can be rejected at a 5% or even at 1% level of significance. As a result, the JB test determines that the series is not normally distributed.

The Anderson-Darling (A-D) test is another type of normality test that is used to determine whether a sample of data came from a population with a normal distribution. The A-D test gives the tail more weight. In order to calculate critical values, the test employs a specific distribution. The null hypothesis in this case is that the data has the specified (Normal) distribution. The A2 statistics for the Sensex in our empirical investigation turn out to be 36.30. The p value for obtaining such an A2 value is 0.00. (See also table 5.2.) Because the p value is zero, the null hypothesis of normality is rejected at the 5% and even 1% level of significance. As a result of the A-D test, the Sensex returns are non-normal for the sample period.

Table 5.2: Normality Test of Sensex Returns

Normality Tests	SENSEX
Jarque - Bera	7029 (0.0000)
Anderson-Darling	36.30 (0.0000)
Lilliefors	0.079 (0.0000)

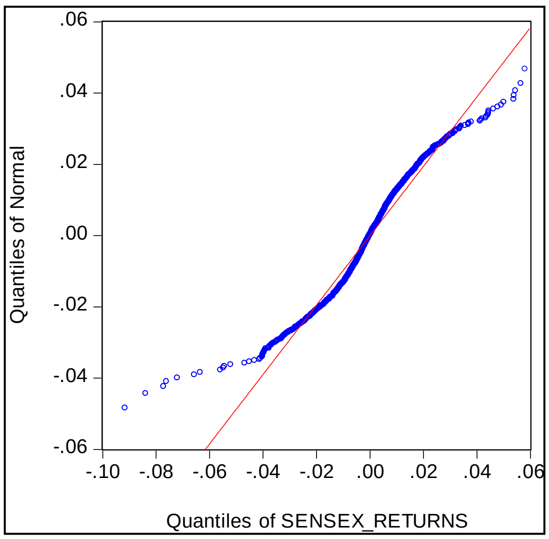
Note: Values in the parenthesis represents the respective p-values
Source: Author's computation

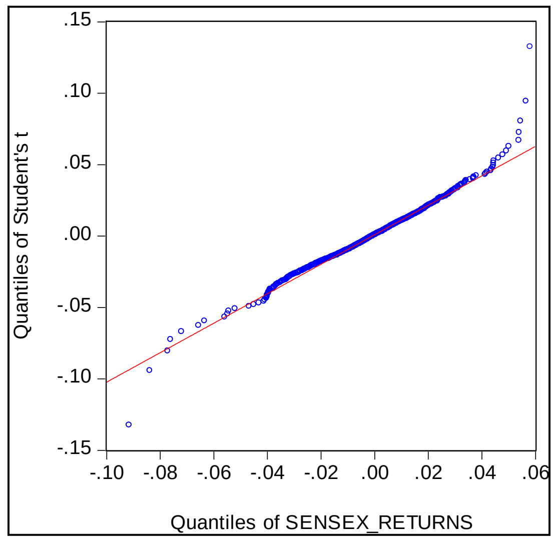
The third type of test is the Lilliefors test. The Kolmogorov-Smirnov goodness-of-fit test is a subset of the Lilliefors goodness-of-fit test. In the Lilliefors test, the Kolmogorov-Smirnov test is implemented by using the sample mean and standard deviation (S.D.) as the mean and S.D. of the theoretical (benchmark) population to which the observed sample is compared. Using a goodness-of-fit test, the Lilliefors statistic is used to determine whether an observed sample distribution is consistent with normality. The maximum difference between the observed distribution and a normal distribution with the same mean and standard deviation as the sample is calculated by this statistic and it determines whether or not the maximum discrepancy is statistically significant. The null hypothesis for this test is that the distribution is normal. The other possibility is that the distribution is non-normal. The empirical test of the Sensex reveals a value of 0.079 for the Lilliefors test statistic, with a p value of 0.0000 for obtaining this value. (See also table 5.2.) As a result, the null hypothesis of normality is rejected for index returns at 5% and even 1% level of significance.

Overall all the tests of normality are rejecting the null hypothesis of normality and it can be strongly inferred that Sensex returns are non-normal over the period concerned.

The study further uses a graphical method quantile- quantile (Q-Q) plot to check the condition of normality and leptokurtosis for the index returns (figure 5.2). The Q-Q plot is a graphical technique used to determine whether or not a data series follows a normal distribution. The Q-Q plot is a superior technique than other graphical methods for assessing normality. The Q-Q plot is a scattered plot and the quantiles of the return series is represented on the horizontal axis and expected normal return quantiles are represented on the vertical axis. In the Q-Q plot a 45^0 reference line is drawn to check the asymmetry from the normal distribution. If the data set is normal, the points should be distributed roughly along the reference 45^0 line. The greater the deviation from this reference line, the more evidence there is that the data set does not follow the reference (normal) distribution. In our empirical test of Sensex returns, the Q-Q plot for the index show the same behavior. The index's Q-Q plot has steeper slopes at the tails, and the slope of the tails differs from the slope of the index's central mass. These findings indicate that the empirical distribution of Sensex returns is not normal and has larger tails than the reference distribution (figure 5.2a).

Figure 5.2: Q – Q Plots of Sensex Return (a&b)





Source: Author's generation

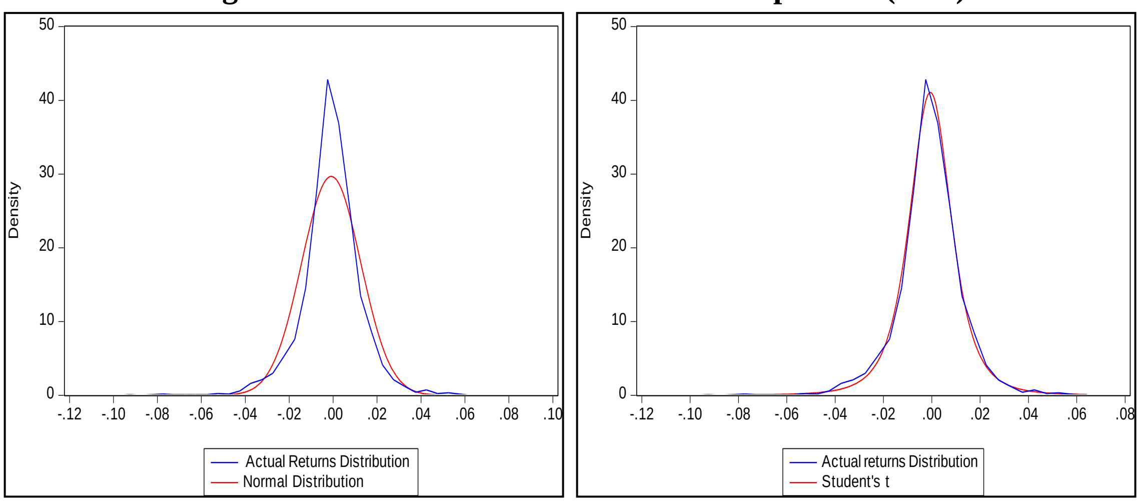
As the evidences presented above are highlighting that there exists lepto-kurtosis in return series, the study also attempts to determine whether theoretical distributions with higher kurtosis than the normal distribution can better represent the return distribution. The study uses the student's 't' distribution for this analysis.

The Q-Q plot of returns is better represented by the 't'-distribution than the normal distribution, as can be seen in figure 5.2(b). The quantiles of Sensex returns are found to be closer to the quantiles of the 't' distribution, implying that the 't' distribution is better at capturing the tails of return series.

The study also compares the actual return distribution with both normal and ‘t’ distributions (Figure 5.3). Figure 5.3(a) shows the original empirical distribution of returns with a superimposed normal distribution curve for making comparison. Actual returns are observed to be peaked at the mean, thin at the waist, and thick at the bottom, as opposed to the normal distribution, and matches all of the features of fat tails behaviour. In figure 5.3(b), the actual return series is compared to a more 'leptokurtic' distribution, student's 't'.

Leptokurtic distributions are fat-tailed distributions with thicker tails that are better equipped to reflect the distribution's extreme moves by providing a significant likelihood of exceeding a particular value in the tails. Figure 5.3(b) indicates that leptokurtic distributions like 't' are superior at capturing the 'fat tails' pattern of financial market returns.

Figure 5.3: Actual return distribution comparison (a&b)



Source: Author’s generation

A crucial assumption and criterion for financial return series is that they must be stationary across the time period under consideration. Otherwise, the results should not be used to forecast future market moves. When using historical data to develop statistical models for future forecasting, stationarity of the variables is desirable and essential. This has been verified using the unit root test in Table 5.3 using Augmented Dickey Fuller 'tau' statistics. With three alternative functional forms, this test checks for non-stationarity; “Random walk, Random walk with drift and Random walk with drift and trend.” The results of all the three tests are indicating that we need to reject the null hypothesis of non-stationarity and conclude that the series is stationary and it can be assumed that the behavior shown by Sensex returns in the past will continue in the future forecasting period as well and the modelling outcome will be reliable for future forecasting purposes.

Table 5.3: Checking Stationarity of Sensex returns

Null Hypothesis: Sensex Returns has a unit root						
Model	**trend parameter**	**drift**	**lagged coefficient**	**tau-Statistic**	**critical values (5% level)**	**H**
Random walk	NA	NA	-0.92	-46.35	-2.56	1
Random walk with drift	NA	0.0003	-0.93	-46.37	-2.86	1
Random walk with drift and trend	-1.70E-07	0.0005	0.93	-46.36	-3.41	1

Note: 'H' Stands for Boolean decision-making where H=0 means null hypothesis cannot be rejected. H=1 means null hypothesis can be rejected.

Source: Author's computation

Next important assumption usually made is that squared returns on the financial assets are usually found to be correlated. It is similar to the 'volatility clustering' phenomena which is also formally tested later by GARCH methods. A widely accepted approach to identifying this is the "Ljung-Box Q-statistic (LBQ statistic)" calculated on the squared return series. It is a test of joint hypothesis that all the ρ_k (auto-correlation coefficient up to lag k) are simultaneously equal to zero. The LBQ statistic is defined as (Equation 5.2):

$$Q = n(n+2)\sum_{k=1}^{m}\left(\frac{\hat{\rho}_k^2}{n-k}\right) \sim \chi^2(m) \qquad .... \qquad (5.2)$$

Where n = sample size, m = number of auto-correlation lags included in the statistic, and $\hat{\rho}_k^2$ is the squared sample auto-correlation at lag k. The LBQ statistic follows the chi-square distribution with m dof. The hypothesis testing is performed for serial dependence by choosing a level of significance and comparing the calculated value of χ^2 with the χ^2 table for critical value. If the calculated χ^2 is smaller than the critical χ^2 value, the null hypothesis of no serial dependence cannot be rejected.

Table 5.4: LBQ Test of Squared Sensex Return

Lags	Auto correlation Value	Q-stat	P-Values	H
5	21%	566	0.00	1
10	15%	1073	0.00	1
15	19%	1668	0.00	1
20	20%	2116	0.00	1

Note: 'H' Stands for Boolean decision-making where H=0 means null hypothesis cannot be rejected. H=1 means null hypothesis can be rejected.
Source: Author's computation

The empirical results of LBQ test statistics are given above in table 5.4. Table 5.4's final column, H, is a Boolean decision flag. H = 0 denotes that there is no significant correlation (i.e. do not reject the null hypothesis). H = 1 indicates that there is a significant correlation (i.e. reject the null hypothesis). The LBQ statistic is estimated at various lags like 5, 10, 15 and 20 lags. From table 5.4, it is observed that in the case of squared returns, the H values are 1 for all the lags which means that there exists serial dependence in squared returns. So, it can be concluded at 5% or even 1% level of significance that the squared return of Sensex has serial dependence. That is, they are not IID.

Next, very important assumption which was also seen graphically (in figure: 5.1) and below on LBQ statistic that volatility of financial return series occurs in clusters. It means that period of high volatility is followed by periods of higher volatility, and low volatility is followed by lower volatility. This phenomenon is called 'Volatility clustering'. To check the presence of volatility clustering, the study has estimated various Generalized Auto-Regressive Conditional Heteroscedasticity (GARCH) models. The GARCH will have the mean and variance equations which are used for forecasting volatility.

For a log return series "r_t, let $a_t = r_t - \mu_t$ which is the corrected mean log return. Then a_t follows a GARCH (p, q) process if (Equation 5.3),

$$a_t = \sigma_t \varepsilon_t,$$

$$\sigma_t^2 = \alpha_0 + \sum_{i=1}^{p} \alpha_i a_{t-i}^2 + \sum_{j=1}^{q} \beta_j \sigma_{t-j}^2 \qquad \cdots \ (5.3)$$

Where $\{\varepsilon_t\}$ is a sequence of IID variable with zero mean and variance one. Then $\alpha_0 > 0$, $\alpha_i \geq 0$, $\beta_j \geq 0$, and $\sum_{i=1}^{i=p}(\alpha_i) + \sum_{i=1}^{i=q}(\beta_j) < 1$. The constraint on α_i *and* β_j implies that the unconditional variance of a_t is finite, where as its conditional variance σ_t^2 evolves over time.

To keep the GARCH model parsimonious and avoid over-fitting, the study has analyzed GARCH models with a maximum of four total lags, i.e. GARCH (1, 1), GARCH (1, 2), GARCH (2, 1) and GARCH (2, 2) for the return series. The results are presented in Table 5.5.

Table 5.5: GARCH Models Estimates of Sensex Return

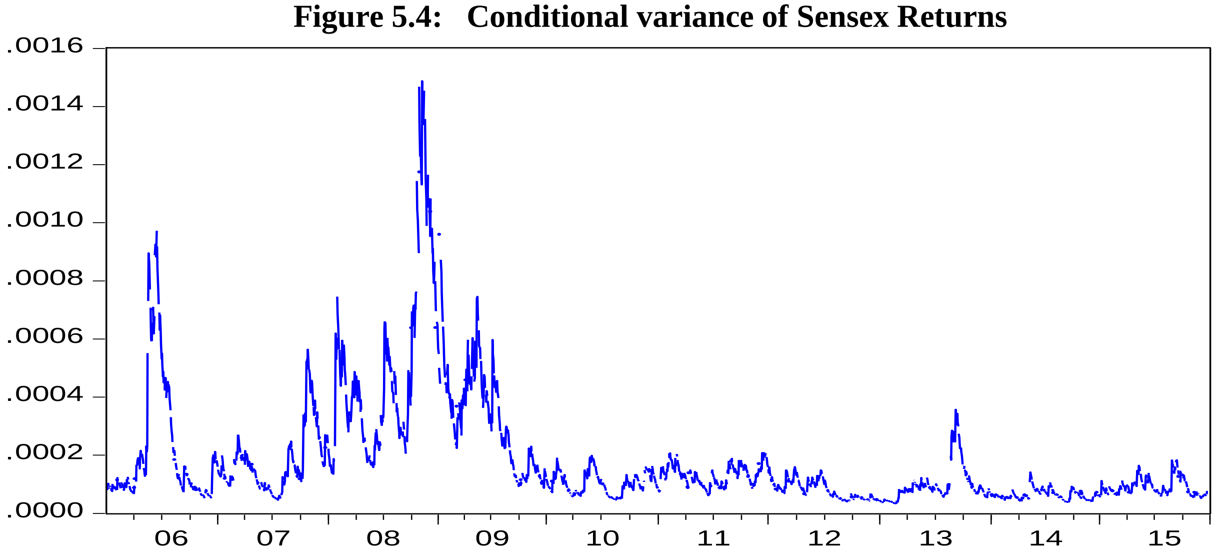
GARCH (p, q)	**Parameters**				
	α_0	**α_1**	**α_2**	**β_1**	**β_2**
GARCH (1, 1)	2.71E-06 (0.000)	0.0929 (0.000)		0.896 (0.000)	
GARCH (1, 2)	2.00E-06 (0.000)	0.067 (0.000)		1.203 (0.000)	-0.278 (0.056)
GARCH (2, 1)	2.76E-06 (0.000)	0.063 (0.000)	0.034 (0.057)	0.891 (0.000)	
GARCH (2, 2)	2.41E-06 (0.1635)	0.062 (0.000)	0.019 (0.762)	1.066 (0.094)	-0.157 (0.783)

Note: Values in the parenthesis represents the respective p-values
Source: Author's computation

The parameters estimate show that none of different order of GARCH model other than GARCH (1, 1) should be used for conditional volatility estimation as they are becoming insignificant (p-value is greater than 5%) such as GARCH (1, 2), GARCH (2, 1) and GARCH (2, 2). Overall, it is observed from Sensex return series that volatility clustering is best captured by GARCH (1, 1). The stationarity condition for GARCH (1, 1) is $\alpha_1 + \beta_1 < 1$. For Sensex, coefficients of GARCH (1, 1) are significant (i.e. α_1 = 0.092 and β_1 = 0.896). As is characteristic of GARCH model estimations for financial asset return data, the sum of the coefficients of the lagged squared error and lagged conditional variance is often found closer to unity (α_1 + β_1 is close to 0.98). But as the sum is less than unity, conditional variance equation tells us that we have 'stationarity' in conditional variance. As the prediction horizon lengthens for stationary GARCH models, conditional variance forecast values will converge on the long-term average value of variance. As the return series is best captured by GARCH (1,1), the study has calculated volatility by using the form GARCH (1,1). GARCH VaR is then computed by using the GARCH volatility and using the parametric formula for VaR (equation 4.6 in chapter 4). For generating backtesting results in the next section, the study has also used the optimal GARCH (1, 1) form for calculating the predicted number of exceptions.

Next, the study shows how the conditional variance changes over time using GARCH (1, 1). The conditional variance of Sensex returns is shown in figure 5.4 which shows its movement over time. It can be seen that there is relatively much higher volatility during the period of 2007-09 in conditional variance of Sensex returns as the world was facing the effects of Subprime mortgage crisis.

Figure 5.4: Conditional variance of Sensex Returns



Source: Author's generation

One major issue with the GARCH modelling is that it treats shocks to the volatility symmetrically. It treats all the shocks whether they are positive or negative equally. It will not be true for markets where 'leverage effects' are present. The empirically observed behavior of the financial returns shows that negative returns tend to influence volatility by a larger magnitude than a similar positive return of the same magnitude, this is known as 'leverage effect' phenomenon. This issue is captured by applying Exponential Generalized auto regressive Conditional Heteroscedasticity (EGARCH) method for volatility estimation which captures this asymmetric response for volatility estimation. The" exponential GARCH (EGARCH)" model was proposed by Nelson (1991). The conditional variance equation is estimated as follows (Equation 5.4):

$$ln(\sigma_t^2) = \alpha_0 + \beta ln(\sigma_{t-1}^2) + \gamma \frac{\varepsilon_{t-1}}{\sigma_{t-1}} + \theta \left[\frac{|\varepsilon_{t-1}|}{\sigma_{t-1}} - \sqrt{\frac{2}{\pi}} \right] \quad \text{.... (5.4)}$$

Leverage effects are captured in the above equation by the coefficient 'γ'. If it is observed to be negative and statistically significant, then it can be inferred that 'leverage effects' are present in the return series.

Table 5.6: EGARCH Model Estimates of Sensex Return

Coefficients	SENSEX
α_0	-0.329 (0.000)
β	0.9785 (0.000)
γ	-0.0809 (0.000)
θ	0.1919 (0.000)

Note: Values in the parenthesis represents the respective p-values
Source: Author's computation

Table 5.6 provides the results of EGARCH estimation. As, the coefficient γ is found to be negative and statistically significant for Sensex, All else being equal, positive return shocks produce less volatility than negative return shocks. Also, all the other coefficients are also statistically significant for Sensex. The presence of a "leverage effect" on stock market returns data during the sample period is indicated by a negative and statistically significant leverage term (*γ = -0.080)* different from zero.

Next, the study tries to find the answer to the first objective which is, finding the most appropriate VaR model for Indian equity market. The last chapter provided theoretical background around 3 parametric VaR methods namely "Variance-covariance (VcV), Exponentially Weighted Moving Average (EWMA) and Generalized Auto-Regressive Conditional Heteroscedasticity (GARCH) and 2 non-parametric methods namely Historical Simulation (HS) and Monte-Carlo Simulation (MCS) method." The study will first find the VaR values for Sensex at 99% confidence level using the 5 methods mentioned above and then will provide the backtesting results to find the most appropriate VaR method.

Table 5.7 below presents the results of VaR computation for Sensex using parametric (VcV, EWMA, GARCH) and non-parametric (HS and MCS) methods.

Table 5.7: VaR Computation for Sensex

Method	**VcV VaR**	**EWMA VaR**	**GARCH VaR**	**HS VaR**	**MCS VaR**
Value at Risk for 1-day horizon (VaR)	-3.603%	-1.719%	-1.547%	-4.382%	-1.683%

Note: VaR figures are at 99% level of confidence with 1day horizon.
Source: Author's computation

According to the study, the historical simulation method yields the highest VaR figure (-4.382 %). This means that there is a 99% likelihood that on a typical trading day, the Sensex will fall in value by a maximum of 4.382 % from its opening value, with only a 1% chance that it will fall more than that. This finding can assist market participants in developing appropriate market trading strategies and portfolio management activities. It is also observed that VaR estimates from other parametric methods (VcV, EWMA, and GARCH) and non-parametric MCS are comparatively lower and showing much diversion from the historical simulation. The huge differences in VaR estimates from different models are attributed to the underlying assumptions used by these models. The findings from the study indicates that Sensex returns have reached lower levels in the past, which are not well captured by normal distribution-based parametric methods. It implies that the normal distribution assumption is insufficient for the Indian equity market, and that returns may also deviate from the normal distribution in the near future. In the following section of backtesting, the study statistically validates this finding.

5.2.2 VaR Backtesting of Sensex returns

Finally, using backtesting, the study attempts to identify the most appropriate VaR method that best captures the market risk arising from the Indian equity market (Sensex). Backtesting is a statistical procedure used to determine the accuracy of a statistical model used for prediction. This methodology compares the actual results to the predictions made by the model used. If the actual loss on a given day exceeds the VaR predicted, the model is found to be unable to predict accurately on that day, and it is considered as an actual exception. An exception is defined as a violation and indicates that the model used is unable to accurately predict the VaR for that given day.

The study uses 1-period ahead rolling window forecast to calculate the predicted number of exceptions. The study uses the first 500 (1-500) data points from the beginning of the total historical time series data (Jan1, 2006 to Jan15, 2008) to project VaR for 501th day (Jan16, 2008). And then Data from day 2 to 501 to project for 502nd day VaR and so on. This continues and the total data points available to perform backtesting is 1980 (up to Dec 31, 2015). Finally, the actual and predicted number of exceptions are compared in backtesting procedure. The study uses 3 different tests to perform backtesting as mentioned below and all of these tests use total number of exceptions occurred as an input.

1. Actual number of exceptions test
2. The Basic Frequency Back-Test
3. Proportion Of Failure likelihood ratio (LR) test

1) **Actual number of exceptions**: This test computes the number of exceptions that occurred during the time period and compares it to the expected number of exceptions. For example, the expected number of exceptions over a 100-day period at 95 percent and 99 percent confidence levels are 5 and 1, respectively. This test only indicates whether total exceptions are under or over predicted by the model used. This test should be used in conjunction with the other two robust statistical methods listed below to determine the best VaR method.

2) **The Basic Frequency Back-Test:** The basic frequency (or binomial) test determines whether the observed frequency of tail losses (or frequency of losses that exceeded VaR) is

consistent with the predicted frequency of tail losses or number of VaR violations. The number of tail losses 'x' ,under the null hypothesis that the model is consistent with the data, follows a binomial distribution. Given 'n' return observations and a predicted frequency of tail losses of 'p,' this tells us the probability of x tail losses as (Equation 5.5):

$$p_r(x|n,p) = \binom{n}{x} p^x (1-p)^{n-x} \qquad \cdots (5.5)$$

Where 'n' is the total number of observations, 'p' is one minus the confidence level and 'x' is the number of exceptions. The binomial distribution can be well approximated by a normal distribution as the number of observation increases. As the present study has significant number of observations for backtesting (1980), the study has employed the normal approximation test as given below (Equation 5.6):

$$\mathrm{Z} = \frac{(x - np)}{\sqrt{n.p(1-p)}} \qquad \cdots (5.6)$$

Where $n.p$ implies the expected number of exceptions and [$n.p.(1 - p)$] determines the variance. This test follows the standard normal distribution with mean of 0 and variance of 1. The test statistic uses left tailed ‘z’ statistic as VaR is concerned with predicting losses and thus the left side of the return distribution is used for calculating the number of exceptions. The null hypothesis assumes that the model is correctly calibrated and if the value calculated is found higher than the critical value of the Z distribution, then the null hypothesis is rejected and the model is recognized as being incorrectly calibrated and unable to predict VaR accurately.

3) **Proportion of Failure LR test**: This is the likelihood ratio test suggested by Kupiec (1995) for backtesting and predicts whether significant difference exists between actual and observed failure rate. Failure rate is defined here as the total number of exceptions (x) observed over the total number of days (n). Here, p is the level of significance. This test uses LR statistic as (Equation 5.7):

$$LR = -2\ln\left[\frac{p^x(1-p)^{(n-x)}}{\left(\frac{x}{n}\right)^x \left(1-\frac{x}{n}\right)^{(n-x)}}\right] \sim \chi^2(1) \qquad \cdots (5.7)$$

The LR statistic follows a chi-square distribution with 1 degree of freedom. The null hypothesis assumes that the model has been correctly calibrated and if the value of the statistic exceeds the critical value of the χ^2 distribution, then the null hypothesis is rejected and the model is recognized as being incorrectly calibrated and unable to predict VaR accurately. Below table 5.8 provides the statistics obtained by using different backtesting methods for 1 day holding period using 95% confidence interval (CI).

Table 5.8: VaR Backtesting statistics at 95% Confidence Interval

METHOD	VCV VaR	EWMA VaR	GARCH VaR	HS VaR	MCS VaR
Actual number of exceptions	100	114	137	92	116
The Basic Frequency Back-Test z value	0.103	1.546	3.91	-0.721	1.752
Proportion Of Failure LR test χ^2 values	0.010	2.285	13.78	0.533	2.919

Note: expected number of exceptions = 99 (5% of 1980)
Note: z critical value at 5% level = 1.645
Note: χ^2 (1) critical value at 5% level = 3.841
Source: Author's computation

From the above table, it is evident that both the two statistical tests (The Basic Frequency Back-Test and LR test) are finding that VcV, EWMA, HS and MCS are able to predict well the VaR as the null hypothesis cannot be rejected for all of them. Hence, the study finds that at 95% CI VcV, EWMA, HS and MCS are all able to predict VaR reasonably well. However, at 95% confidence level the tails of the distribution may not be captured appropriately by the models and for observing the actual tails behavior of the return series, the study further performs backtesting of VaR at 99% confidence interval. Below table 5.9 provides the statistics obtained by using different backtesting methods for 1 day holding period using 99% confidence interval.

Table 5.9: VaR Backtesting statistics at 99% Confidence Interval

METHOD	VCV VaR	EWMA VaR	GARCH VaR	HS VaR	MCS VaR
Actual number of exceptions	32	40	53	24	43

The Basic Frequency Back-Test z value	2.755	4.56	7.49	0.94	5.24
Proportion Of Failure LR test χ^2 values	6.39	16.06	38.53	0.84	20.57

Note: expected number of exceptions = 20 (1% of 1980)
Note: z critical value at 1% level = 2.33
Note: χ^2 (1) critical value at 1% level = 6.63
Source: Author's computation

The above table shows that only the historical simulation method predicts well and the null hypothesis cannot be rejected for either of the two backtesting tests (the Basic Frequency Back-Test and the LR test). None of the other methods predict well, and the null hypothesis of the model being correct must be rejected for all other VaR methods (VcV, EWMA, GARCH and MCS). The only exception being VCV VaR where z test is still failed. Hence, only historical simulation predicts exceptions that are closer to the actual number of exceptions, given the actual number of exceptions. As a result, the study concludes that historical simulation is the best method for predicting VaR at 99% confidence level.

The findings also support the previously observed phenomenon of 'fat tails' behaviour in the Indian equity market. The 99% confidence interval is better able to capture fat tail behaviour and variation in distribution tails where fat tails actually occur. This is due to the fact that historical simulation method does not make any distributional assumption and provides VaR figure incorporating the fat tails behavior.

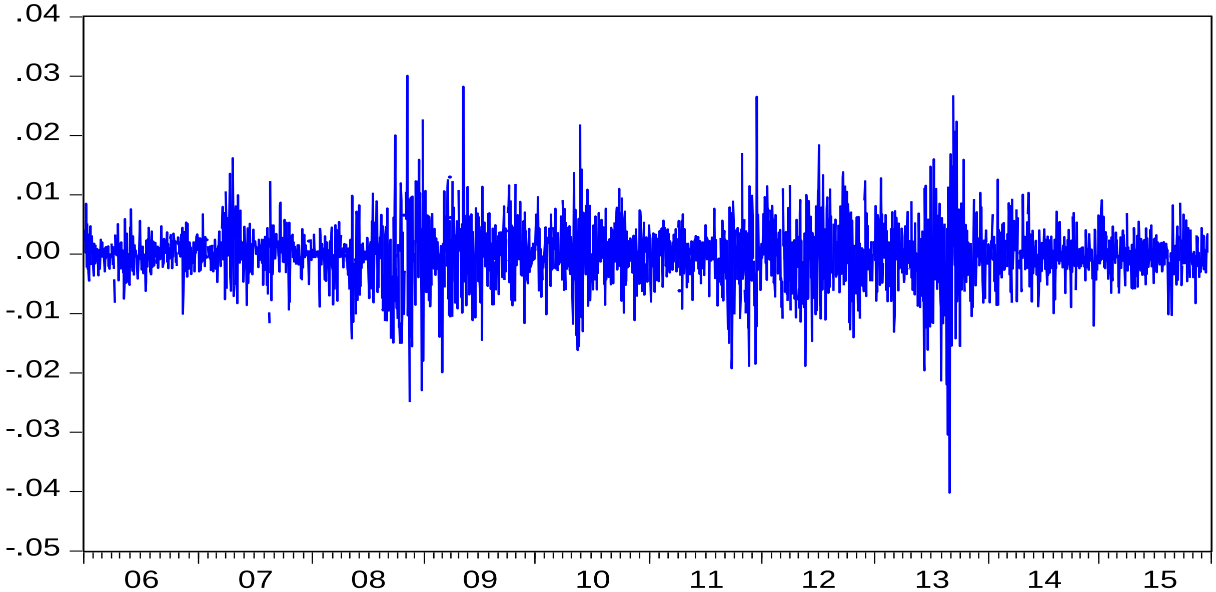
Overall, combining the backtesting results at 95% and 99%, the study concludes that Historical simulation is the best predictive VaR model for Indian equity market (Sensex).

5.3 Objective II: Market Risk assessment of Indian Currency Market

The second objective of study aims at finding the most appropriate VaR model for Indian currency market. Indian rupee/ US dollar (₹/$) exchange rate is taken as a benchmark to measure the risk arising out of Indian currency market as most of the international transactions related to foreign direct investment and foreign portfolio investment are routed through US $. For this objective, data on Indian-Rupee versus US dollar exchange rate is taken from the RBI's official website over the period from Jan 1, 2006 to Dec 31, 2015 covering a total of 2416 daily exchange rates. This range of data set allows the study to draw meaningful conclusions regarding the statistical behavior of exchange rate returns as the period is sufficiently long enough to study the behavior of currency market. Then continuously compounding returns are generated for the index as $\boldsymbol{R_t = \ln (I_t / I_{t-1})}$, where, R_t is the return at time t, I_t is the index value at time t , I_{t-1} is the index value at time $t - 1$ and ln is the natural logarithm. The study does not use percentage returns as they are not symmetric. Because of the lack of symmetry, when the index value rises from a current level to a higher level, the calculated return will not be equal when the index value falls from the same increased level to the previous level.

The results presented below are generated by taking rupee as the reference currency showing how much U.S dollars are required to buy one Indian rupee. This is achieved by simply taking the reciprocal of (USD/INR) exchange rate data taken from the RBI's official website. This is justified because in this case, positive returns would imply appreciating rupee and negative returns would imply depreciating rupee. The analysis therefore, is done from the perspective of the Indian investor who is interested in appreciating rupee. An Indian investor will calculate the VaR figure by considering the depreciation of Indian rupee as a negative return and appreciation of Indian rupee as a positive return.

Figure 5.5: Exchange rate Return Plot over 2006-2015



Source: Author's generation

Figure 5.5 above shows the graphical plot of Exchange rate returns. From the figure, it is evident that the return series is volatile during and after the global financial meltdown of 2007- 09. Significant volatility spikes are observed during year 2013 as Indian rupee was depreciating during that time. As Figure 5.5 shows, returns reached close to -4% which are lowest in the history of the 10-year period considered for the study. This depreciation was caused by Foreign Institutional Investors (FII) pulling out money from Indian financial market on the expectation that USA would phase out its Quantitative Easing (QE) policy and interest rates were expected to rise for financial investments in USA. Quantitative easing is a type of "unconventional monetary policy in which a central bank purchases government securities or other marketable securities in order to increase the money supply and encourage lending and investment". USA adopted Quantitative Easing after the global financial meltdown to spur economic growth.

Table 5.10: Descriptive Statistics of Exchange Rate Return

Variables	Exchange Rate Return series
Mean	-0.016%
Median	0.000
Maximum	3.006%
Minimum	-4.02%
Std. Dev.	0.53%

Skewness	-0.189
Kurtosis	7.52
Total Observations	2415

Source: Author's computation

Table 5.10 above shows the descriptive statistics of Exchange rate returns. From the descriptive statistics, it is evident that the returns over this period are negatively skewed with skewness value of -0.189. It is also observed that daily mean returns are on average negative and close to 0% (-0.016%) while daily standard deviation is found to be relatively significant (0.53%). Negative mean returns indicate that over this period due to mainly the impact of rupee depreciation caused by capital outflows, on an average, investor have lost over this 10-year period (0.016%). Asymmetric behavior in volatility is also observed. The volatility is much higher on the negative side (returns are reaching to -4.02% whereas positive returns are reaching to a maximum of close to 3%). "Fat Tailed" behavior in returns series is also observed as the Kurtosis value is 7.52. It is showing that empirically exchange rate returns have reached extremes on both positive and negative sides much more recurrently than predicted by a normal distribution.

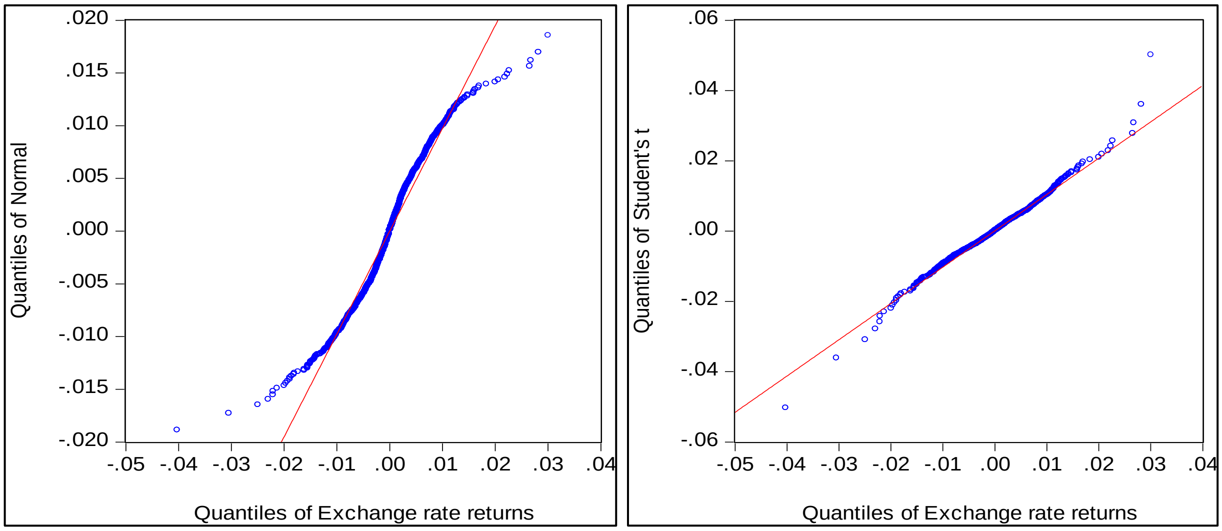
Table 5.11: Normality Test of Exchange Rate Returns

Normality Tests	SENSEX
Jarque - Bera	2075 (0.0000)
Anderson-Darling	24.32 (0.0000)
Lilliefors	0.070 (0.0000)

Note: Values in the parenthesis represents the respective p-values
Source: Author's computation

Table 5.11 shows normality tests of exchange rate returns. Overall, all the tests of normality are rejecting the null hypothesis of normality and it can be strongly inferred that exchange rate returns are non-normal over the period concerned.

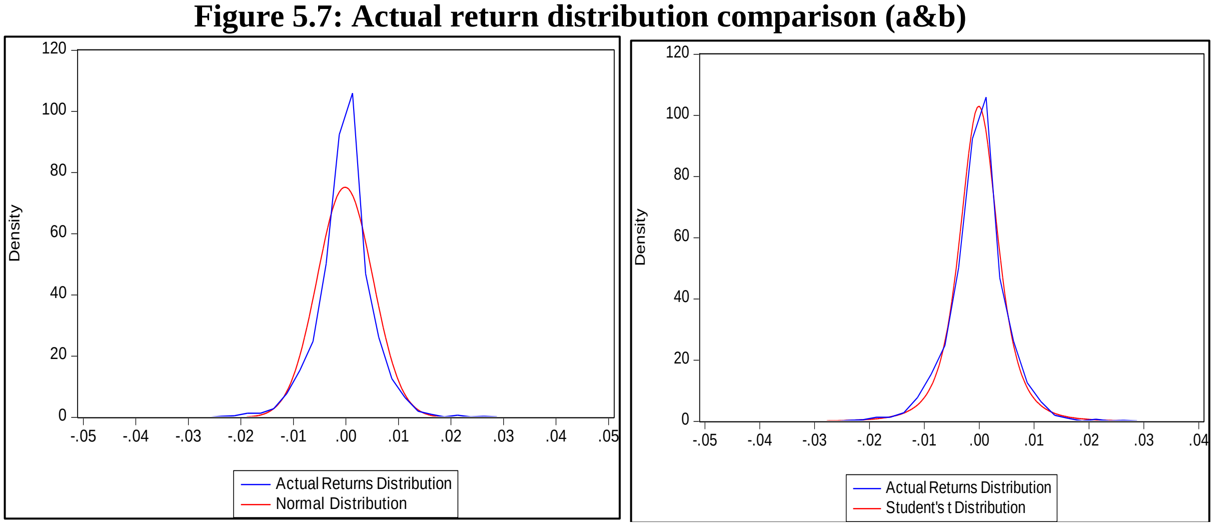
Figure 5.6: Q – Q Plots of Exchange Rate Return (a&b)



Source: Author's generation

The study further uses the graphical method quantile-quantile (Q-Q) plot to check the condition of normality and leptokurtosis for the exchange rate returns. From the Q-Q plot of returns in figure 5.6 (a & b), the Q-Q plot of returns is better approximated by 't'-distribution than the normal distribution. The quantiles of exchange rate returns are found more closer to 't' distribution quantiles (figure 5.6.b) and hence it can be inferred that 't' distribution is better able to capture the tails of returns series.

Figure 5.7: Actual return distribution comparison (a&b)



Source: Author's generation

The study further compares the actual distribution of returns with both normal and 't' distributions (Figure 5.7). The original empirical distribution of returns is plotted in Figure 5.7(a) with a superimposed normal distribution curve for making comparison. Figure 5.7(a&b) shows that leptokurtic distribution such as ‘t’ are better able to capture the peak and 'fat tails' behavior of actual returns of exchange rate series.

Next, the study tests the stationarity of Exchange Rate returns in table 5.12 below.

Table 5.12: Checking Stationarity of Exchange Rate returns

Null Hypothesis: Exchange Rate returns has a unit root						
Model	**trend parameter**	**drift**	**lagged coefficient**	**tau-Statistic**	**critical values (5% level)**	**H**
Random walk	NA	NA	-0.988	-48.53	-1.94	1
Random walk with drift	NA	-0.0001	-1.054	-48.57	-2.86	1
Random walk with drift and trend	-1.72E-07	4.83E-05	-0.989	-48.58	-3.41	1

Note*: 'H' Stands for Boolean decision-making where H=0 means null hypothesis cannot be rejected. H=1 means null hypothesis can be rejected.*
Source: Author's computation

From table 5.12, the results of all the three forms of stationarity tests are indicating that we need to reject the null hypothesis of unit root and conclude that the series does not contain a unit root and is thus stationary. It can thus be assumed that the behavior shown by exchange rate returns will continue in the future forecasting period as well and the model built on exchange rate returns can be relied upon for future forecasting purposes**.**

Next, the study tests whether squared returns are correlated in table 5.13 below.

Table 5.13: LBQ Test of squared Exchange Rate Return

Lags	**Auto correlation Value**	**Q-stat**	**P-Values**	**H**
5	15.9%	547	0.00	1
10	13.2%	910	0.00	1
15	12.8%	1157	0.00	1
20	7.3%	1345	0.00	1

Note: 'H' Stands for Boolean decision-making where H=0 means null hypothesis cannot be rejected. H=1 means null hypothesis can be rejected.

Source: Author's computation

From table 5.13, it is observed that in case of squared returns, the H values are 1 for all lags which means that there exists serial dependence in squared returns. So, it can be concluded at 5% or even at 1% level of significance that the squared return of exchange rate return series has serial dependence. That is, they are not IID.

Next, the study finds the optimal GARCH parameters by using various lags. To keep the GARCH model parsimonious and avoid over-fitting, the study has analyzed GARCH models with a maximum of four total lags, i.e. GARCH (1, 1), GARCH (1, 2), GARCH (2, 1) and GARCH (2, 2) for the return series. The results are presented in Table 5.13 below.

Table 5.14: GARCH Models Estimates of Exchange Rate Return

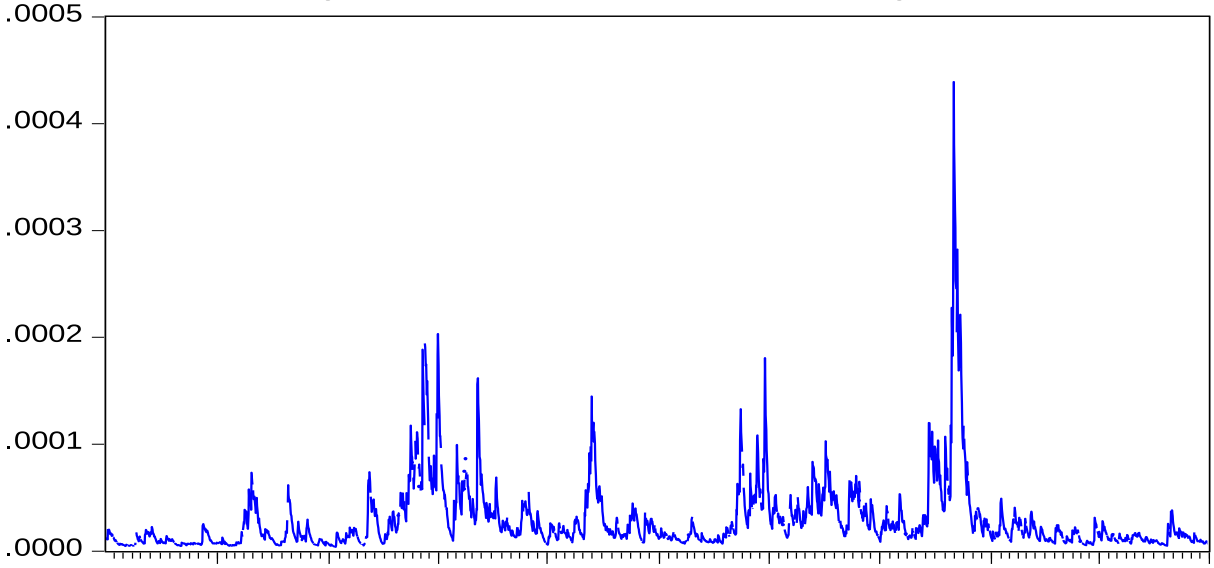
GARCH (p, q)	**Parameters**				
	α_0	**α_1**	**α_2**	**β_1**	**β_2**
GARCH (1, 1)	5.51E-07 (0.000)	0.1546 (0.000)		0.8317 (0.000)	
GARCH (1, 2)	5.69E-07 (0.000)	0.173 (0.000)	-	0.6250 (0.000)	0.1884 (0.1333)
GARCH (2, 1)	3.13E-07 (1.000)	0.2115 (0.000)	-0.0987 (0.0006)	0.8805 (0.000)	-
GARCH (2, 2)	5.65E-09 (0.0415)	0.1990 (0.000)	-0.1957 (0.000)	1.7266 (0.000)	-0.7300 (0.000)

Note: Values in the parenthesis represents the respective p-values
Source: Author's computation

Table 5.14 shows the GARCH Models estimates of exchange rate returns with different lags, i.e. GARCH (1,1), GARCH (1,2), GARCH (2,1) and GARCH (2,2) for the exchange rate return series. The parameters estimate show that GARCH (1,1) is the most appropriate to be used for conditional volatility estimation. Other models are either giving insignificant coefficients (i.e. GARCH (1, 2)) or, it is observed that stationarity condition of long-term variance ($\alpha_1 + \beta_1 < 1$) is violated (i.e. (2, 1) (2, 2)) and these models are thus not appropriate to be used for conditional volatility estimation. Hence, the study will use GARCH (1, 1) extension for calculating GARCH VaR and for performing backtesting in the next section.

Next, figure 5.8 shows the conditional variance using GARCH (1, 1). The conditional variance of exchange rate returns shows relatively much higher volatility during the year 2013 due to high depreciation of rupee caused by outflow of FII from Indian economy in the expectation or rising interest rates in USA.

Figure 5.8: Conditional variance of exchange rate returns



Source: Author's generation

To capture asymmetric changes to volatility, the study now uses EGARCH in table 5.15 below.

Table 5.15: EGARCH Model Estimates of Exchange Rate Return

Coefficients	**Exchange Rate Returns** ($/₹)
α_0	-0.6113 (0.000)
β	0.9632 (0.000)
γ	-0.0574 (0.000)

θ	0.2798 (0.000)

Note: Values in the parenthesis represents the respective p-values
Source: Author's computation

Table 5.15 shows that the leverage term (= -0.0574) is negative and statistically distinct from zero, showing that there was a leverage effect on exchange rate returns over the sample period. this is implying that positive return shocks cause less volatility than negative return shocks, if all other factors are equal. Finally, the study tries to find the answer to the second objective which is, finding the most appropriate VaR model for Indian currency market.

Table 5.16 below presents the results of VaR computation for exchange rate returns using parametric (VcV, EWMA, GARCH) and non-parametric (HS and MCS) methods.

Table 5.16: VaR Computation for exchange rate returns

Method	VcV VaR	EWMA VaR	GARCH VaR	HS VaR	MCS VaR
Value at Risk for 1-day horizon (VaR)	-1.251%	-0.617%	-0.488%	-1.494%	-0.654%

Note: VaR figures are at 99% level of confidence with 1day horizon.
Source: Author's computation

It is observed that the highest VaR figure is observed by using HS VaR method (-1.494 %). It means that there is a 99% probability that on a typical trading day, investors can expect that US dollar/ Indian rupee ($/₹) exchange rate can rise to a maximum up to 1.494%. (Depreciating rupee and appreciating dollar, negative return for an Indian investor) from its opening value and there is only 1% probability that it can rise more than that. This information can help forex market participants and hedge funds to form appropriate market trading strategies and portfolio management related activities. VaR calculated by other parametric methods (VcV, EWMA, and GARCH) and non-parametric MCS are found comparatively lower and showing much diversion from the historical simulation. The huge differences in VaR estimates from different models are attributed to the underlying assumptions used by these models. The results are suggesting that exchange rate returns have reached lower levels in the past which are not well captured by the normal distribution based parametric methods. It suggests that normal distribution assumption is not adequate for Indian currency market and in the near future, it can be expected that the returns may very well deviate from the normal distribution. The study further tests this finding statistically in the next section of backtesting.

5.3.1 VaR Backtesting of exchange rate returns

Below table 5.17 provides the statistics obtained by using different backtesting methods for 1 day holding period using 95% confidence interval.

Table 5.17: VaR Backtesting statistics at 95% Confidence Interval

METHOD	VCV VaR	EWMA VaR	GARCH VaR	HS VaR	MCS VaR
Actual number of exceptions	124	116	148	119	126
The Basic Frequency Back-Test z value	2.95	2.11	5.47	2.43	3.17
Proportion Of Failure LR test χ^2 values	8.02	4.21	25.85	5.50	9.15

Note: expected number of exceptions = 96 (5% of 1915)
Note: z critical value at 5% level = 1.645
Note: χ^2 (1) critical value at 5% level = 3.841
Source: Author's computation

From the above table, it is observed that EWMA method gives the least number of exceptions among all the methods. However, from the basic Frequency back-test and LR test, none of the method is found to be predicting VaR well enough statistically wherein the null hypothesis cannot be rejected and the model can be accepted as calibrated well. Hence, combining the results of all the three methods, it is evident that there is no single VaR method which passes all the tests yet EWMA VaR seems to be relatively better VaR method going by the actual number of exceptions.

The study further tries to capture the tail behaviour adequately by performing backtesting at 99% confidence interval. Backtesting at higher confidence interval can capture the tail behaviour adequately if there is a presence of heavy tails in the returns dataset.

Below table 5.18 provides the exceptions obtained by using different backtesting methods for 1 day holding period using 99% confidence interval.

Table 5.18: VaR Backtesting statistics at 99% Confidence Interval

METHOD	VCV VaR	EWMA VaR	GARCH VaR	HS VaR	MCS VaR
Actual number of exceptions	47	49	62	32	51
The Basic Frequency Back-Test z value	6.39	6.85	9.83	2.94	7.31
Proportion Of Failure LR test χ^2 values	29.10	32.81	60.90	7.23	36.71

Note: expected number of exceptions = 20 (1% of 1915)
Note: z critical value at 1% level = 2.33
Note: χ^2 (1) critical value at 1% level = 6.63
Source: Author's computation

From the above table, it is observed that HS VaR method gives the least number of exceptions among all the methods. However, from the basic Frequency back-test and LR test, none of the method is found to be predicting VaR well enough statistically wherein the null hypothesis cannot be rejected and the model can be accepted as calibrated well. Hence, combining the results of all the three methods, it is evident that there is no single VaR method which passes all the 3 tests yet HS VaR seems to be relatively the best VaR method going by the actual number of exceptions.

At 95% however, EWMA was found to be relatively the best method. The 99% confidence interval is better than 95% as it can capture the tail behaviour and can capture the variation in the tails of distribution. Since, risk management is more concerned about predicting risk well during unfavorable scenarios, the study gives 99% confidence interval results more weightage compared to 95% confidence level.

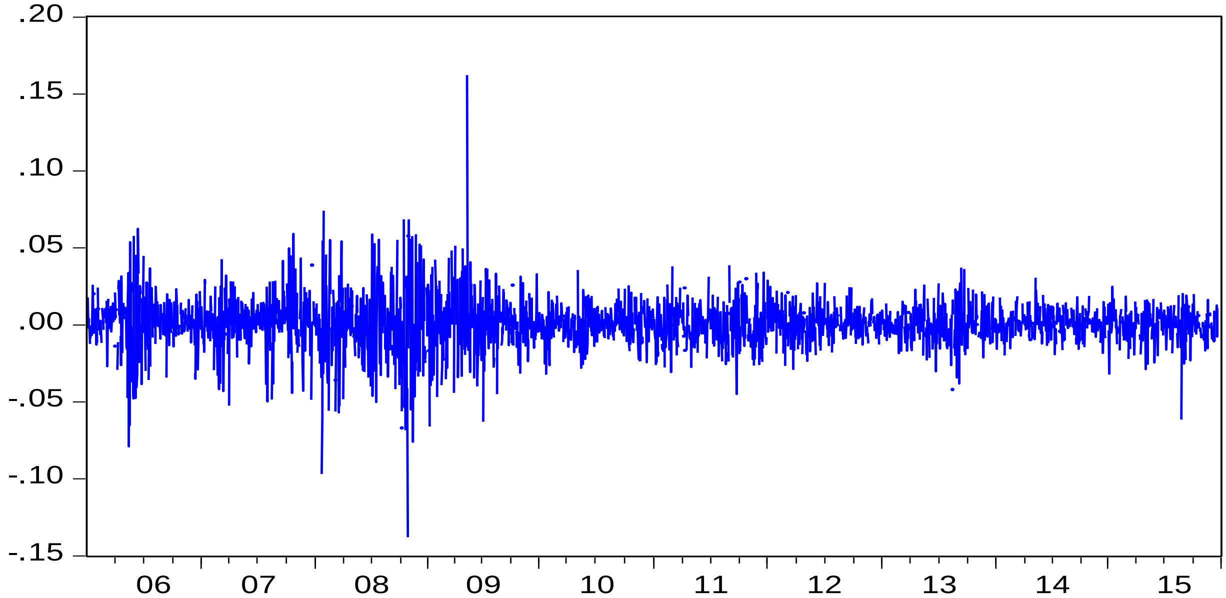
Overall, combining the backtesting results at 95% and 99%, the study concludes that Historical simulation is relatively better VaR predictive model for Indian currency market (Indian rupee/ US dollar (₹/$) exchange rate).

5.4 Objective III: Market Risk assessment of Indian Futures Market

A derivative is a financial instrument whose value is derived from the value of an underlying asset. It is a contract between two or more parties in which the price of the derivative is determined by changes in the underlying asset. Futures contracts are standardized derivatives that are exchanged on futures exchanges. “A futures contract is a legally binding agreement to acquire or sell a certain asset at a preset price and at a future date”. A futures contract's 'buyer' accepts the responsibility to purchase the underlying asset at a defined price and at a particular period in the future. The seller of the futures contract agrees to sell the asset at a predetermined price and at a predetermined time in the future. A buyer or the one who has a "long" position in futures is someone who will benefit if the current price of the underlying security rises. The seller or the one having ‘short’ position in the futures is someone who will benefit when the current price of the underlying security falls. The analysis presented in the study assumes that the investor is long in futures and will experience positive returns when the underlying (Nifty futures) will increase in value.

The third objective of the present study aims at finding the most appropriate VaR model for Indian Futures (derivative) market. Nifty is one of the two national level stock exchange (Sensex being the other one) and most of the derivative trading (close to 90%) in Indian Financial Market is accounted by “National Stock Exchange (NSE)”. Nifty futures are contracts that give their buyer or seller the right to buy or sell the Nifty 50 index at a predetermined price for delivery at a later date. Nifty futures index is taken as a benchmark to measure risk arising out of Indian futures market. NIFTY 50 Futures Index has been developed to track the performance of Nifty 50 Futures contract. For the third objective, data on Nifty 50 futures Index is taken from the NSE's official website over the period from Jan 1, 2006 to Dec 31 2015, covering a total of 2480 data points. This range of data set allows the study to draw meaningful conclusions regarding the statistical behavior of index returns as the period is sufficiently long enough to study the behavior of futures market. Then continuously compounding returns are generated for the index as $\boldsymbol{R_t = \ln (I_t / I_{t-1})}$, where, R_t is the return at time t, I_t is the index value at time t and I_{t-1} is the index value at time $t-1$.

Figure 5.9: Nifty Futures returns plot over 2006-2015



Source: Author's generation

Figure 5.9 above shows the graphical plot of nifty futures returns. From the figure, it is evident that the return series is volatile during the global financial meltdown of 2007-09. This is supporting the fact that most of the major economies of the world's financial system were influenced by the subprime mortgage crises originated in USA. It is also observed regarding the normally made assumption for continuous compounded returns that daily returns are on an average 0% while daily volatility is not and is generally found to be significant. This behavior can also be observed as over the 10 years' period, returns are more or less hovering around 0% but significant spikes in volatility are observed.

Table 5.19: Descriptive Statistics of Nifty Futures Returns

Variables	Nifty Futures Returns
Mean	0.0639%
Median	0.0890%
Maximum	16.22%
Minimum	-13.80%
Std. Dev.	1.64%
Skewness	-0.109
Kurtosis	11.35

Total Observations	2480

Source: Author's computation

Table 5.19 above shows the descriptive statistics of Nifty Futures. From the statistics, it is evident that the returns over this period are negatively skewed with skewness value of -0.109. It is also observed that daily mean returns are close to 0% (0.063%) while daily standard deviation is found to be relatively significant (1.64%). Positive mean returns (0.0639%) indicate that over this period, an investor holding 'long' position in futures have seen on an average positive return. 'Fat Tailed' behavior in returns series is also observed as the kurtosis value is 11.35. It is showing that empirically Nifty Futures returns have reached extremes on both positive and negative sides much more frequently than what is predicted by a normal distribution.

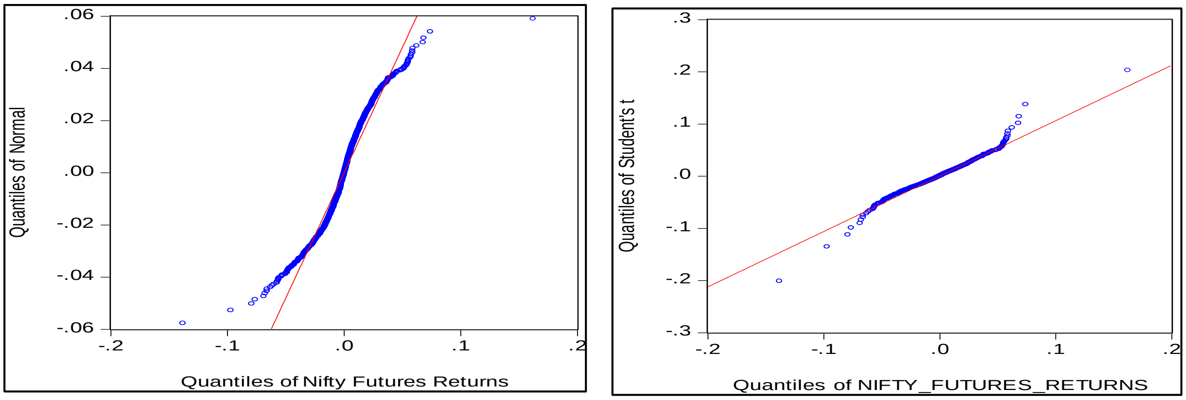
Table 5.20: Normality Test of Nifty Futures Returns

Normality Tests	Nifty Futures
Jarque - Bera	7210 (0.0000)
Anderson-Darling	38.52 (0.0000)
Lilliefors	0.079 (0.0000)

Note: Values in the parenthesis represents the respective p-values
Source: Author's computation

Table 5.20 shows different normality tests of Nifty futures returns series. Overall, all the tests of normality are rejecting the null hypothesis of normality and it can be inferred that Nifty futures returns are non-normal over the period concerned.

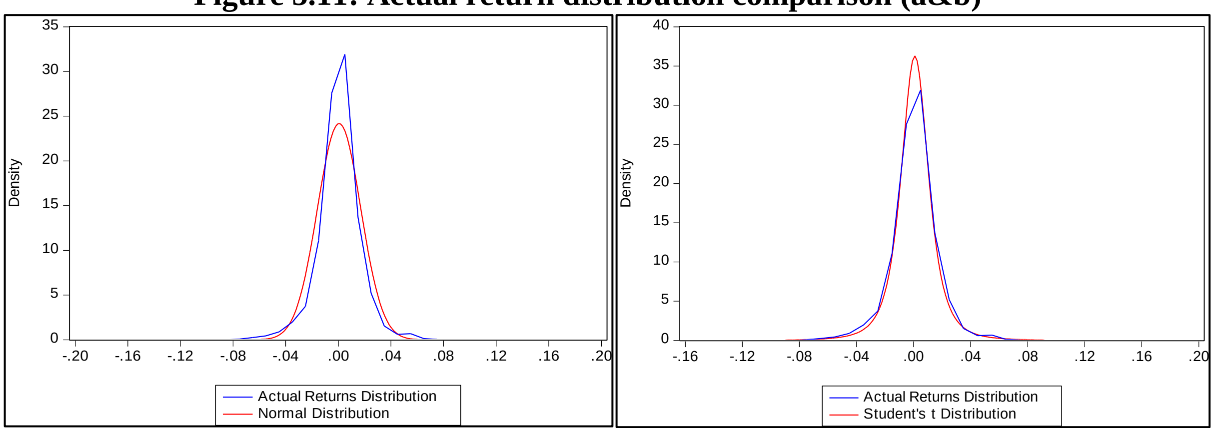
Figure 5.10: Q – Q Plots of Nifty Futures Returns (a&b)



Source: Author's generation

The study further uses the graphical method quantile-quantile (Q-Q) plot to check the condition of normality and leptokurtosis for the Nifty futures returns. From the Q-Q plot of returns in figure 5.10 (a & b), the Q-Q plot of returns is better approximated by 't'-distribution than the normal distribution. The quantiles of exchange rate returns are found closer to 't' distribution quantiles (figure 5.10.b) and hence it can be inferred that 't' distribution is better able to capture the tails of returns series.

Figure 5.11: Actual return distribution comparison (a&b)



Source: Author's generation

The study further tries to compare the actual distribution of returns with both normal and 't' distributions (Figure 5.11). The original empirical distribution of returns is plotted in Figure 5.11(a) with a superimposed normal distribution curve for making comparison. Figure 5.11(a&b) shows that leptokurtic distributions such as 't' performs relatively better to capture the peak and 'fat tails' behavior of Nifty futures returns series.

Next, the study tests the stationarity of Nifty futures returns in table 5.21 below.

Table 5.21: Checking Stationarity of Nifty Futures Returns

Null Hypothesis: Nifty Futures Returns has a unit root						
Model	**trend parameter**	**drift**	**lagged coefficient**	**tau-Statistic**	**critical values (5% level)**	**H**
Random walk	NA	NA	-0.9797	-48.79	-1.94	1
Random walk with drift	NA	0.0006	-0.9812	-48.85	-2.86	1
Random walk with drift and trend	-3.64E-07	0.0010	-0.981	-48.85	-3.41	1

Source: Author's computation

From table 5.21, the results of all the three tests are indicating that we need to reject the null hypothesis of having a unit root and conclude that the series does not contain a unit root and is thus stationary. It can hence be assumed that the behavior shown by Nifty Futures Returns will continue in the future forecasting period as well**.**

Next, the study tests whether squared returns are correlated in table 5.22 below.

Table 5.22: LBQ Test of Nifty Futures Returns

Lags	Auto correlation Value	Q-stat	P-Values	H
5	18.1%	367	0.00	1
10	19.1%	677	0.00	1
15	13.8%	883	0.00	1
20	11.00%	1023	0.00	1

Source: Author's computation

From table 5.22, it is observed that in case of squared returns, the H values are 1 for all lags which means that there exists serial dependence in squared returns. So, it can be concluded at

5% or even at 1% level of significance that the squared return of Nifty Futures series has serial dependence and they are not IID.

Next, the study finds the optimal GARCH parameters by using various lags in table 5.23 below.

Table 5.23: GARCH Models Estimates of Nifty Futures Returns

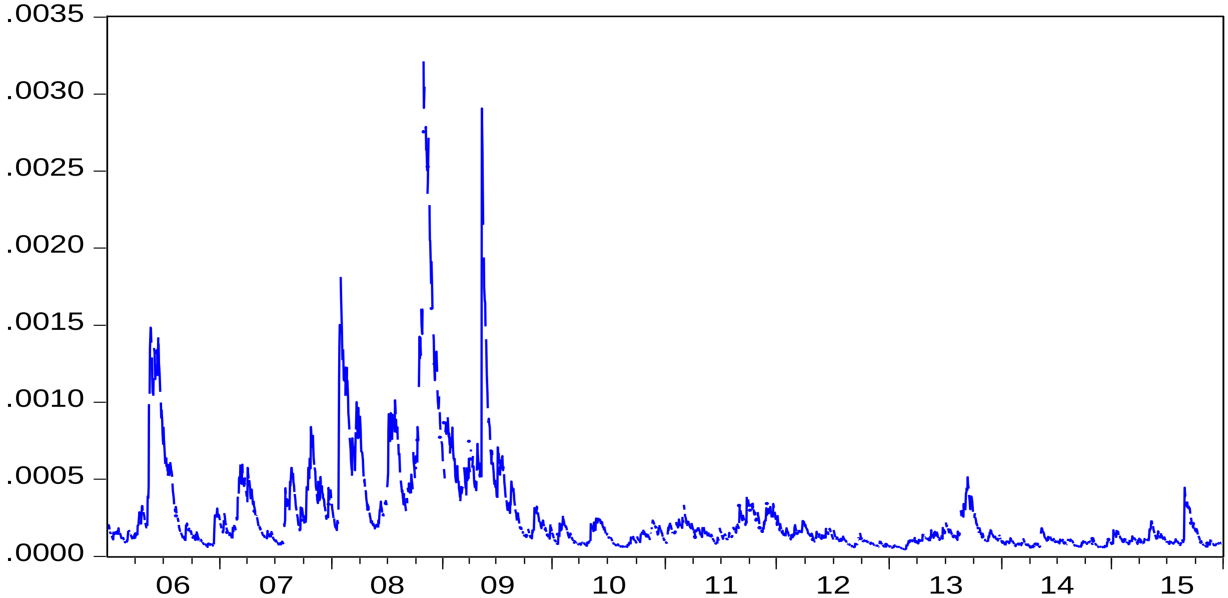
GARCH (p, q)	Parameters				
	α_0	**α_1**	**α_2**	**β_1**	**β_2**
GARCH (1, 1)	2.99E-06 (0.000)	0.096 (0.000)	-	0.893 (0.000)	-
GARCH (1, 2)	2.44E-06 (0.000)	0.079 (0.000)	-	1.143 (0.000)	-0.2298 (0.0862)
GARCH (2, 1)	3.25E-06 (0.000)	0.073 (0.000)	0.033 (0.0498)	0.883 (0.000)	-
GARCH (2, 2)	2.97E-06 (0.128)	0.0729 (0.000)	0.0239 (0.7314)	0.9834 (0.1364)	-0.0890 (0.879)

Note: Values in the parenthesis represents the respective p-values
Source: Author's computation

Table 5.23 above shows the GARCH model estimates of Nifty futures returns with different lags, i.e. GARCH (1,1), GARCH (1,2), GARCH (2,1) and GARCH (2,2) for the index series. The parameters estimate show that none of different order of GARCH other than GARCH (1,1) should be used for conditional volatility estimation as they are becoming insignificant (p-value is greater than 5%) such as GARCH (1, 2), GARCH (2, 1) and GARCH (2, 2). Hence, the study will use GARCH (1, 1) extension for calculating GARCH VaR and also for performing backtesting in the next section.

Next, figure 5.12 below shows the conditional variance for optimal volatility forecasting model (GARCH (1, 1). It can be seen that there is relatively much higher volatility during the period of 2007-09 in conditional variance of Nifty futures returns as the world was facing the effects of Subprime mortgage crisis.

Figure 5.12: Conditional variance of Nifty Futures Returns



Source: Author's generation

To capture asymmetric changes to volatility, the study now uses EGARCH in table 5.24 below.

Table 5.24: EGARCH Model estimates of Nifty Futures Returns

Coefficients	Nifty Futures Returns
α_0	-0.3771 (0.000)
β	0.9747 (0.000)
γ	-0.0880 (0.000)
θ	0.2113 (0.000)

Note: Values in the parenthesis represents the respective p-values; Source: Author's computation

From Table 5.24, it is observed that the leverage term (γ = *-0.0880)* is negative and statistically different from zero, indicating that positive return shocks produce less volatility than negative return shocks, all else being equal, and leverage effects are present in the Nifty futures returns.

Finally, the study tries to find answer to the third objective which is finding the most appropriate VaR model for Indian futures (derivative) market.

Table 5.25 below presents the results of VaR computation for Nifty future returns using parametric (VcV, EWMA, GARCH) and non-parametric (HS and MCS) methods.

Table 5.25: VaR Computation of Nifty futures returns

Method	**VcV VaR**	**EWMA VaR**	**GARCH VaR**	**HS VaR**	**MCS VaR**
Value at Risk for 1-day horizon (VaR)	-3.77%	-1.68%	-1.48%	-4.80%	-2.78%

Note: VaR figures are at 99% level of confidence with 1day horizon.
Source: Author's computation

It is discovered that the HS VaR method yields the highest VaR figure (-4.80%). It means that there is a 99 percent chance that on a typical trading day, investors can expect Nifty futures returns to fall by a maximum of 4.80 % from their opening value, with only a 1% chance that it will fall more than that. This analysis can help market participants in developing appropriate market trading strategies and portfolio management activities. VaR estimates from other parametric methods (VcV, EWMA, and GARCH) and non-parametric MCS are comparatively lower and showing much diversion from the historical simulation. The huge differences in VaR estimates from different models are attributed to the underlying assumptions used by these models. The findings indicate that Nifty futures returns have reached lower levels in the past, which are not well captured by normal distribution-based parametric methods. It implies that the normal distribution assumption is insufficient for the Indian futures market, and that returns can be expected to deviate from the normal distribution in the near future. In the following section of backtesting, the study statistically tests this finding.

5.4.1 VaR Backtesting of Nifty futures returns

Below table 5.25 provides the statistics obtained by using different backtesting methods for 1 day holding period using 95% confidence interval.

Table 5.26: VaR Backtesting statistics at 95% Confidence Interval

METHOD	VCV VaR	EWMA VaR	GARCH VaR	HS VaR	MCS VaR
Actual number of exceptions	91	114	141	88	111
The Basic Frequency Back-Test z value	-0.82	1.54	4.33	-1.13	1.23
Proportion Of Failure LR test χ^2 values	0.69	2.28	16.67	1.33	1.47

Note: expected number of exceptions = 99 (5% of 1980)
Note: z critical value at 5% level = 1.645
Note: χ^2 (1) critical value at 5% level = 3.841
Source: Author's computation

From the above table, it is evident that both the two statistical tests (The Basic Frequency Back-Test and LR test) are finding that VcV, EWMA, HS and MCS are able to predict well the VaR as the null hypothesis cannot be rejected for all of them. Hence, the study finds that at 95% CI VcV, EWMA, HS and MCS are able to predict VaR reasonably well. However, at 95% confidence level the tails of the distribution may not be captured appropriately by the models and for observing the actual tails behaviour of the return series, the study further performs backtesting at 99% confidence interval. Below table 5.27 provides the statistics obtained by using different VaR backtesting methods for 1 day holding period using 99% confidence interval.

Table 5.27: VaR Backtesting statistics at 99% Confidence Interval

METHOD	VCV VaR	EWMA VaR	GARCH VaR	HS VaR	MCS VaR
Actual number of exceptions	34	40	59	23	37
The Basic Frequency Back-Test z value	3.20	4.56	8.85	0.72	3.88

Proportion Of Failure LR test χ^2 values	8.46	16.06	51.22	0.49	12.01

Note: expected number of exceptions = 20 (1% of 1980)
Note: z critical value at 1% level = 2.33
Note: χ^2 (1) critical value at 1% level = 6.63
Source: Author's computation

According to the above table, both statistical tests (the Basic Frequency Back-Test and the LR test) show that only the historical simulation method predicts well, and the null hypothesis cannot be rejected for either of the test. None of the other methods predict well, and the null hypothesis of the model being correct must be rejected for all other methods (VcV, EWMA, GARCH and MCS). The actual number of exceptions also shows that only historical simulation predicts exceptions that are closer to the expected. As a result, the study concludes that historical simulation is the best method for predicting VaR at 99% confidence interval. The findings also support the previously observed phenomenon of 'fat tails' behaviour in the Nifty futures market. The 99 percent confidence interval is more suitable of capturing tail behaviour and variation in the distribution of the tails.

Overall, combining the backtesting results at 95% and 99%, the study concludes that Historical simulation is the best predictive VaR model for Indian Futures market.

5.5 Conclusion

The present chapter has given the empirical findings related to the 3 objectives of the present study. All the major assumptions before any modelling exercise are also tested for the 3 objectives. VaR for the 3 markets are calculated and backtesting is performed at 95% and 99% confidence level. The study finally concludes that historical simulation method is the most appropriate VaR method for each of the Indian financial market namely, equity, forex and derivative.

CHAPTER - 6

SUMMARY, FINDINGS AND CONCLUSIONS

6.1 Introduction

Indian financial system has undergone various transformations primarily in the last 3 decades. The introduction of innovative and complex financial products such as derivatives is one such development. As a result, the level of risk associated with financial investments has also increased. It has led to many financial innovations and disasters. These financial disasters can create instability in the smooth functioning of the economy. As a result of this, many financial institutions, regulators and researchers are trying their level best to develop a good risk measurement and management tool. VaR has emerged as a trustworthy tool for market risk measurement in the discipline of financial risk management. It is basically a probabilistic measure. VaR is defined as the maximum amount one can lose over a given period of time and with a certain predefined confidence level. Due to its simplicity and accuracy, VaR has become the most popular method of market risk measurement and has been suggested by many regulatory authorities across the world (e.g. Basel). Market risk, credit risk, liquidity risk, and operational risk are all examples of financial risks. VaR mainly tries to measure the market risk. Market risk is the risk which arises from the movement in the level of market prices of financial assets like stocks, bonds, exchange rates and other market traded financial instruments.

The present study aims at finding the most appropriate VaR model for various Indian financial markets namely equity, forex and derivative. The study has selected various benchmarks representing each of the market. BSE Sensex, Indian rupee/ US dollar (₹/$) exchange rate and Nifty futures are taken as benchmark indices for Indian equity, forex and derivative markets respectively.

6.2 Main Findings

The theoretical review of different VaR models found that VaR can be calculated by parametric and non-parametric models. In the parametric domain, a probability distribution function to model the return distribution is assumed. VaR is measured by estimating the parameters of the assumed distribution. Methods such as “variance-covariance (VcV), Exponentially Weighted

Moving Average (EWMA) and Generalized Auto-Regressive Conditional Heteroscedasticity (GARCH)" come under this category. In the case of non-parametric models, there is no assumption of any probability distribution and does not involve any parameter estimations. They are based on the actual realized distribution obtained from the historical data. Non parametric models does not involve any estimation of parameters and hence reduces the model risk. "Historical Simulation and Monte Carlo simulation" methods comes under this category.

The study observed the empirical findings for the different Indian financial markets namely: equity, forex and derivative. It is observed across all the markets that financial returns are non-normal, skewed and characterized by excess kurtosis and hence exhibit fat tails behavior. It shows that the probability of experiencing extreme returns (positive and negative) on either side of the mean is much higher than what is suggested by the usually assumed normal distribution. This observation leads to the finding that financial return series is captured adequately by using 'leptokurtic distributions' which allow for fat tails behaviour like student's 't' distribution.

The level of volatility is relatively more for all the markets during the global financial meltdown of 2008- 09. This is evidencing that though Indian growth rate was not much impacted from the crisis, its financial markets have seen very volatile swings during that period (2007-08). It is also observed that continuously compounded daily returns are on an average around 0% while daily volatility is not and is generally found to be significant for all the markets.

Financial return series exhibit the 'volatility clustering' phenomenon as well. It means that high volatility is followed by higher volatility, and low volatility is followed by lower volatility. The GARCH (1, 1) model captures volatility clustering the best across all markets. Within volatility clustering, there is also the presence of leverage effects, in which negative returns tend to influence volatility by a larger magnitude than a positive return of the same magnitude.

All the financial return series are found to be stationary and it can be assumed that the behavior shown by returns in the past will continue in the future forecasting period as well. Thus, appropriate VaR model chosen for each market can be expected to predict well in the future. The study then computes VaR for each market at 99% confidence level using 1 day time horizon. VaR estimates from different markets show that there are significant differences between VaR estimates from different markets and also there are differences between different methods within the same financial market. These differences are attributed to the underlying assumptions made by the VaR models which include volatility calculation and underlying return distribution.

The predictive accuracy of various methods is tested by backtesting using three different statistical tests at 95% and 99% confidence levels. The 99% confidence level can provide actual variation in the tails of the distribution which are not well captured at 95% confidence level. Hence, the study has given higher weightage to the results generated at 99% confidence level. The study finally concludes on the best method for VaR computation for different financial markets as:

Table 6.1: Best VaR Method for equity, forex and derivative markets

Financial Market	Best VaR Method
Indian equity market (Sensex)	Historical simulation
Indian Currency Market (Indian rupee/ US dollar (₹/$) exchange rate)	Historical simulation
Indian Futures Market (Nifty Futures index)	Historical simulation

Source: Author's research output

The study thus finds and concludes that the appropriate method for VaR computation for equity, forex and derivative markets in India is Historical simulation. This finding can help market participants, traders, risk managers and researchers who are interested in systematic and quantitative study on Indian financial markets. This finding can also be used by any individual, financial/non-financial institution who are interested in the potential risk to their individual stocks due to movements in overall market. Each individual institution can calculate their respective sensitivity to market indices (e.g. Capital Asset Pricing Model (CAPM) 'β') and then using the index VaR can gauge the potential loss to their individual security.

6.3 Contribution of the study

The study observed from the literature review that a relatively limited number of studies on the application of "Value at Risk models" specific to "Indian financial markets" have been undertaken. As a result, the current study estimated and compared the predictive performance of various VaR models in three distinct financial markets: the equity market, the forex market, and the derivative market. The study finally concludes by finding the most suitable VaR method (Historical simulation) for various Indian financial markets based on a sufficiently large historical time series input data which includes the financial crisis of 2007-08. The study is different from previous studies from the fact that selection of best VaR method is based on the results primarily generated by using the confidence level of 99% which is appropriate for capturing the fat tails of the return distribution and the study has found one single VaR method (Historical simulation) which is appropriate at capturing the market risk across various Indian financial markets. This research can hence, assist market participants, traders, risk managers, and researchers who are interested in conducting a systematic and quantitative study of the Indian financial market.

6.4 Scope for Further Research

The study is based on only daily closing prices. Further research with high frequency data which uses computer algorithms to enter into and close the position, may better capture the risk and provide more realistic risk estimates. Modelling of risk can be improved by taking more leptokurtic distributions like Students 't', Laplace (double exponential) etc. “Extreme value theory” which focuses on the tails of the distribution can also be incorporated for the 'fat tails' behavior observed in the financial return series. This can be used to provide better fit to the actual distribution. The study has used 1-day time horizon for calculating VaR. Research can be undertaken considering longer time horizons which is the case with illiquid assets. The study is also limited to using only linear payoff profile instruments, further research can be undertaken on appropriate VaR for financial products which have non-linear payoff profile like options and structured financial products. Also, the study has used VaR models for market risk estimation only, further research can also be undertaken on the suitability of VaR for credit, liquidity and operational risks. Further research on designing Annual stress testing regime similar to CCAR in USA (chapter 4) for Indian banks can also make the Indian financial system more vibrant and robust to financial shocks originated elsewhere in the world (e.g. Global financial crisis of 2008).

BIBLIOGRAPHY

- Acerbi, C., & Tasche, D. (2002). Expected shortfall: a natural coherent alternative to value at risk. *Economic notes*, *31*(2), 379-388.
- Adrian, T., & Shin, H. S. (2008). *Financial intermediary leverage and value-at-risk* (No. 338). Staff Report.
- Aktham I., M., & Haitham, A.-Z. A. (2006). Value-at-risk under extreme values: the relative. International Journal of Managerial Finance, Vol. 2 Iss: 2 pp. 154 – 172
- Alexander, C. (2009). *Market risk analysis, value at risk models* (Vol. 4). John Wiley & Sons.
- Alexander, C. O., & Leigh, C. T. (1997). On the covariance matrices used in value at risk models. *Journal of Derivatives*, *4*(3), 50-62.
- Angelidis, T., Alexander, B., and Stavros, A. D. (2004) "The Use of GARCH Models in VaR Estimation", *Statistical Methodology*, Vol.1, Issue.2, 105-128.
- Artzner, P. (1997). Thinking coherently. *Risk*, 68-71.
- Artzner, P., Delbaen, F., Eber, J. M., & Heath, D. (1999). Coherent measures of risk. *Mathematical finance*, *9*(3), 203-228.
- Baixauli-Soler, J. S., Alfaro-Cid, E., & Fernandez-Blanco, M. O. (2011). Mean-VaR portfolio selection under real constraints. *Computational Economics*, *37*(2), 113-131.
- Bali, T. G. (2003). An extreme value approach to estimating volatility and value at risk. *The Journal of Business*, *76*(1), 83-108.
- Basak, S., & Shapiro, A. (2001). Value-at-risk-based risk management: optimal policies and asset prices. *The review of financial studies*, *14*(2), 371-405.
- Basel Committee on Banking Supervision. (1996). Supervisory framework for the use of "backtesting" in conjunction with the internal models approach to market risk capital requirements.
- Beder, T. S. (1995). VaR: Seductive but dangerous. *Financial Analysts Journal*, *51*(5), 12-24.
- Berkowitz, J., & O'Brien, J. (2002). How accurate are value-at-risk models at commercial banks?. *The journal of finance*, *57*(3), 1093-1111.

- Berkowitz, J., Christoffersen, P., & Pelletier, D. (2011). Evaluating value-at-risk models with desk-level data. *Management Science*, *57*(12), 2213-2227
- Best, P. (2000). *Implementing value at risk*. John Wiley & Sons.
- Bjerksund, P., & Stensland, G. (2002). How to extend the Risk Metrics market risk universe.
- Butler, C. (1999). *Mastering value at risk: a step-by-step guide to understanding and applying VaR*. Financial Times/Prentice Hall.
- Cabedo, J. D., & Moya, I. (2003). Estimating oil price 'Value at Risk'using the historical simulation approach. *Energy economics*, *25*(3), 239-253.
- Campbell, R., Huisman, R., & Koedijk, K. (2001). Optimal portfolio selection in a Value-at-Risk framework. *Journal of Banking & Finance*, *25*(9), 1789-1804.
- Chernozhukov, V., & Umantsev, L. (2001). Conditional value-at-risk: Aspects of modeling and estimation. *Empirical Economics*, *26*(1), 271-292.
- Chowdhury, P. D., & Bhattacharya, B. (2015). Estimation of Value at Risk (VaR) in the Context of the Global Financial Crisis of 2007-08: Application on Selected Sectors in India. *Indian Journal of Research in Capital Markets*, *2*(2), 7-25.
- Christoffersen, P., & Pelletier, D. (2004). Backtesting value-at-risk: A duration-based approach. *Journal of Financial Econometrics*, *2*(1), 84-108.
- Christoffersen, P., Hahn, J., & Inoue, A. (2001). Testing and comparing value-at-risk measures. *Journal of empirical finance*, *8*(3), 325-342.
- Coronado, M. (2000). *Comparing Different Methods for Estimating Value-at-Risk (VaR) for Actual Non-Linear Portfolios: Empirical Evidence*. Working paper, Facultad de Ciencias Economicas y Empresariales, ICADE, Universidad P. Comillas de Madrid, Madrid, Spain
- Danielsson, Jon, and Casper G. De Vries. "Value-at-Risk and Extreme Returns." *Annales d'Economie et de Statistique*, 2000, 239–70.
- Dimitrakopoulos, D. N., Kavussanos, M. G., & Spyrou, S. I. (2010). Value at risk models for volatile emerging markets equity portfolios. *The Quarterly Review of Economics and Finance*, *50*(4), 515-526.
- Dowd, K. (1998). Beyond value at risk: the new science of risk management.

- Duffie, D., & Pan, J. (1997). An overview of value at risk. *Journal of derivatives, 4*(3), 7-49.
- Dutta, D., & Bhattacharya, B. (2008). A Bootstrapped Historical Simulation Value at Risk Approach to S&P CNX Nifty. In *The National Conference on Money and Banking, IGIDR, Mumbai, India*.
- Engle, R. F., & Manganelli, S. (2004). CAViaR: Conditional autoregressive value at risk by regression quantiles. *Journal of Business & Economic Statistics*, *22*(4), 367-381.
- Fan, J., & Gu, J. (2003, March). Data-analytic approaches to the estimation of value-at-risk. In *2003 IEEE International Conference on Computational Intelligence for Financial Engineering, 2003. Proceedings.* (pp. 271-277). IEEE.
- Favre, L., & Galeano, J. A. (2002). Mean-modified value-at-risk optimization with hedge funds. *The journal of alternative investments*, *5*(2), 21-25.
- Gaivoronski, A. A., & Pflug, G. (2005). Value-at-risk in portfolio optimization: properties and computational approach. *Journal of risk*, *7*(2), 1-31.
- Garp, P. J. (2011). Financial Risk Manager Handbook Plus Test Bank.
- Gençay, R., Selçuk, F., & Ulugülyağci, A. (2003). High volatility, thick tails and extreme value theory in value-at-risk estimation. *Insurance: Mathematics and Economics*, *33*(2), 337-356.
- Ghaoui, L. E., Oks, M., & Oustry, F. (2003). Worst-case value-at-risk and robust portfolio optimization: A conic programming approach. *Operations research*, *51*(4), 543-556.
- Gilli, M. (2006). An application of extreme value theory for measuring financial risk. *Computational Economics*, *27*(2-3), 207-228.
- Giot, P., & Laurent, S. (2003). Value-at-risk for long and short trading positions. Journal of Applied Econometrics, 18(6), 641-663.
- Giot, P., & Laurent, S. (2004). Modelling daily value-at-risk using realized volatility and ARCH type models. *Journal of empirical finance*, *11*(3), 379-398.
- Glasserman, P., Heidelberger, P., & Shahabuddin, P. (2002). Portfolio value-at-risk with heavy-tailed risk factors. *Mathematical Finance*, *12*(3), 239-269.
- Gupta, A., & Liang, B. (2005). Do hedge funds have enough capital? A value-at-risk approach. *Journal of financial economics*, *77*(1), 219-253.

- Haas, M. (2009). Value-at-Risk via mixture distributions reconsidered. *Applied Mathematics and Computation*, *215*(6), 2103-2119.
- Hendricks, D. (1996). Evaluation of value-at-risk models using historical data. *Economic policy review*, *2*(1).
- Holton, G. A. (2012). Value-at-Risk: Theory and Practice, e-book 2014. *URL: http://value-at-risk. net*.
- Horcher, K. A. (2011). *Essentials of financial risk management* (Vol. 32). John Wiley & Sons..
- Hull, J., & White, A. (1998). Value at risk when daily changes in market variables are not normally distributed. *Journal of derivatives*, *5*, 9-19.
- Hull, J., Treepongkaruna, S., Colwell, D., Heaney, R., & Pitt, D. (2013). *Fundamentals of futures and options markets*. Pearson Higher Education AU.
- Jackson, P., Maude, D., & Perraudin, W. (1998). Bank capital and value at risk.
- Janes, H., Pepe, M. S., & Gu, W. (2008). Assessing the value of risk predictions by using risk stratification tables. *Annals of internal medicine*, *149*(10), 751-760.
- Jorion, P. (2002). How informative are value-at-risk disclosures? *The Accounting Review*, *77*(4), 911-931.
- Jorion, P. (2007). *Value at risk: the new benchmark for managing financial risk*. The McGraw-Hill Companies, Inc..
- Kisacik, A. (2006). High volatility, heavy tails and extreme values in value at risk estimation. *Institute of Applied Mathematics Financial Mathematics/Life Insurance Option Program Middle East Technical University, Term Project*.
- Kuester, K., Mittnik, S., & Paolella, M. S. (2006). Value-at-risk prediction: A comparison of alternative strategies. *Journal of Financial Econometrics*, *4*(1), 53-89.
- Kupiec, P. (1995). Techniques for verifying the accuracy of risk measurement models. *The J. of Derivatives*, *3*(2).
- Kupiec, P. (2002). Stress Testing in a Value at Risk Framework, *Risk management: value at risk and beyond*, *76*.
- Linsmeier, T. J., & Pearson, N. D. (1996). *Risk measurement: An introduction to value at risk* (No. 1629-2016-134959).

- Longerstaey, J., & Spencer, M. (1996). Risk metrics—technical document. Morgan Guaranty Trust Company of New York: New York, 51, 54.
- Lopez, J. A. (1999). Methods for evaluating value-at-risk estimates. *Economic Review-Federal Reserve Bank of San Francisco*, (2), 3.
- Maghyereh, A. I., & Al-Zoubi, H. A. (2006). Value-at-risk under extreme values: the relative performance in MENA emerging stock markets. *International journal of managerial finance*.
- Manganelli, S., & Engle, R. F. (2001). Value at risk models in finance.
- Markowitz, H. M. (1959). Efficient Diversification of Investments–New York.
- Marshall, Chris, and Michael Siegel. "Value at Risk: Implementing a Risk Measurement Standard." *The Journal of Derivatives* 4, no. 3 (1997): 91–111.
- Mittnik, Stefan, and Marc S. Paolella. "Conditional Density and Value-at-Risk Prediction of Asian Currency Exchange Rates." *Journal of Forecasting* 19, no. 4 (2000): 313–33.
- Nath, G. C. and Samanta, G. P. (2003) "Value at Risk: Concepts and its Implementations for Indian Banking System", *Working Paper*, Nov, NSE, Pages 26
- Neftci, Salih N. "Value at Risk Calculations, Extreme Events, and Tail Estimation." *The Journal of Derivatives* 7, no. 3 (2000): 23–37.
- Pérignon, Christophe, and Daniel R. Smith. "The Level and Quality of Value-at-Risk Disclosure by Commercial Banks." *Journal of Banking & Finance* 34, no. 2 (2010): 362–77.
- Pflug, Georg Ch. "Some Remarks on the Value-at-Risk and the Conditional Value-at-Risk." In *Probabilistic Constrained Optimization*, 272–81. Springer, 2000. http://link.springer.com/chapter/10.1007/978-1-4757-3150-7_15.
- Poornima, B. G., & Reddy, Y. V. (2017). An Analysis of Portfolio VaR: Variance-Covariance Approach. *IUP Journal of Applied Finance*, *23*(3).
- Pritsker, Matthew. "Evaluating Value at Risk Methodologies: Accuracy versus Computational Time." *Journal of Financial Services Research* 12, no. 2–3 (1997): 201–42.

- Longerstaey, J., & Spencer, M. (1996). Risk metricstm—technical document. Morgan Guaranty Trust Company of New York: New York, 51, 54.
- Reserve, U. F. (2011). SR 11-7: Guidance on Model Risk Management.
- Samanta, G. P., Jana, P., Hait, A., & Kumar, V. (2010). Measuring Market Risk-An Application of Value-at-risk to Select Government Bonds in India. *Reserve Bank of India Occasional Papers*, *31*(1), 2-32
- Saunders, A., & Allen, L. (2010). Credit risk management in and out of the financial crisis: new approaches to value at risk and other paradigms (Vol. 528). John Wiley & Sons.
- **Sawant, S. (**2001) "Principal Component Analysis for VaR Estimation", *ICICI, July*, Pages: 20, www.iciciresearchcentre.org.
- Schachter, B., & Butler, J. S. (1996). Improving value-at-risk estimates by combining kernel estimation with historical simulation. *Available at SSRN 7408*.
- Şener, E., Baronyan, S., & Mengütürk, L. A. (2012). Ranking the predictive performances of value-at-risk estimation methods. *International Journal of Forecasting*, *28*(4), 849-873.
- Sethapramote, Y., Prukumpai, S., & Kanyamee, T. (2014). Evaluation of Value-at-Risk Estimation Using Long Memory Volatility Models: Evidence from Stock Exchange of Thailand. *Available at SSRN 2396531*.
- Smith, V. Kerry, and William H. Desvousges. "An Empirical Analysis of the Economic Value of Risk Changes." *The Journal of Political Economy*, 1987, 89–114.
- Sollis, R. (2009). Value at risk: a critical overview. *Journal of Financial Regulation and Compliance*.
- Supervisory Guidance on Model Risk Management: https*://www.federalreserve.gov/supervisionreg/srletters/sr1107a1.pdf*
- Taamouti, A. (2009). Analytical Value-at-Risk and Expected Shortfall under regime-switching. *Finance Research Letters*, *6*(3), 138-151.
- Tian, H. W., Zhan, Y. R., & Qiu, J. (2000). Empirical Analysis of Value-at-Risk Estimation Methods Using Extreme Value Theory [J]. *Systems engineering-theory & practice*, *10*.

- Uyemura, Dennis G., Charles C. Kantor, and Justin M. Pettit. “EVA® for Banks: Value Creation, Risk Management, and Profitability Measurement.” *Journal of Applied Corporate Finance* 9, no. 2 (1996): 94–109.
- Varma, J. R. (1999) “Value at Risk Models in Indian Stock Market”, Indian institute of Management, *Working paper no.99-07-05*.
- Venkatraman, S. (1997) “Value at Risk for a Mixture of Normal Distribution: The Use of Quasi-Bayesian Estimation Technique*”,* Federal Reserve Bank of Chicago, *Economic Prospective,* Vol.21, March / April, 2-13
- Yamai, Yasuhiro, and Toshinao Yoshiba. “Value-at-Risk versus Expected Shortfall: A Practical Perspective.” *Journal of Banking & Finance* 29, no. 4 (2005): 997–1015.
- Zangari, P. (1996). An improved methodology for measuring VaR. *RiskMetrics Monitor, 2*(1), 7-25.
- **Zhou, K. (**2002**) “**Calculating VaR with the Extreme Value Approach: An Empirical Analysis of Hang Sang Index”, *Seminar Paper* Presented at City University of Hong Kong, Department of Economics, 18th July, Pages. 16-24.

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Value-at-Risk Estimation of Equity Market Risk in India

Jitender
School of Economics, University of Hyderabad, Hyderabad-500046 (India)
jitendergame@gmail.com

Abstract. The value-at-risk (Va) method in market risk management is becoming a benchmark for measuring "market risk" for any financial instrument. The present study aims at examining which VaR model best describes the risk arising out of the Indian equity market (Bombay Stock Exchange (BSE) Sensex). Using data from 2006 to 2015, the VaR figures associated with parametric (variance–covariance, Exponentially Weighted Moving Average, Generalized Autoregressive Conditional Heteroskedasticity) and non-parametric (historical simulation and Monte Carlo simulation) methods have been calculated. The study concludes that VaR models based on the assumption of normality underestimate the risk when returns are non-normally distributed. Models that capture fat-tailed behaviour of financial returns (historical simulation) are better able to capture the risk arising out of the financial instrument.

Keywords: value-at-risk (VaR), equity market risk, variance–covariance, historical simulation, financial risk management
JEL Classification: C52, C58

1. Introduction

The research on financial risk management in India has from a long time been concentrated on mainly credit risk. The extent of risk posed by market risk instruments in Indian financial market has not been systematically and deeply studied. There is a relatively less number of studies dealing with market risk as compared to credit risk. This is largely because Indian financial market has from a long time been dominated by mainly credit products relating to retail, auto, housing, and personal finance. The commercial banks in India have traditionally focused mainly on the borrowing and lending business, which primarily generates credit risk. As the world is becoming more and more integrated in financial flows and the Indian financial market is also becoming more and more open to foreign