CHAPTER 1

INTRODUCTION
1.1 INTRODUCTION

The beginning of the twentieth century witnessed radical changes in the structure and nature of business operations of both financial and non-financial companies on account of phenomenal liberalisation, globalisation and privatisation concepts since 1990s in the Indian economy. Along with this, financial markets developed at an exponential rate with new financial instruments, to provide uninterrupted access to the financial requirements of the business corporations in India. The total number of business corporations, volume of transactions, capital requirements, and market capitalisation of the companies in the financial markets have alarmingly increased in the last five decades due to the rapid progress of technological revolution. Added to this, economic factors (like interest rate changes, inflation rates, tax incentives, investors or shareholders expectations, etc.), political factors (economic system, rules and regulations of trade policies, environmental issues, changing patterns of employment, overlaps between government departments, licensing etc.) social factors (customer demands and expectations, growth in the consumer awareness, trade unions etc.) and internal factors (vision and mission of the corporations, culture of the industry, etc.) greatly influence and pose a threat to the functioning of the business operations. These factors in turn give rise to various elements of risk.

Risk is the vital component that influences the effective functioning of business operations. In the absence of risk there is no necessity for robust financial markets and new financial instruments to cater to the various financial needs of companies. However in real world, risk is pervasive due to the presence of financial element in all decisions whether it’s a single household, business firm, governments and especially any financial institution\(^1\). The decisions in this case would be focussed towards management of risk. Hence the need for studying Financial Risk Management and various internal and external risks faced by the
organisations. Financial risks is faced by any kind of organisations whether financial institutions or non-financial institutions. The quantum of risk faced is more in case of financial institutions relatively. Hence more focus is needed for identifying, measuring, analysing and managing the various risks faced by the financial institutions. Risk Management assumes pivotal role in financial institutions. Risk Management has been recently gaining importance due to increased global competition, increasing regulations, complicated securitisation and derivative products. Despite, world has witnessed various financial disasters in the past (Jorion, 2000) as listed below:

<table>
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<tr>
<th>Years</th>
<th>Financial Disasters Incidents</th>
<th>Impact</th>
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<tbody>
<tr>
<td>1971</td>
<td>Break down of Bretton wood system</td>
<td>Flexible and volatile exchange rates</td>
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<tr>
<td>1973</td>
<td>Oil Price Shocks</td>
<td>High inflation and high interest rates</td>
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<tr>
<td>1987</td>
<td>Black Monday – Collapse of US Stock Markets by 23%</td>
<td>Wiped $1 trillion capital from the market</td>
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<tr>
<td>1989</td>
<td>Japanese Stock Price Bubble</td>
<td>Lost $2.7 trillion in capital from markets</td>
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<td>1994</td>
<td>Bond Debacle</td>
<td>Erased $1.5 trillion in global capital</td>
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<tr>
<td>1995</td>
<td>Bankruptcy of Barings PLC</td>
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<tr>
<td>1997</td>
<td>Asian Turmoil</td>
<td>Wiped off about 3/4th of dollar capitalisation of equities in Indonesia, Korea, Malaysia and Thailand</td>
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| 2008  | Sub Prime Crisis             | - Had severe impact on US and European Economies  
- US Stock market fell nearly 30% |

The only thing which remained unchanged across all the above mentioned event was **risk**.
The questions that requires to be answered in this context are -

- Where the risk is coming from?
- How to identify?
- How to measure and predict it?
- Why market risk is gaining importance?
- Why market risk management is required by the institutions?

Hence the need for research on Risk Management. The present study tries to get the answer for the above mentioned questions.

**BRICS – AN INVESTMENT OPPORTUNITY**

BRICS economies gained tremendous attention in recent years. The name BRIC an acronym was coined by Goldman Sachs in the year 2001 for Brazil, Russia, India and China. In 2010 South Africa joined BRIC nations and the group was renamed as BRICS. These emerging markets have shown remarkable economic growth that rendered high return for investors. BRICS economies account for 40% of the world population and 25% of the world’s GDP. As such the international investment trends are shifting from developed markets to emerging economies (*Bohn & Tesar, 1996*)\(^3\). There has been empirical research which analyses the economic prospects of BRICS countries and the investment opportunities (*Wilson & Purushothaman, 2003*)\(^4\). Same time one cannot deny the risks inherent in the emerging markets on account of transparency in reporting, regulatory system and compliance challenges. Further, government / bureaucratic intervention are hurdles for the smooth functioning of the markets. The present study also consider the BRICS economies for calculating market risk using equity indices along with the developed markets (US and UK) equity indices. More focus on the BRICS investment opportunities and risks is discussed in fourth chapter.
1.2 REVIEW OF LITERATURE

The study has identified three objectives after going through various studies of international and national articles in reputed journals and PhD thesis. Relatively the number of research on risk management is less at national level and hence more review of literature is of international studies. The literature considered for the study hence is classified on the basis of the objectives of the study which is provided in the later part of the Chapter 1.

1.2.1 FIRST OBJECTIVE:

To measure, compare and rank the predictive ability of selected VaR approaches in assessing Market Risks of Indian Financial Markets (Equity / Derivative / Forex)

Shan-Shan Shen, (2006)⁵ use student-t distribution to estimate VaR to capture market risk. The results of VaR-t and VaR-x models are compared with VaR-n model. The empirical results criticise student-t distribution. This is because the asymmetry of distribution of asset returns is not able to capture by student-t distribution. Value at Risk (VaR) can also be estimated using the student-t distribution to capture the market risk. Two alternative VaR models, VaR-t and VaR-x models, are used and compared with the benchmark model (VaR-n model). The Student-t distribution is criticized for its inability to capture the asymmetry of distribution of asset returns. The extreme value theory (EVT)-based model, VaR-x model takes into account the asymmetry of distribution of asset returns. In addition, two different approaches, excess-kurtosis and tail-index techniques, for determining the degrees of freedom of the Student-t distribution in VaR estimation can be introduced. The student-t distribution for estimating VaR can improve the VaR estimation and offer accurate VaR estimates, particularly when tail index technique is used to determine the degrees of freedom and the confidence level exceeds 98.5 percent.
Alper Ozun, (2010) forecast stock returns of Istanbul Stock Exchange using Filtered Extreme Value theory (EVT) model. Filtered EVT is compared with (GARCH), GARCH with student-t distribution, GARCH with skewed student-t distribution, and FIGARCH models. The backtesting results of Kupiec test, Christoffersen test, Lopez test, Diebold and Mariano test, root mean squared error (RMSE), and h-step ahead forecasting RMSE are used for comparing the predictive performance of the model. The results show that filtered EVT ability to captures fat-tails in stock returns are better than the other parametric models. The author also states that the number of violations can be reduced with the increase in the conditional quantile. As such filtered EVT with higher conditional quantile should be used for forward looking forecasting.

Alex Yi-Hou Huang, Tsung-Wei Tseng, (2009) use a non parametric Kernel Estimator(KE) model for forecasting VaR. KE approach is able to consider recent extreme shocks as the approach model the behaviour of tails independently and directly of the return distribution. The data of 37 equity indices for more than 26 years are used. The authors compare the performance of KE with five major VaR models. Using the backtesting algorithms they conclude that KE models produce better estimates.

Fotios C., Linyan, & Yifan (2006), calculate VaR on the daily returns of six equity indices and four currency pairs for a period of 10 years. The equity indices considered are S&P500, DAX, CAC, Nikkei, TSE, and FTSE. The currency pair used are US dollar vs Euro, Yen, Pound, and Canadian dollar. VaR models like historical simulation, Gaussian, Generalized Pareto (peak over threshold (POT) technique of extreme value theory (EVT)) and Stable Pareto distribution (both symmetric and non-symmetric) are used. The results show that historical model and PoT model produce accurate forecasts. Gaussian model underestimates ES, while Stable Pareto framework overestimates ES.


Timotheos & Stavros, (2005)\textsuperscript{9} check the accuracy of parametric, non-parametric and semi-parametric methods in predicting one day VaR measure in three types of markets Viz, Stock Exchanges, Commodities and Exchange rates, both for short and long trading positions and based on backtesting measures and a loss function evaluation method, the author finds that modeling of the main characteristics of asset returns produces the most accurate VaR forecasts. Especially for the high confidence levels, a risk manager must employ different volatility techniques in order to forecast accurately the VaR for the two trading positions.

Robert, (2009)\textsuperscript{10} critically evaluate VaR approaches in the frame of Basel II regulatory framework. The author identifies the flaws in the VaR models which failed to predict the financial crisis. He points out that serious efforts should be taken to improve the estimation techniques of VaR and in backtesting procedures. He further goes on criticising the variance covariance approach developed by Riskmetrics. VCV no doubt is popular because of the simplicity in understanding and calculation. VCV approach assumes that assets are normally distributed. But in practice, the assets returns does not follow the normal distribution. As such, the VaR estimates based on CVC approach will underestimate true VaR. the author also says that MCS and historical simulation are also computationally inefficient in producing accurate VaR estimates particularly for large portfolios. Moreover, any of the techniques are open for manipulation by altering the window size or the confidence interval to produce the required VaR estimates.

Aktham I. & Haitham, (2006)\textsuperscript{11} compare the performance of VaR models for seven Middle East and North Africa (MENA) countries. The results demonstrate that Extreme Value Theory approach provide accurate VaR estimates. This imply that the MENA markets returns are characterised by fat tails.
Aktham & Haitham, (2008)\textsuperscript{12} use Extreme Value Theory VaR model to analyse the tail behaviour of daily stock returns for three emerging stock in the Gulf region namely Bahrain, Oman, and Saudi Arabia. The study covers a period from 1998 to 2005. The returns are prefiltered in order to obtain the residual series which are i.i.d. to estimate the innovation distribution if the tails “Peaks-Over-Threshold” (POT) model is applied. POT model perform better at higher quantiles compared to conventional methodologies like historical simulation and normal distribution models in understanding the tail behaviour of Gulf market returns.

Stuart, (2007)\textsuperscript{13} consider four European countries namely France, Germany, Italy, and the UK to study the sensitivity analysis of stock returns at the industry level to market, exchange rate and interest rate shocks. The methodology proposed by Campbell and Mei (1993) is used to segregate systematic risk into various components. The factors causing systematic risk are the news of future dividends, real interest rates and excess returns. Besides the impact of market risk, substantial influence of exchange rate risk on the industries are also detected in all the four European countries. The results demonstrate that there exists significant influence of market risk, real interest rate risk and exchange rate risk on the industry and these risks are influenced by the information of futures cash flows and excess returns.

Wafa & Mhamed, (2012)\textsuperscript{14} identifies specific criteria to the microstructure of emerging markets. The study consider low liquidity, very pronounced asymmetric information, and high volatility which affect the risk market as components of specific criteria. The authors aim to test whether specific criteria have any impact on market risk and hedging capital? Secondly, the author also try to detect whether in calculating VaR any adjustments are done for risk measurement to the specifications of emerging markets. The result indicate that
adjusted VaR provides better estimates. Backtesting results indicate that VaR models which are adjusted to liquidity and to asymmetry of information provide better estimates.


**Carlo, Stefano, & Svetlozar (2007)**\(^{16}\) employed univariate models for comparing the performance of Value-at-Risk and Expected Shortfall. These two models are based on stable laws and extreme value theory (EVT). Block maxima method is used to obtain EVT based methods. The results of the backtesting show that \(\alpha\)-stable models perform better pure EVT-based methods in VaR estimates. Peaks-over-threshold based VaR is also calculated. The results suggest that PoT method is preferable for the estimation of expected shortfall.

**Markus (2009)**\(^{17}\), consider daily closing prices of three European stock markets namely, MSCI indices for France, Germany and United Kingdom for a period of January 1990 to April 2009 with a total observations of 4993. VaR is calculated for individual series as well as for the portfolio using univariate and multivariate models. Gaussian and Student’s t mixture properties are accommodated in the model. The empirical results show that univariate mixture of two Student’s t distributions performs best overall.

**Qian, Richard, & Zudi (2012)**\(^{18}\) calculate VaR for daily series of four international stock market indices and two exchange rates. The equity markets considered are S&P 500(US), FTSE100(UK), AORD All index(Australia) HANG SENG Index (Hong Kong). The AU dollar to the US dollar and Euro to the US dollar for foreign exchange markets.they use VaR and Expected Shortfall the two parametric approaches for forecasting market risk. GJR-GARCH model is used for capturing leverage effect. Asymmetric Laplace form is assumed in order to capture the skewness and heavy tails of the series. The results suggest that ES is able to assess the quantum of extreme losses in the market.
Stavroyiannis, Makris, Nikolaidis, & Zarangas, (2012)\textsuperscript{19} apply VaR models on six equity indices of daily returns namely DJIA, NASDAQ Composite, FTSE100, CAC40, DAX, and S&P500. Backtesting is performed through, success-failure ratio, the Kupiec LR test, the Christoffersen independence and conditional coverage tests, the expected shortfall with ESF1 and ESF2 measures, and the dynamic quantile test of Engle and Manganelli. The study results demonstrate that the VaR models based on Pearson type-IV distribution gives better results at high confidence interval.

Christoph, Stefan, & Marc (2006)\textsuperscript{20} use three stock indices namely DAX, NASDAQ Composite and Nikkei 225 and two foreign exchange rates namely Japanese-Yen / US Dollar and the US-dollar / British Pound. The data period ranges from 1990 to 1995. They employ two models i.e AR(1)-GARCH(1,1) and t-AR(1)-GARCH(1,1) model for forecasting VaR. The results suggest that normal GARCH model provides promising estimates comapred to t-GARCH model.

Abhay, David, & Powell, (2012)\textsuperscript{21} use Extreme Value Theory, C VaR or Expected Shortfall, GRACH(1,1) models for VaR estimation of the Australian Index i.e ASX-All Ordinaries and USA Index i.e S&P500. The results show that EVT provides better outcomes to model extreme market risk.

Toshinao & Yasuhiro, (2005)\textsuperscript{22} addresses the serious problem faced by VaR models. An important issue raised is that VaR disregards any loss beyond the VaR level. This problem is termed as ‘tail risk’. The problem of tail risk can be addressed by expected shortfall through two cases: concentrated credit portfolio and foreign exchange rates under market stress. However, the results suggest that expected shortfall requires a larger sample size than VaR to provide the same level of accuracy.
Alexander & Ru’diger, (2000)\textsuperscript{23} use the VaR method which describes the tail of the conditional distribution of a heteroscedastic financial return series to measure the market risk. Pseudo-maximum-likelihood fitting of GARCH models estimate current volatility. EVT is used to estimate GARCH models are combined to tail of the innovation distribution of the GARCH model. Conditional quantiles VaR and conditional expected shortfalls are estimated. The backtesting results demonstrate that the model gives better 1-day estimates.

Stelios & Dimitris, (2005)\textsuperscript{24} compare the predictive performance of two methodologies related to the Extreme Value Theory (EVT): the Peaks over Threshold (POT) and the Blocks Maxima (BM). The models are tested on USD-denominated, daily returns of the Dow Jones Industrial Average (DJIA) and the Cyprus Stock Exchange (CSE) indices. The study period ranges from 1997 to 2002. The backtesting process show that at very high confidence levels the EVT-based methodology produces the most accurate forecasts of extreme losses.

Assaf, (2009)\textsuperscript{25} use Extreme value theory VaR approach for four emerging markets belonging to the MENA region (Egypt, Jordan, Morocco, and Turkey). The main focus is on understanding the behaviour of the tails in each market. It is observed that the returns are significantly fat tailed and hence the need for EVT approach. The empirical results show that VaR estimates based on tail index are higher compared to those of normal distribution in all the markets. Hence the need for proper risk valuation not ignoring the tail behaviour of the markets.

Dimitris, Manolis, & Spyros, (2010)\textsuperscript{26} assess the market risk in developed and emerging equity markets portfolio. A comparative analysis is done on the performance of various VaR models in developed and developing markets during normal, crisis and post-crisis periods. The result are intriguing. The results show that the most successful VaR models are common for both asset classes. On the other hand, in case of markets with fat tailed 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 estimation becomes difficult during the crisis period particularly in case of emerging markets. Further, the estimation power is least affected in case of developed markets. The performance of the parametric (non-parametric) VaR models improves (deteriorates) during post-crises periods due to the inclusion of extreme events in the estimation sample.

Anurag & Bing, (2005)\textsuperscript{27} analyse the relationship between hedge funds and capital requirement using VaR approach. The monthly return data for a period from 1977 to 2003 of 3702 hedge funds are collected from TASS Management Limited. They employ Extreme Value Theory approach to determine the capital requirement of the hedge funds. The empirical results found that around 3.7% live hedge funds and 10.9% dead hedge funds are undercapitalised. The undercapitalised funds form a small proportion out of the entire sample. The variability in fund capitalisation is attributed to size, investment style, age and management fee. The authors conclude that VaR measures are superior to traditional measures in examining risk. Because traditional measures like standard deviation of returns and leverage ratios understate risk.

Roxana & Winfried (2012)\textsuperscript{28} make a comparative study of stability of standard and new VaR estimates based on certain criterias like choice of the asset, model, assumptions of the distributions and window estimation before and during the financial crisis period. The authors consider US small, middle and Large Cap indices. The data analysed for the period is from 2007 to 2009. The author employ historical simulation, Filtered HS, Risk metrics-fix approach, ARMA-GARCH method for sampling window sizes of 250, 500, 750 and 1000. The empirical results suggest that newly developed methods have outperformed in assessing the market risk.
Julia (2012) analyse VaR models for the daily closing prices of DAX, FTSE 100, EuroSTOXX50 and S&P 500 for a period ranging from 2003 to 2006. The authors employ non parametric quantile regression or Doble Kernel Local Linear VaR model, EVT and CAViaR models. The backtesting results lead to the conclusion that EVT VaR model outperform in estimating VaR.

Lennart & Herman, (2010) propose to forecast VaR and Expected Shortfall with Bayesian framework. This requires the adoption of Quick Evaluation of Risk using Mixture of ‘t’ approximations (QERMit). The model is applied for daily S&P 500 returns. The results show that QERMit approach performs better.

Pilar & Sonia, (2012) use the daily closing prices for the Spanish IBEX35, French CAC40, German DAX, UK FTSE100, US Dow Jones Industrial Average (DJAI), S&P 500, Japanese Nikkei 225 and Hong Kong Hang Seng (HSI) indexes. The backtesting results show that parametric models with asymmetric GARCH student t distribution perform well.

Woon K. W., (2010) show that Monte Carlo simulations is extremely accurate and powerful for small samples. The results show that the presence of downside tail risks in S&P 500. The risk model with jumps, skewed and fat tailed fail to capture the tail risk during the 1987 stock market crash.

Panayiotis, Anastassios, & Georgios, (2011) use the daily data for three groups of stock market indices, namely Developed, Southeast Asia and Latin America are taken into account for a period of 1987-2009. APARCH student distribution is used for analysing the fat left and right tails of the returns distribution. The results demonstrate that Student APARCH one-day ahead VaR forecasts for long and short trading positions provide accurate estimates.
Stavros, Christos, & Pamela, (2012)\textsuperscript{34} calculate VaR for 1-day-ahead, 10-day-ahead and 20-day-ahead forecasting horizons. The findings are that VaR models are underestimated as the forecasting horizon increases. GARCH model provide lower VaR estimates for majority of the indices under the study for 10-day and 20-day forecasting horizon. Therefore, a long memory volatility model compared to a short memory GARCH model does not appear to improve the VaR and ES forecasting accuracy, even for longer forecasting horizons.

Hans, (2004)\textsuperscript{35} is of the opinion that financial risk management deals with low-probability events in the tails of asset price distributions. As such one must consider those VaR models which will give more attention on the behaviour of tails. Extreme Value Theory VaR models does exactly the same. The results demonstrate that Conditional EVT generate precise VaR estimates. The Conditional EVT model is compared with GARCH models and the backtesting results demonstrate that EVT model provide superior results than the GARCH models.

Abderrahim, (2009)\textsuperscript{36} view that financial risks are underestimated if the VaR models with Gaussian distribution is considered. The Gaussian models fail to capture volatility clustering and heavy tails. And hence the large fluctuations in the market returns are not accounted for in the Gaussian based VaR models. In order to overcome the serious drawbacks, the author suggest the use of regime-switching models. The empirical results show that VaR and Expected Shortfalls approaches using simulations yield almost the same results.

Brooks, Clare, Dalle Molle, & Persand, (2005)\textsuperscript{37} apply different Extreme Value VaR models for three LIFFE futures contract data. The results demonstrate that semi parametric approach yield accurate results. The semi-nonparametric approach tail events are modelled using the generalised Pareto distribution. While the normal market conditions are caught by empirical distribution function.
Emrah, Sayad, & Levent, (2012)\textsuperscript{38} compare and rank the predictive ability of different VaR models. They consider the credit crisis period offers an exclusive opportunity for analysing the success of different VaR models both in developing and developed countries. They suggest a VaR ranking model which tries to minimise the magnitude of errors between predicted losses and actual losses and also reduces the autocorrelation problems of the residuals. Their VaR ranking model try to incorporate the balance between government rules for financial stability and cost-effective risk management. The authors consider eighteen equity indices, eleven from emerging and seven from developed markets. The results demonstrate that CAViaR Asymmetric and EGARCH gives better VaR estimates. They results also indicate that the performance of VaR models depends on how effectively the asymmetric behaviour is captured by the VaR models. And not on whether they belong to parametric, non-parametric, semi-parametric or hybrid model.

Samanta et al (2010)\textsuperscript{39}, measure the market risk using VaR models on select government bonds in India. The authors employ non-normal VaR models like Historical Simulation, Risk Metric, hyperbolic distribution fit and Extreme Value Theory. The authors say that government securities market in India is not vibrant as found in developed markets. The study period ranges from August 2005 to July 2008 of the two most liquid Government bonds. For evaluating the VaR results Kupiec’s backtesting and Penalty/Loss-Function – Lopez’s Loss-Function were employed. The empirical results show that historical simulation can estimate more accurately VaR numbers in the Indian Bond Market.

Roy (2011)\textsuperscript{40} employ Filtered Historical Simulation approach for estimating VaR in two Indian Stock prices namely BSE Sensex (BSE) and NSE-NIFTY (NSE) for a period ranging from January 2003 to December 2009. Using FHS VaR and GARCH Model the author calculated one day VaR. In order to account for global financial condition in the
specification of the GARCH mean equation, S&P 500, INR-EURO and INR-USD exchange rate and gold price data series are used as proxies. It is observed that global financial condition have significant impact on the Indian capital market.

1.2.2 SECOND OBJECTIVE:

To analyse risk spillover between financial markets

Zeno, Roland, & Reint, (2012) developed a state-dependent sensitivity value-at-risk (SDSVaR) approach as a function of the state of financial markets (tranquil, normal, and volatile) to enable to quantify the direction, size, and duration of risk spillovers among financial institutions like Commercial Bank Index, Insurance Company Index, Investment Bank Index and Hedge Fund Index. Using a system of quantile regressions for four sets of major financial institutions (commercial banks, investment banks, hedge funds, and insurance companies) result indicate that while small during normal times, equivalent shocks lead to considerable spillover effects in volatile market periods. Commercial banks and hedge funds appear to play a major role in the transmission of shocks to other financial institutions. Further spillover effects is traced over time in a set of impulse response functions and find that they reach their peak after 10 to 15 days using daily data.

Pigildin, (2009) analysed the Performance of four risk quantification methodologies widely known as Value at Risk are calculated and assessed them against several accuracy and efficiency criteria. The results reveal that at 95% confidence level GED-GARCH method performs better than any other alternative: the VaR series obtained with this method are statistically accurate. Also the method provides least likely to result in forgone profits from speculation. The VaR series calculated with GED-GARCH are used to investigate extreme risk spillover between the respective markets. It is shown that there is a significant risk spillover from oil market to natural gas market during the period in consideration, while there is no spillover in the reverse direction, applying the Hong’s concept of Granger
causality in risk. Further, the upside risk spillover from oil to gas markets is found to be more statistically and economically significant and protracted than the downside risk spillover.

Pošta, (2012) evaluate the risk in three segments of the Czech financial market: capital market, money/debt market and foreign exchange market. First, the univariate techniques are used to capture the evolution of risk in the three segments. Followed by the use of GARCH models. Results indicate that, the estimated time-varying variances show possible relationships among the three segments of the financial market. As per the univariate analysis, increased risk in all three segments during the period of the world financial crisis. To examine possible spillover effects between the three segments of the Czech financial market the bivariate GARCH models are constructed. All possible interactions between the three segments, three bivariate GARCH models are set up to capture. The estimated coefficients in the two dimensional conditional variance equation points out the existence of spillover effects among the three segments of the financial market.

Jin & Hangyong, (2009) examine the risk spills over between stock market and foreign exchange market in the context of Korea. Granger causality tests in risk proposed by Hong, Liu, and Wang (2009) to identify causality is employed by the authors. The Study compared the results from Granger causality test in risk with the results from traditional Granger causality test in mean. It is found that Granger causality in mean runs only from stock returns to foreign exchange returns. While causality in risk runs in both directions.

Yongmiao, Yanhui, & Shouyang, (2003) study analyses spillover of extreme downside market risk among Shares A, B and H in the Chinese stock market, between different stock markets in Greater China, and between the Chinese stock market and other international capital markets. Study reveals that ‘strong risk spillover between Share A indices and Share B indices, and the occurrence of a large downside risk in Share B markets can help predict
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The occurrence of a similar future risk in Share A markets’. Further strong risk spillover between Share A and Share H, and particularly between Share B and Share H. Share B, and particularly Share H, have significant risk spillover with the Asian and international stock markets. Although Share A has some risk spillover with Korean and Singapore stock markets, it has no risk spillover with leading international mature capital markets—Japan, U.S. and Germany. Study suggests that the market segmentation between Share A and Share B is effective in avoiding large adverse shocks from international capital markets.

Fan, Zhang, Tsai, & Wei, (2008) study used GARCH-type models, based on the Generalized Error Distribution (GED), for both the extreme downside and upside Value-at-Risks (VaR) of returns in the WTI and Brent crude oil spot markets. Using Granger causality in risk, a kernel-based test is proposed to detect extreme risk spillover effect between the two oil markets. The study indicate that the GED-GARCH-based VaR approach appears more effective than the well-recognized HSAF (i.e. historical simulation with ARMA forecasts). Moreover, this approach is also more realistic and comprehensive than the standard normal distribution-based VaR model that is commonly used. Results confirms that there is a significant two-way risk spillover effect between WTI and Brent markets. Further at the 99% confidence level, when negative market news arises that brings about a slump in oil price return, historical information on risk in the WTI market helps to forecast the Brent market. Historical information on risk in the two markets can facilitate forecasts of future extreme market risks for each other.

Hong, (2003) analysed kernel-based tests to detect extreme downside risk spillover between financial markets, where risk is measured by the left tail of the distribution or equivalently Value at Risk, based on a new concept of Granger causality in risk. The study check a large number of lags and thus can detect risk spillover that occurs with a time lag or that has weak spillover at each individual lag but carries over very long distributional lags.
Usually, tests using a large number of lags may have low power against alternatives of practical importance, due to the loss of a large number of degrees of freedom. Such power loss is fortunately alleviated for tests because kernel approach naturally discounts higher order lags, which is consistent with the stylized fact that financial markets are often more affected by the recent events than the remote past events. A simulation study indicate a reasonable levels and power against a variety of empirically plausible alternatives in finite samples, including the spillover from the dynamics in mean, variance, skewness and kurtosis respectively. The proposed tests are useful in investigating adverse large market co-movements between financial markets such as financial contagions.

Jing, Zhong, & Kai W., (2006)\(^4\) considered four GARCH-type volatility processes exponentially weighted moving average (EWMA), generalized autoregressive conditional heteroskedasticity (GARCH), exponential GARCH (EGARCH), and fractionally integrated GARCH (FIGARCH) for estimating the VaR is done on Shanghai Stock Exchange A Share Index. The statistical tests including the Kupiec’s likelihood ratio (LR) test, the Christofferson’s LR test, the CHI (Christoffersen, Hahn, and Inoue) specification test, and the CHI non-nested test is used for Performance evaluation of VaR. In comparison to other two model EGARCH and FIGARCH models perform much better than the other.

Timotheos & Stavros, (2005)\(^4\) check the accuracy of parametric, nonparametric and semi parametric methods in predicting one day VaR measure in three types of markets Viz, Stock Exchanges, Commodities and Exchange rates, both for short and long trading positions and based on backtesting measures and a loss function evaluation method, finds that modeling of the main characteristics of asset returns produces the most accurate VaR forecasts. Especially for the high confidence levels, a risk manager must employ different volatility techniques in order to forecast accurately the VaR for the two trading positions.
**Woon, Guobin, & Yong (2012)** use the expected shortfall (ES), which measures the average loss when a VaR is exceeded, and the tail-risk-of-VaR (TR), as Value-at-Risk (VaR) disregards tail losses beyond the VaR boundary. ES is applied for major stock markets. ES and VaR are said to be complementary to each other. The results are evaluated using backtesting models. *The study to show that (a) the correct specification of distribution tail, rather than heteroscedastic process, plays a key role to accurate risk forecasts; and (b) it is best to model the tails separately from the central part of distribution using the Generalized Pareto Distribution (GPD).* The authors conclude saying that the performance of the model depends upon market conditions or the historical period of the data.

**Stavros, Christos, & Alexandra (2012)** employ three VaR approaches for measuring and forecasting market risk before and after financial crisis for five international developed and emerging stock market indices UK (FTSE 100), Germany (DAX30), the USA (S&P500), Turkey (ISE National 100) and Greece (GRAGENL) from 2004 to 2008. The three VaR approaches used are EWMA of Riskmetrics, classic GARCH (1, 1) model of conditional variance assuming a conditional normally distributed returns and asymmetric GARCH with skewed Student-t distributed standardized innovations. The findings suggest that ARCH based VaR models provide satisfactory forecasting results not only before the financial crisis period (pre-2008) but also post financial crisis period when the stock markets returns is expected to be highly volatile. *Thus, the blame for financial crisis should not be cast upon quantitative techniques, used to measure and forecast market risk, alone.*

**Semper & Ismael (2003)** put forward Autoregressive Conditional Heteroscedasticity (ARCH) factor in combination with multivariate analysis. The authors first arrive at a least uncorrelated risk factors in a set of correlated portfolio using multivariate analysis. Secondly, ARCH schemes are employed for modelling the uncorrelated factors historical
Chapter 1

Introduction

behaviour. Thirdly, the models are used for forecasting the future values of standard deviation factors. Fourthly, VaR is calculated. The authors demonstrate that the proposed methodology provides better results for a set of foreign exchange risk exposed portfolio, than compared with J.P. Morgan’s Riskmetrics.

Imad & Bernard (2002)\textsuperscript{53} use the ‘realised volatility,’ in order to obtain daily Value at Risk. The parametric and historical approaches to VAR are examined to arrive at a number of estimates. The authors demonstrate that the biasedness in the VaR estimates are accounted for the sample sizes and the methodology adopted to estimate daily volatility. They conclude saying that the VaR estimates based on the exponentially weighted moving average volatility with a high decay factor are unbiased and relatively efficient.

Omer, Birdal, & Yeliz (2011)\textsuperscript{54} estimate VaR\(_\alpha(X)\) by \(|-\ln(1 - \alpha)|/\hat{\beta} \hat{\theta}\) for the two-parameter Weibull distribution. MLE method is the most commonly used methods for VaR\(_\alpha(X)\) estimation. MLE, GSE, LSE, WLSE, PE, ME, MMLE-I and MMLE-II methods of estimation are employed in the study. These methods solve nonlinear equations for the parameters. ‘Whereas TMMLEs have been proved to be explicit functions of the sample observations and do not need any iterative computational processes.’ In case of large samples MLE and TMMLE methods for estimating \(\theta\) and \(\beta\) are recommended by the authors as their performance does not deviate from each other and they are asymptotically equivalent.

J. David & Ismael Moya, (2003)\textsuperscript{55} estimated value at risk (VaR), autoregressive conditional heteroskedastic (ARCH) factor, which combines multivariate analysis with ARCH models is put forward. Firstly, from a set of correlated portfolio risk factors, a smaller uncorrelated risk factors set is derived by applying multivariate analysis. Secondly, ARCH schemes to model uncorrelated factors historical behaviour is used. Thirdly, the estimated models are used to predict future values for factors standard deviation. From them, VaR calculation is
immediate. In this way, ARCH factor methodology overcomes the multivariate ARCH models drawbacks, which, in practice, make these unworkable for VaR calculation purposes. The proposed methodology over a set of foreign exchange risk exposed portfolios, obtain better results than those reached when J.P. Morgan’s Riskmetrics is used.

Chung, Jin, & Yu (2009)\textsuperscript{56} compare the EVaR a downside risk measure which is more sensitive to extreme losses than the QVaR (Quantile based VaR). The authors say that relative cost of the expected margin fall is represented by $\theta$. It reflects the level of prudentiality. The VaR expectile corresponds to the confidence level chosen under different distributions. They say that EVaR flexibility is similar to that of QVaR. In other words the tail probability or the expected loss is based on the assumption of the type of distribution followed. Some stylized facts in financial time series can be accommodated by Conditional EVaR and various Conditional Auto Regressive Expectile models.’ The authors say that Newey and Powell proposed asymmetric least squares can be employed for model estimation, which ‘extend their asymptotic results to allow for stationary and weakly dependent data.’ The authors employ EVaR approach to assess the risk of stock market indices.

Szilard & Imre, (2001)\textsuperscript{57} analysed the Riskmetrics model, which is based on the unrealistic assumption of normally distributed returns, and it ignores the presence of fat tails in the probability distribution. Because of this, model seriously underestimate risk. But for market participants RiskMetrics performed satisfactorily well due to which the method become a standard in risk measurement. The success of RiskMetrics is actually the artifact of the choice of the risk measure: ‘for higher significance levels fat tails in the distribution of returns will make the simple RiskMetrics rule of calculating VaR to underestimate risk and the effect of the fat tails is minor when one calculates Value-at-Risk at 95%’.
Kozaki & Sato, (2008) studied the application of the Beck model to markets. ‘The model with fluctuating temperature, or volatility in finance, and thus consistent with heteroskedasticity observed in financial markets’. Authors’ examined how well stock markets can be represented with Beck model with data of S&P500 index from the viewpoint of a relaxation time, distributions of volatility, and distributions of returns. As the result confirms that the time constant of volatility is of the order of months and that the inverse temperature $\beta$ approximately obeys t-distribution, Beck model support this assumption. Also, returns obey q-Gaussian distribution in broad time scales, as expected by the Beck model.

1.2.3 THIRD OBJECTIVE:

To analyse the Co-Variances and Correlations of Market Risks using selected VaR approaches in Financial Markets of India and its 5 international counterparts

Marcos & Pablo (2011), use Stochastic Factor Models (SVFM) to measure and analyse the risk and problems of the portfolio. To what extent the VaR and Expected Shortfall are sensitive are analysed by changing the parameters in the model. Linear portfolio positions of assets are compared using SVFM, Black and Scholes Model. Three stock of the Asian market is considered for the application of the above mentioned models. The empirical results show that stochastic volatility parameters are significant. The analysis shows that the parameters of the stochastic volatility part are statistically significant and that such parameters make a difference on the risk return trade-off of the portfolio as well as the dynamics of the risk measures considered.

Hsin (2008) aim to analyse the VaR efficient frontier portfolio selection using polynominal goal programming. The data for the study consists of monthly rates of 10 equity indices of
Pacific Rim Countries. They are US, Canada, Mexico, Chile, Peru, Japan, Korea, Singapore and Hong Kong. The period studied is for 1991 to 2006. The author use VaR instead of standard deviation of the returns for calculating risk in portfolios. The results demonstrate that polynomial goal programming model is superior to the traditional techniques as it has the ability to consider the risk-return trade-off between the expected return and VaR. as such the author advices the usage of this model for the fun mangers and investors.

Chu, Chang, & Sunwu (2006)\(^6\), use returns of the daily closing prices of six international indices. The author construct three hypothetical portfolio as follows:

- Portfolio (1): S&P500, FTSE 100 and DAX
- Portfolio (2): TAIEX, Nikkei 225 and Hang Seng
- Portfolio (3): S&P500, FTSE 100, DAX, TAIEX, Nikkei 225 and Hang Seng

The data was collected from 1990 to 2004. The Power EWMA (exponentially weighted moving average) method suggested by Guermat and Harris (2002) in conjunction with historical simulation is used for estimating portfolio VaR. The Power EWMA was able to capture volatilities and time varying tail-fatness of financial returns. The backtesting results of Kupiec (1995) suggest that Power EWMA model enhance the estimation accuracy of portfolio VaR.

Mazin, (2007\(^6\)) aim to test the risk parameters using VaR methodology for foreign exchange portfolios. The author use 40 currencies against US dollar for a period of 10 year from 1995-2005. Adjustments for the illiquidity of short and long trading / investment positions are done for risk exposure for foreign exchange securities. The VaR is calculated for developed and emerging economies for various time horizons using matrix-algebra techniques.
Ramazan, Faruk & Adburrahman (2003)\textsuperscript{63}, assess the performance of VaR models for daily closing prices of Istanbul Stock Exchange (ISE-100) Index for the period from 1987 to 2001 with a total of 3383 observations. They consider variance-covariance approach, historical simulation, GARCH(1,1), GARCH(1,1)-t, adaptive GPD and nonadaptive GPD models. VaR is calculated for different window sizes of 500, 1000 and 2000 days. The result conclude that GARCH(1,1) and GARCH(1,1)-t models provide high volatile forecasts. Variance-covariance approach, historical simulation, adaptive GPD and nonadaptive GPD models provide stable forecasts.

Carlo et al (2012)\textsuperscript{64} consider two portfolios A and B. Portfolio A is more diversified and it consists of two US stocks each from four different industries. Portfolio B is strongly correlated and it consists of eight US stocks from a single industry. Portfolio A is more realistic from investor point of view with wide diversified stocks, Portfolio B is considered as a stress test portfolio. The data covers the period from 1991 to 2008. The study consider Multivariate Stable-Like Risk factors, Multivariate t-Like Risk factors and Multivariate meta-Like Risk factors and VaR by simulation for forecasting VaR. Backtesting is done for the above models and it is concluded that meta-t and meta-stable laws offer good performances on least diversified portfolios.

Joel et al (2012)\textsuperscript{65} consider the daily returns of 48 industry portfolio from 1963 to 2007. The authors has proposed a new risk measure called Partitioned VaR (PVaR) for portfolio optimization by separating the distributions of the returns of the assets as upside risk and downside risk half-spaces. They compare PVaR with the traditional Markowitz mean-variance approach. The results show that PVaR estimates are more useful for portfolio allocations when asset return distributions are asymmetrical.
Cathy, Richard, Bruce, & Michael (2012)\textsuperscript{66} in order to incorporate intra-day price ranges, propose nonlinear threshold conditional autoregressive VaR (CAViaR). Bayesian approach along with Skewed-Laplace distribution is used for model estimation. The performance of various VaR models are examined in 2008-2009 financial crisis period. They use standard backtesting criteria for evaluating the models and they demonstrate that the crisis effects the performance of the VaR models forecasting. They applied the VaR techniques on five Asia-Pacific Economic Cooperation stock market indices and two exchange rate series. They conclude saying that the threshold CAViaR model, incorporating range information, provides a better forecast of VaR more effectively.

Gordon, John, & Liam (2011)\textsuperscript{67} demonstrate that how the correlation between equity and foreign exchange components in a portfolio can help reducing foreign exchange exposure risk. The authors employ Variance Covariance VaR model for calculating portfolio VaR. The equity indices of Argentina, Brazil, China, India, Mexico and Russia are used to decompose portfolio risk. For the purpose of comparison similar model is used in US market for decomposing portfolio risk. The authors carry their research from the equity investor perspective in European market who invests in equity indices of each emerging economy. The authors suggest that the investors should consider the correlation between foreign exchange market and equity market while making investments in emerging market equity portfolio. ‘The results uniquely demonstrate significant variation in foreign exchange risk in emerging markets.’

David & Desheng (2011)\textsuperscript{68} VaR has become a popular model in financial risk management. Since the sub-prime crisis of 2008 in US housing markets and the global financial market, the reliability and the appropriateness of the VaR models are questioned. The question are raised even on the presence of fat tails (bad events) and their severe impact. The data with
the assumptions of normal and logistic distributions are used for the portfolios with various probabilistic models. The results indicate that simulation based models provide better estimates compared to the optimisation models. The results of Chi-square test indicate that the data is characterised by logistic distribution than the normal distribution. Monte Carlo Simulations aids in demonstrating the errors in the assumption of Value at Risk estimates.

Khindanova, Rachev & Schwartz (2001)\textsuperscript{69}, use traditional VaR approaches like variance-covariance, historical simulation, Monte Carlo simulation and stress testing approaches. They conclude that traditional VaR models do not provide satisfactory results for assessing the possible losses. As such they try to use stable Paretian distributions in VaR modeling. They conclude that stable Paretian model provide superior estimates in VaR modeling.

Ramazan & Faruk (2004)\textsuperscript{70}, try to compare the performance of various VaR models using the daily stock returns of nine emerging markets. They use variance-covariance, historical simulation and Extreme Value Theory VaR models. They forecast the VaR estimates at 0.99% and 95% confidence interval. Their results show that EVT VaR estimates are more accurate at higher confidence interval. Further, they also observe that daily return distributions exhibit varying moments for right and left tails. As such risk and reward are not the same in all the emerging markets considered.

(Monica & Loriana, 2000)\textsuperscript{71} Four Regime Switching Models namely SSRM, SRBM for single asset, MSRM for two asset portfolio and FSRM 10 asset portfolio are used in order to consider non-normal distribution. Value at Risk is calculate for 10 Italian stocks and MIB30 stock market index. Riskmetrics Variance-Covariance and GARCH(1,1) models are used for calculating VaR. It is found that SRBM and MSRM perform well for portfolios with one and two assets at all confidence interval. The SRBM model produce accurate VaR estimates than SSRM, GARCH and GARCHB models implying the necessity of relationship with market for calculating equity risk. RM model performs better for all portfolios. The PF
test and TUFF test is used to select the appropriate model. The result suggest that one-FSRM is preferred over RM and RMB. This indicate that more number of factors should be considered for getting reliable estimates of market risk under FSRM.

1.3 IMPORTANCE OF THE STUDY

The present study on the Market Risk is relevant on account of the following factors:

a) Indian markets have witnessed fundamental changes since 1990s which marked the beginning of opening up the Indian economy through liberalisation, globalisation and privatisation. As such the financial markets are no more confined to only domestic limits of the economy but also exposed to the international markets due to technological advancements and other economic and political factors.

b) Further, increased volatility in exchange rates, interest rates, commodity prices are in turn effecting directly or indirectly the financial markets comprising Spot and the Derivative markets. Considering the fact of rising risk in the spot market, derivative instruments like forward, future and option were introduced to hedge the risk. Derivatives markets were aimed at increasing returns and reducing the risks. In India, financial derivatives were introduced in 2000 and since then the derivative market has grown considerably both in terms of volumes and number of contracts traded. It is to be noted that 99% of the derivative market in India Financial Market is accounted by National Stock Exchange (NSE). The trading figures of NSE and BSE show that the performance of NSE is more encouraging than the BSE in terms of volumes and the numbers of contracts traded in all categories of products. Total turnover in the BSE has increased from Rs 5,021.81 crores in 2003-2004 to Rs 1,94,21,854.8 crores in 2013-2014. Total turnover in the NSE has increased from Rs 2,365 crores in 2000-2001 to Rs 2,64,44,804.86 crores in 2013-2014. The World Federation of Exchanges (WFE) Market Highlights 2013 ranked third for the number of single stock futures contracts
traded in 2013 for NSE. While NSE was ranked First for the number of stock index options contracts traded in 2013. In the year 2006 NSE was ranked 15th, in 2008 it was ranked eight, in 2009 it was ranked seventh, fifth in 2010 and 2011 and in 2012 it was ranked fourth. While it improved its position still to third in 2013 and it has maintained its ranking consistently till now in terms of traded volume in futures and options put together. NSE witnessing a rise of 6.3 percent75 in 2013, was ranked fourth worldwide in terms of traded volumes in derivatives segment.

c) Derivatives market aimed to control, avoid, shift and manage efficiently different types of risks through various strategies like hedging, arbitraging, spreading etc. But due to the rising participation of the speculators, volatility in the exchange rates etc. the risk in the derivative market also are increasing. Hence the need to identify, measure and manage the market risk.

d) One of the popular method available to quantify the market risk arising both in the spot and derivative markets is the Value at Risk, which revolutionised the Risk Management concept in the recent past. VaR is used mostly by the financial institutions to quantify market risk. But its applications is extended to calculate credit risk, liquidity risk, and operational risk.

e) Further, the number of study with respect to the Indian context on Value at Risk is very less. Hence an attempt is made to study the application of various VaR models for the Indian Financial Markets consisting of Equity, Forex and Derivative Markets.
1.4 OBJECTIVES OF THE STUDY

1. To measure, compare and rank the predictive ability of select VaR approaches in assessing Market Risks of Indian Financial Markets (Equity / Derivative / Forex).

2. To analyse risk spillover between Indian Financial Markets.

3. To analyse the Co-Variances and Correlations of Market Risks using selected VaR approaches in Financial Markets of India and its international counterparts.

1.5 METHODOLOGY

1.5.1 Data Period and Structure:
The following table gives the details of the data employed for the study which is self-explanatory.

<table>
<thead>
<tr>
<th>Series</th>
<th>Period</th>
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<tbody>
<tr>
<td>Equity Market</td>
<td>Nifty Index Spot</td>
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<tr>
<td></td>
<td>January 2000 - December 2014</td>
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<tr>
<td>Forex Market</td>
<td>INR/USD Spot</td>
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<td></td>
<td>August 2008 - December 2014</td>
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<td></td>
<td>INR/EURO Spot</td>
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<td>January 2010 - December 2014</td>
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<td></td>
<td>INR/GBP Spot</td>
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<td></td>
<td>January 2010 - December 2014</td>
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<tr>
<td>Derivative Market</td>
<td>Nifty Index Future</td>
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<td>January 2000-December 2014</td>
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<td>INR/USD Future</td>
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<td>INR/GBP Future</td>
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<td>January 2010 - December 2014</td>
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1.5.2 Sources of Data:
The above data is taken from Bloomberg database, Bombay Stock Exchange, National Stock Exchange and Reserve Bank of India websites and other required journals and magazines.

1.5.3 Methodology Based on Objectives:

1. To measure, compare and rank the predictive ability of select VaR approaches in assessing Market Risks of Indian Financial Markets (Equity / Derivative / Forex)

For achieving the first objective the study employs VaR models like, Historical Simulation, HS symmetric GARCH, HS Asymmetric GARCH, Monte Carlo VaR, Exponentially Weighted Moving Average VaR and Conditional VaR. For testing the accuracy of VaR models backtesting models are used.

2. To analyse risk spillover between Indian Financial Markets

For the second objective Granger Causality in Mean and Granger Causality at Risk developed by Hong is employed. The following null hypothesis are tested:

- \( H_0: \) Futures Market is equally Riskier than Spot Market
- \( H_0: \) No Granger Causality of Risk Spillover between Financial Markets.

3. To analyse the Co-Variances and Correlations of Market Risks using selected VaR approaches in Financial Markets in India and its 5 international counterparts

- USA, UK, JAPAN and BRICS Nations

The third objective considers Variance Covariance VaR model for construction of hypothetical portfolios of domestic and international market.
1.6 LIMITATIONS OF THE STUDY

- **Derivative Market data available is limited.**

  The Indian Derivative Market is not developed as compared to the developed economies. The data available for derivative instruments for equity and stock indices are not continuous for some periods. Moreover, the derivative instruments for currency markets was introduced only for INRUSD currency pair since August 2008 and for INRGBP, INREURO and INRJPY since September 2010.

- **The study considers calculating market risk only.**

  Value at Risk models applications are extended for calculating credit risk, operational risk and liquidity risk. As the present study considers only market data, more weightage is given for assessing market risk.

- **The study considers only one day time horizon for assessing market risk.**

  Even though there are quiet good number of studies for assessing market risk for various time horizons ranging from one day to thirty day, the study employs one day time horizon only due to time constraint. However, the scope of the research can be extended by making a comparative study of various time horizons.

- **The statistical distributions assumed are limited to normal and student-t distributions only.**
1.7 CHAPTERISATION
The study is divided into 6 chapters.

The Chapter 1 INTRODUCTION deals with the background with which the study has been carried out. The importance and the necessity of the study in the Indian context is highlighted through Review of Literature. The chapter also mentions objectives of the study, source of the data and the methodology used for each objective. The chapter points out the limitations of the study and the chapter layout.

The Chapter 2 THEORETICAL BACKGROUND gives an overall picture of various financial risks. It also provides an understanding of various Value at Risk models used in the study. Certain statistical key concepts are also explained in this chapter.

The Chapter 3 gives the empirical results of THE PREDICTIVE ABILITY OF VaR MODELS IN INDIAN FINANCIAL MARKETS. Various VaR models are calculated, compared and ranked. The chapter aims at suggesting an appropriate model applicable for the Indian Financial Market.

The Chapter 4 analyses THE RISK SPILLOVER BETWEEN INDIAN FINANCIAL MARKETS. The chapter employs Granger Causality in Risk for this purpose.

The Chapter 5 provides the results of PORTFOLIO VaR of domestic and International hypothetical equity portfolios. This chapter uses Variance Covariance technique for calculating market risk of a portfolio.

The Chapter 6 gives the FINDINGS, CONCLUSIONS AND SUGGESTIONS. The chapter summarises the findings according to the objectives. It provides suggestions for the investors. The scope for further research has been included in this chapter.
1.8 REFERENCES


Chapter 1

Introduction


Chapter 1


73 https://www1.nseindia.com/homepage/nse_mkt_trd_detail.htm
