CAPITAL UNIVERSITY OF SCIENCE AND TECHNOLOGY, ISLAMABAD

Evaluation of Value at Risk and Expected Shortfall Models: A Study of Emerging and Frontier Markets

by

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This work is dedicated to my beloved parents who have encouraged me to achieve this milestone and to my respected supervisor Dr. Arshad Hassan, who has been a constant source of inspiration.

CERTIFICATE OF APPROVAL

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Abstract

This study provides evidence about the accuracy of value at risk and expected shortfall models for forecasting risk in emerging as well as frontier markets including Pakistan. The study focuses on performance of various models in prediction of VAR and Expected Shortfall and their validation through backtesting.

The sample comprises of five emerging markets and ten frontier markets for the period of 2000 to 2017 and daily data is employed. The study estimates VaR under different distributional assumptions such as non-parametric approach and parametric approaches. Furthermore, it estimates VaR under the assumption of time varying volatility. The models under this assumption include EWMA and the conventional GARCH model. Backtesting is done to test the predictability of these methods. Violation ratios and volatility are also computed to evaluate the performance of the aforementioned methods of risk forecasting Finally, Kupiec test & Christoffersen test are used to check the unconditional coverage and independence of violations. The findings indicate that the Historical Simulation method has highest accuracy in risk estimation in emerging as well as frontier markets at 95% confidence level which is a clear indication of perfect modeling. Therefore, the results imply that Historical simulation method is recommended to be used at 95% confidence level for emerging as well as frontier markets. However, higher confidence level of 99% comes out with over estimation of risk.

Keywords: Value at Risk, Non parametric models, Parametric models, Kupiec tests, Christoffersen tests, Back testing, Emerging markets, Frontier markets.

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Abbreviations

ARCH	Autoregressive Conditional Heteroscedasticity
CVaR	Conditional Value at Risk
ES	Expected Shortfall
EVT	Extreme Value Theory
EWMA	Exponentially Weighted Moving Average
FIGARCH	Fractionally Integrated Generalized Autoregressive Conditional Heteroscedasticity
GARCH	Generalized Autoregressive Conditional Heteroscedasticity
GJR	Glosten, Jagannathan, and Runkle
HS	Historical Simulation
LR	Likelihood Ratio
MA	Moving Average
n-APARCH	Normal Asymmetric power Autoregressive Conditional Heteroscedasticity
POF	Proportion of failure
POT	Peak Over Threshold
QML	Quasi Maximum likelihood
VaR	Value at Risk

Chapter 1

Introduction

1.1 Theoretical Background

Financial and monetary turmoil had occurred since the inception of financial markets particularly stock markets. The effect of these crises in the emerging market economies from the last years of nineteenth century was more holistic and more nocent to the equilibrium state of economy and political stability as compared to the past crises. These events that commenced in countries like Thailand in late nineties finally reached over many Asian countries and as well as American economies. Among all the crises of the financial markets, Financial Crisis in global markets was termed as the worst financial crisis after the Great Depression that occurred in 1930s.Economies globally decelerated as credit situation became worsened resulting international trade to relapse. Governments as well as central banks showed monetary policy expansion and institutional bailouts in response to this unparalleled stimulus. Among the many causes for the financial crisis suggested, the document by Levin–Coburn (2011) propose that the crisis was not an outcome of calamity, but due to elevated risk, complicated products, unrevealed clashes of interest of the agencies rating credit and the straight failure of regulators. It was a policy challenge of great significance to sort out different methods to mitigate the future risk of crises and to improvise crises management on its occurrence.

The variety of investments is more important to investors these days. Previously emerging markets capitals were considered as the hive of earning and funds. These days there are a huge variety of funds to choose from; such as: frontier market mutual funds and ETF's and many frontier country-specific funds. As the more and more frontier markets are achieving the status of developed markets. Frontier markets are becoming more important, as they have potential for higher growth and earnings.

Numerous perspectives render risk management a vast concept. Involving the mathematical perspective, risk management can be termed as a procedure for carving shape to a distribution of loss. The widely accepted measure of risk is VaR after volatility. It is defined to be a statistical risk measure having single summary, distribution independent and is regarded as a tool to measure losses arising out of 'common' market fluctuations. Apart from its catalogued flaws, VaR has continued to be the prioritized measure of risk chosen in the business and financial world. The theoretical characteristics compared with the implementation issues as well as very convenient back testing, the reason becomes quite evident of choosing VaR over other measures. VaR produces the equilibrium among the risk measures that are available and therefore constructs practical and robust risk models. Different VaR models are derived due to ever increasing availability and access to the financial world data and developments in information technology so that they are made applicable for the risk management profession.

With the same confidence level, a very close correspondence between VaR and CVaR is observed. VaR is related as lower bound for CVaR. Rockafellar & Uryasev (2000) coined Conditional value at risk to be a famous measure for risk quantification and management. VaR is very much similar to the risk measure CVaR as both are the percentiles of an extreme distribution of loss.

The methods of computation of value-at-risk for risk measurement are by now well developed. Until its visibility in the report by Group of Thirty made published in the month of July 1993 as well as the outburst of the very first published version of Risk Metrics in the month of October 1994, value-at-risk is almost unknown except for being used by the large derivatives dealers whereas now it is difficult to find financial professionals who are not acquainted with value-at-risk. Presently, value-at-risk is in use by banks of all types and sizes, pension plans, fund managers, brokerage firms, and other institutional investors, insurance companies, other financial institutions and non-financial corporations. Stress testing is used in conjunction with value-at-risk and is almost equally well accepted as the complementary risk measurement methodology. Three approaches to computing value-at-risk were proposed initially at the outset i.e. the delta-Normal method, historical simulation and Monte Carlo, for which reprising the entire portfolio for each factor realization is required. While these three techniques remain the basis of value-at-risk computations, the years since their outset, release of Risk Metrics have witnessed significant refinements of and elaborations upon these approaches.

Emerging economies are those markets that are heading towards being what are called developed markets. This becomes possible when they become more industrialized and practice economics of free market. These markets possess liquidity and per-capita income at very low level. Consequent upon larger growth in the future these markets will immensely impact trade businesses and global economics. Ultimately, emerging economies support the global economy to expand. Due to this robust growth and rapid development, emerging markets are more enticing for investors as compare to the developed counterparts. The performance of the developed markets like America and Europe during the last decade reveals dormant economic growth since the financial crisis of 2007-2008 resulting in very low interest rates causing investors to face with odd factors which ultimately caused shift of investor's focus and they searched for other markets to reap the gains while western economies were focusing on shelter from the storm and were hiding the fallout situation from the crisis. After that investors started to look elsewhere for the benefits that western markets used to offer. Hence emerging markets offer golden opportunities for investors who are looking for an economy to be accelerating making them ideal for upcoming studies for investment and risk studies. Like wisely, the countries having less economic resources for investment and lower market capital fall under the term frontier markets. The term was introduced in 1990's by International Finance Corporation's Farida Khambata. These markets have a promising potential to generate long term results for attracting investors. They have capability to eventually match the emerging or even developed market status. The variety of investments is becoming more and more significant to investors these days. Emerging markets capitals were considered as the hive of earning and funds earlier but nowadays there are a variety of funds to choose from like frontier markets mutual funds, Exchange traded funds and many frontier country specific funds. As the more and more frontier markets are achieving the status of developed markets, frontier markets along with emerging markets are becoming more significant as they have potential for higher growth and earnings promising huge returns for investors. Therefore, this study provides insight for the investors about the risk associated with these markets and about using various models for forecasting risk using tools such as VaR and ES.Hence there is a need to identify which model best forecasts these tools in the emerging as well as frontier markets.

Following is a brief orientation about the emerging as well as frontier markets and their indexes that are used for analysis in this study.

The trading in the Indian stock market takes place through two exchanges i.e. National Stock Exchange and the Bombay Stock Exchange. The BSE is existing since 1875and has list majority of major firms of India. Sensex termed to be the remotest for equities, includes thirty firms listed on the BSE representing majority of the market capitalization of free float index.

One of the major indexes of China is the SSE Composite (Shanghai Composite) Index. It is a widely used signal for imaging the market performance. It constitutes all listed stocks (A and B shares). The Base Day for this index is December 19, 1990 while the total market capitalization of all particular stocks of the day form the base period having base value of 100.

The Brazilian Stock Exchange is regarded to be the 59th largest exchange. The country coins the GDP of approximately $2.19 trillion. In terms of population, Brazil is ranked fifth in terms of population and falls in top 100 markets in terms of GDP out of total 240 countries and country equivalents tracked so far. IBOVESPA is a Billion Brazil Real Money accumulation by year media industries index and exhibits the present value of a portfolio that had started on 2 January 1968, with a base value of 100 and considers the share price acceleration including the re-investments.

The MOEX Index of Russia is the benchmark of the Russian stock market. It was started on 22 September 1997; possess same composition as the RTS Index which is dollar denominated. The component stocks depend on frequency and liquidity of trading. The domestic investors prefer MOEX Russia Index conventionally.

South Africa has FTSE/JSE Africa All Shares Index which is a market capitalization weighted index. It includes the companies that form part of the top 99% of the market capitalization of all listed companies on the Johannesburg Stock Exchange.

The Karachi Stock Exchange 100 Index is major stock market index of Pakistan which considers the performance of largest companies by market capitalization from each sector of Pakistani economy listed on The Karachi Stock Exchange. It is operating as free-float since 15th October, 2012.

DSEX is the Broad Index of the Exchange of Bangladesh stock market which forms 97% of the market capitalization of equity. DS30 is created with thirty leading companies making it investable Index of the exchange. It covers 51% of the total equity market capitalization.

The EGX 30 Index is regarded as a free-float capitalization weighted index of the top thirty highly capitalized liquid stocks that are traded on the Egyptian Exchange. The index was established with a base level of 1000 as of January 1st 1998 was formerly named CASE 30 Index.

Indonesia Stock Exchange is a stock exchange based in Jakarta, Indonesia. By the end of 2017, the Indonesia Stock Exchange constituted 566 listed companies having cumulative market capitalization of IDR 7,052.39 trillion. By the end of 2017, total daily transactions averaged more than 312,000.

The Korea Composite Stock Price Index or KOSPI is the index of all common stocks traded on the Stock Market Division. It is the representative stock market index of South Korea.KOSPI was introduced in 1983 with the base value of 100 as of January 4, 1980.

The Mexican Stock Exchange (MEX) is securities exchange of the country dealing in fixed income products, cash equities, derivatives. It was established in 1886 and is currently the second largest stock exchange of Latin America.

The BMV IPC Index exhibits the largest and most volatile stocks. The consumer staples, materials, financials, telecommunication services, industrial, consumer discretionary and utilities sectors comprise the index indicative of the huge economy. Approximately 150 companies in were listed on the exchange at the end of 2017.

All listings are included in the Nigerian Stock Exchange All Shares index. The Nigerian Stock Exchange is the third largest stock exchange in Africa in terms of market capitalization, Philippine Stock Exchange is the 67th largest exchange out of the tracked stock exchanges. Philippines ranks 12th in terms of population and 224th in terms of GDP out of 240 countries and country equivalents.

The BIST is the sole exchange of Turkey combining the former Istanbul Stock Exchange (ISE).It was formed as an incorporated company and began its operations on April 5, 2013. Shareholders of BIST include Government of Turkey, members, brokers and IAB members.

The Vietnam Stock Index is a capitalization-weighted index of all the companies listed on the Ho Chi Minh City Stock Exchange. The index was formed with a value of 100 having base period of July 28, 2000.

1.2 Research Gap

Value at risk and Expected shortfall (conditional value at risk) are not jointly evaluated using same techniques. Moreover, studies on frontier markets do not consider Expected Shortfall into account. This study tries to attempt to mitigate this existing vacuum. It contributes by offering more insight into the Emerging stock-markets as well as frontier markets characteristics and depicts the need of considering Expected Shortfall in risk management based on our outcomes. Moreover, if we talk about specifically Pakistan almost negligible work has been done on Value-at-Risk or Conditional Value-at-risk or both making it a very enticing domain to be worked on.

1.3 Problem Statement

The academic literature highlights the issue of the choosing between VaR and CVaR especially in the domain of risk management in finance. The reasons that affect the decision of choosing between VaR and CVaR are coined on the different mathematical and theoretical properties, stability of statistical estimation, parsimony in optimization procedures, and acceptability by regulators and many more. Outcomes drawn from these properties may be quite contradictive.

1.4 Research Questions

The research-questions formulated for this study are stated as below:-

1. How do Value at Risk models perform in determining the loss in frontier and emerging market?
2. How do Conditional Value-at-Risk models perform in determining the worst case losses in frontier and emerging markets?
3. Which model(s) is more appropriate in capturing the value at risk of frontier and emerging markets?
4. Which model(s) is more appropriate in capturing the Conditional value at risk of frontier and emerging markets?
5. Do the estimation models for Value at risk and Conditional Value-at-risk (Expected shortfall) specifically for emerging as well as frontier markets perform the same when back tested?

1.5 Objectives of the Study

The objectives of the current study are listed as under

1. To evaluate Value-at-Risk using estimation techniques for returns in emerging and frontier markets.
2. To evaluate the Conditional Value-at-Risk techniques for both frontier and emerging markets.
3. To propose risk estimation models for Value at Risk and Expected shortfall (Conditional value at risk) on the basis of back testing for both frontier and emerging markets.

1.6 Significance of the Study

The significant implications towards financial institutions are drawn by accurate forecast of VaR and Expected Shortfall parameters are also important for the business practitioners, fund managers, the portfolio managers and regulators. Hence, this study is a significant contribution in the sphere of risk measurement techniques evaluation on the basis of validation of models through backtesting. The empirical analysis to be performed on different market returns in order to compare the performance, robustness and validity of all the approaches in the study gives more comprehensive insight towards their implementation.

While considering the robustness of alternative methods for calculating VaR results, the outcomes of particular test may vary based on the quantity of out of sample observations and of course the specific tenure under observation. Not even a single method visibly outperforms the rest of techniques, and is rejected by one test at least in one out of sample period. Therefore, it is coined that parsimonious predictions that are the most competitive and robust ones having fundamentals on the conditional variance development by the use of asymmetric GARCH type models and of errors that are asymmetric leptokurtic. Despite the time variant skewness as well as kurtosis of the distribution of returns, the VaR forecasts do not get improved. After the bias correction introduction, the reliability and robustness of VaR forecasts as well as validation through back testing are significant areas that require more in depth research in order to achieve more conclusive results on the validity of alternative measures. Although the purpose of the study is particularly dedicated to the evaluation of VaR and CVaR forecasting procedures, it is hence already proposed in the Basel accords that the expected shortfall (ES) be used in place of VaR.

1.7 Outline Structure of the Thesis

This thesis is composed of five main chapters. The initial three chapters lay emphasis on theoretical areas of thesis whereas the two last chapters cover up the empirical aspects of the study.

Chapter 1 lime lights the fundamental idea underlying the research. It gives introduction to the thesis topic by giving the basic information along with defining the problem statement as well as its objectives and its contribution.

Chapter 2 narrates about corresponding literature to this research. The chapter presents a deep investigation on topic including theoretical along with empirical arguments made by the past authors, past academicians and fellow researchers.

Chapter 3 catalogues the approaches adopted to carry out the research. It narrates a thorough breakdown of the methodologies as well as methods for data collection that help to fulfill the purpose of the study.

Chapter 4 elaborates on the outcomes of empirical tests and explains findings that are derived from the finalized results of this research. On the basis of objectives of the research, the detailed analysis of the findings are filtered and on the basis of back testing a comparison is done on various methods of estimations of VaR.

Chapter 5 concludes off this research by summarizing the entire research outcomes and derived results as well as addressing the mentioned research problems.

In the end, it highlights the avenues that need to be improved existing in this study that could be advanced and developed in upcoming future research.

Chapter 2

Literature Review

The effectiveness and validity of the measure of Value at Risk in different distributional models under the most highlighted context regarding the latest financial world turmoil and the issue of efficient estimation of the parameters of the return distributions are examined.

A dual step procedure is used for the three distributions which are specifically suitable for computing the tail risk, i.e. the generalized Pareto distribution, α stable distribution and the g and h distribution. The QML is used for sieving the returns, and then these are fitted towards the standardized residuals derived from the initial step. The stable and g and h distributions are likely to perform well enough for data which is heavy tailed in the sample period (Diazet al., 2017).

An evaluation of performance comparing the predictability of VaR models with particular attribution to the latest turmoil of emerging markets is conducted which covers the financial crisis in Asian economies. A systematic ranking among the models could not be revealed. For separate countries, based on same periods, different levels of tail probability, and for variant evaluation procedures, different outcomes relating to risk forecasting performances are received. It is derived by both Christofferen tests and reality check that methods of Monte Carlo and models of ARCH in general exhibit more reliable consistent and valid risk forecasts relatively to models of EVT. However it cannot be said with certainty that which of the methods evaluated shows consistently better predictability for all of the countries and for all the periods (Saltoglu et al., 2006).

BenSaida et al. (2017) have reconsidered the evidence on predictability potential of GARCH type models for estimation of Value at Risk of returns associated with stocks of global market with better returns. Twenty one models of VaR being produced by a mutual combination of major three conditional volatility approaches such as GJR, FIGARCH and GARCH are evaluated and seven different assumptive conditions of distributions for return innovations are probed into. Backtesting done for crisis tenure as well as post crisis time periods for emerging as well as frontier and developed markets conclusively exhibit that skewed t with that of tailed Levy distributions specially fat tail distributions get significantly make better the predictions of one- day-ahead values of Value at Risk attached to long as well as short positions of trading in turmoil period, irrespective of the volatility model.

Similarly, Georgoutsos and Bekiros (2003) have also conducted a comparative analysis of the predictability performance of several models for Value at Risk (VaR). The special emphasis is laid on two main methodologies related particularly to the Extreme Value Theory, the first being Peaks over Threshold (POT) and the second one is Blocks Maxima (BM). The results reinforce previously obtained ones, accordingly conventional methods may produce same outcomes at traditional confidence levels but at very high values the EVT method gives the most accurate and valid forecasts of extreme losses distribution.

Perote et al. (2014) contributes fuel to the debate through comparison of the performance of alternative available specifications designed for models of the returns sieved by Parametric distributions particularly Student's t and skewed t, the EVT (extreme value theory), methods that are semi nonparametric and based on the GC (GramCharlier) expansion and lastly the normal distribution (regarded as benchmark). Backtesting techniques are implemented for the periods of pre-crisis as well as crisis periods simultaneously for returns of stock index as well as hedge fund created from emerging markets which reveals that the Student's t has failed in estimation of VaR for the crisis period, whereas market risk is well captured by EVT and GC.

A comparison relating to the performance of widely used value at risk methods for estimation for stock indices from both developed and emerging markets is done using newly developed KE (kernel estimator) approach for predicting VaR apart from using common conventional time-series models. As KE methods shape tail behaviors, it takes recent extreme shocks directly into account. With the use of moving window through the models are back tested and with likelihood ratio tests, it reveals that KE models generate significantly better VaR estimations and it outperforms the other common methods (Tseng, 2009).

Kumar and Maheswaran (2017) propose an approach which is based on unbiased the extreme value of volatility estimator. It is used for calculation and prediction of the different market positions and the backtesting techniques evaluate forecasting validity. A comparison run of the outcomes with that of different alternative available models and their combinations indicate that the proposed framework performs better than the alternative available models. It therefore provides the least accumulated loss for different long and short positions VaR. Hence it is aligned to characteristics of the framework in prediction of VaR more precisely.

Aziz and Ansari (2017) aims to evaluate the role played by value at risk of stock returns in the Indian equity market between 1999-2014 taking the methodology proposed by Bali and Cakici in 2004 in order to find the relation of VaR and stock returns. It takes in account Fama and French 1993, Fama and Macbeth 1973 and Fama and French 2008 for computation of separate regressions particularly for small, medium and huge stocks to vet the pervasiveness related to the anomaly. The positive nature of premium can be said to have attribution to constraints of short selling.

Zewotir (2017) propose a new approach to extreme value modeling for the forecasting of Value at Risk. The block maxima and the peaks over threshold techniques are generalized specifically to exchangeable random sequences. It serves for the dependencies, such as financial returns for serial auto-correlation obtained empirically. Moreover, this approach allows for parameter variations within each VaR estimation window.

Kramer and Wied (2015) propose entirely new method relevant to backtesting models specifically for value at risk and therefore suggest an improvement in latest VaR backtesting techniques based on time intervals prevalent between VaR violations. It depicts by simulations of Monte-Carlo that the test has more robustness than its rivals among various existing alternatives. The test does not consider the big values for Gini-coefficient of durations present among Value at Risk violations. It is therefore countered by various deviations exhibited from VaR violations.

Another study reveals that for different kinds of partial settings of information, very edgy bounds are obtained for VaR for individual and accumulative models related to risk along with the correlating extreme scenario of marginal risks and also for the correlating functions among these relating to copula. In contrast to the already done studies, these sharp bounds are observed under various part settings of information through a combined method merging convex order as well as latest developments of joint mix-ability (Yang et al., 2018).

Cerrata et al. (2014) studies pattern on the robustness of models as well as techniques in expected shortfall estimation, taking into account separate asset classifications, magnitude of estimation windows and levels of significance. It has used unconditional and conditional as well as models based on quantile expectile regression. The study assess the outcomes of these models by using the usual Expected Shortfall backtesting and also suggest a new test based on dispersion hurdled by VaR. VaR forecasting is significant for ES estimation as one inaccurate violation will lead to low probability values when back tested. Moreover, different quantiles of interest, size of estimation windows ultimately lead to inferior Expected Shortfall estimated results.

Sirtori et al. (2008) review some classical arguments that are revealed in recent years in the debate done on Value at Risk as tool for evaluating the risks particularly financial risks of a portfolio and evaluates another measure of risk which is termed to a modified version of Expected Shortfall in Extreme Value Theory and the comparison between these two risk measures is run on a rather technical basis by evaluating mathematical properties having a very significant role in the explanation of a risk measure.

A comparison of the out of sample performance of current methods and few novel models for univariate forecasting of value at risk using more than 30years of the daily return data on the NASDAQ is carried out. Moreover, a merged hybrid method that uses a merged combination of a heavy-tailed GARCH filter using an EVT (extreme value theory) approach shows overall best performance finally using a variance on a well sieved historical simulation and recent one which is model based on distributions that are heteroskedastic mixture (Paolella et al., 2006).

M-estimators are used for generalized autoregressive conditional heteroskedastic GARCH models for forecasting of value at risk VaR of Karachi Stock Exchange. Symmetric and asymmetric GARCH models are fitted to these pre, during and post crisis tenures and in sample as well out of sample forecasted values of VaR are calculated. The findings reveal that M-estimators generate accurate and authentic estimates of VaR in variant volatile time and further show that this asymmetric model gives better fit than that by the symmetric model proposed for the KSE (Iqbal, 2017).

Another study by Afzal and Nawaz (2011) figure out as to how the margin computed on Value at Risk impact volume of business and trade for Pakistani bourse. This Pro method is considered as more correct one as compared to other two proposed models at $\lambda = 0.85$ and 500 days at level of 99% confidence interval. Based on the study it is therefore found that in current Slab System, the initial margin asked by clients generally fall in range of $5-25$ percent. The given margin limits known as cap, found in VaR system, is almost 5 percent. This margin system is shown to outperform slab system when observed on the theoretical and empirical grounds.

Ruiz and Neito (2016) review latest contributions in the forecasting as well as backtesting of the Value at Risk as measure quantifying risk. These different procedures are illustrated by estimation of the Value at Risk of a daily series of S&P−500 returns taken for a time period that has coverage on the latest global financial turmoil. This study is specific to the evaluation of Value at Risk forecasting ways and methodologies. It is observed that when taking into consideration the adequacy and reliability factors of substitute procedures for achieving VaR estimations, the outcomes of a specific test may vary.

Dent et al. (2013) addresses the accounting specifically for long memory of VaR and expected shortfall across twenty indices of equity worldwide. It is seen for accounting of fractional integration related to the conditional variance that it does not seem to enhance the accuracy of the VaR values for the one day, 10 day and 20 day ahead forecasting avenues related to the short memory GARCH. Ultimately, the rolling sample of estimated FIGARCH measure fluctuation is less flat for this time period when compared to the other GARCH models. Hence, the arrival of market news information as well as the FIGARCH model processing itself is the main cause of such change.

Zhao (2016) analyzes semi parametric CVaR computation and there inference for parametric model combined with nonparametric distribution of noise. Therefore a bootstrap approach has been introduced for facilitation of new users who are not experts to carry out construction of confidence interval for CVaR. The methodology is well explained by Monte Carlo studies as well as an overall application and usage to S&P 500 index.

Walther (2017) analyses the conditional volatility of the VN-Index and the HNX-Index with a special emphasis on its implementation on risk management measures like Expected Shortfall. The study perform test on indices related to both long memory in returns as well as returns that are squared and afterwards apply some GARCH models to take into account asymmetrical effects and long memory impact appearing for conditional volatility. When they are back tested the models of GARCH family forecasts well for Value at Risk and Expected-Shortfall. Major differences are found in both indices for the asymmetrical effect of both bad (negative) as well as good (positive) news on volatility factors and of course about this perseverance of shocks. These long memory based models exhibit best performance while estimation of risk measures coined for both of the series.

Assaf (2014) also examines the predictability performance of the Value at Risk models specifically in MENA stock-markets and also usage of the Asymmetric Power –ARCH model for analyzing emerging markets namely Morocco, Egypt, Jordan and Turkey. Upon considering short position for each market, it is observed that the returns got noticeably fatter tails as compared to the normal distribution. The model called Asymmetric Power ARCH is introduced to predict the value at risk existing in these markets and afterwards the influence of asymmetry found in conditional variance is studied and furthermore deep analysis on estimating VaR through fat-tail distributions on estimating Value at Risk is carried out. The findings show that VaR results which are based on the model Student-APARCH are deemed to be accurate than those generated through n-APARCH models. Hence the long memory as well as tail behavior exhibited in these four markets shall not be ignored.

Which is the best model in forecasting values of different parameters of risk is a question that needs to be figured out still. Unfortunately no single reply to this question is available that can be regarded to be accurate & consistent. Different studies have proposed models to be accurate in different circumstances. One can forecast individual single models through testing for parameter significance as well as by evaluation of residuals; however the risk forecasting characteristics of the models underlying consideration are usually not addressed properly. Hence this study focuses on performance of various models in prediction of VAR and Expected Shortfall and their validation through backtesting.

Chapter 3

Data Description and Methodology

3.1 Population & Sample of the Study

The sample comprises of five emerging markets and ten frontier markets for the period of 2000 to 2017. These five emerging countries are India, China, Brazil, Russia, and South Africa and ten frontier markets are Pakistan, South Korea, Philippines, Bangladesh, Vietnam, Indonesia, Iran, Mexico, Nigeria, Egypt and Turkey. Time period of sample for analysis is 17 years and daily data is employed. Data is secondary in nature and there is no problem faced in data collection. All data is collected conveniently from the web sources.

Table 3.1: Sample Description.

S. No.	Country	Index	Period	No. of Obs.
		EMERGING MARKETS		
1	INDIA	BSE Sensex	2011-2017	1697
2	CHINA	SHANGAI Composite	2000-2017	4361
3	BRAZIL	BOVESPA	2000-2017	4241
4	RUSSIA	MOEX	2000-2017	4498
5	SOUTH AFRICA	JSE All share	2011-2017	1508

S. No.	Country	Index	Period	No. of Obs.
		FRONTIER MARKETS		
1	PAKISTAN	KSE100	2000-2017	4694
2	BANGLADESH	DSEX30	2013-2017	1187
3	EGYPT	EGX 30	2010-2017	1841
4	INDONESIA	Jakarta Stock exchange	2000-2017	4208
5	SOUTH KOREA	KOSPI100	2011-2017	1520
6	MEXICO	BMVIPC	2001-2017	4222
7	NIGERIA	NSE All share	2012-2017	1465
8	PHILLIPINES	PSE	2012-2017	1391
9	TURKEY	BIST100	2000-2017	4515
10	VIETNAM	FTFYTT	2010-2017	1918

3.2 Data Analysis

The methods for forecasting VaR and ES can broadly be divided into two main categories, non-parametric and parametric. In certain scenarios a combination of these two is also seen to be used. Non-parametric forecasting of risk is generally referred to as historical simulation. It uses the data distribution empirically for computing risk forecasts. There are no statistical models assumed and there is no parameter estimate necessary for non-parametric methods particularly HS.In contrast to this, parametric methods have fundamental bases on estimation of the underlying return distributions and afterwards getting these estimated distribution are used to calculate the required risk forecasts.

Most of the times, the initial step in the process is predicting covariance matrix. The common methods utilized for forecasting this matrix include EWMA, MA or GARCH. They are mostly used along with normal distribution and rarely with Student-t. Therefore the parametric approach is also known as the variance covariance method. The study estimates VaR under different distributional assumptions such as non-parametric approach including Historical Simulation and parametric approaches like Normal Distribution, Student-t distribution. Furthermore, it estimates VaR under the assumption of time varying volatility. The models under this assumption include EWMA and the conventional GARCH model.

These mentioned models are validated by using daily returns data collected from various web sources for the time period from January 1, 2000 to December 31, 2017 related to the fifteen countries. Afterwards, the calculation for continuously compounded returns is carried out for each country separately. These returns are calculated to be the first difference arising of natural logarithm of every series, $R_t = \ln(p_t/p_t - 1)$, whereas R_t coins the return for a specific date t and the p_t shows the index price at time t. Lastly, the loss $L_t = -R_t$ is explained.

For all the models under consideration, a rolling window of 500 days is used to compute new estimate of value of VaR or ES as risk prediction for the following trading day by using *R* programming software. Backtesting is done to test the predictability of these methods. Violation ratios and volatility are also computed via *R* programming software to evaluate the performance of the aforementioned methods of risk forecasting. This procedure is used for the comparison of the various models coined for risk. It takes the ex-ante value at risk forecasted values from a specific model and then compares these with ex-post return realized (also called as historical observations). Hence, whenever the losses exceed the value of VaR, a violation of VaR occurs.

3.2.1 Historical Simulation

Historical simulation is an uncomplicated method of risk forecasting. It is based on the assumption that things get repeated after some interval of time i.e. one value of the past returns obtained is likely to get repeated in the returns of next period. Every observation has the same weight in proportion in Historical Simulation forecasting method. In the univariate method, VaR at a certain level of probability (p) is the negative $(T \times p)^{\mathrm{Th}}$ observed value in return sorted out having the product with the value of the entire portfolio in monetary terms.

It is quite simple to get the value of expected shortfall by Historical Simulation. At first Value at Risk is calculated by using Historical Simulation method, and then after that Expected Shortfall is computed by taking the mean value of all existing observations which may be equivalent to or may be having more negative value than VaR.

3.2.2 Normal Distribution

The normal distribution has been regarded as a standard way of calculating VaR in the field of finance. In normal distribution, the VaR is simply as

$$\mathrm{VaR}_\alpha = \mu + \sigma(\phi^{-1}(\alpha))$$

It is generally observed that the volatility gets enhances in the period of overall crisis in the financial global world and it ultimately gets back to its actual original level when the crisis is over as towards its original value.

$$\mathrm{ES}_\alpha = \mu + \sigma\frac{\theta(\phi^{-1}(\alpha))}{1-\alpha}$$

In the above equation the symbol ϕ represents the function of standard normal distribution and θ represents the function of density (Embrechts, Frey, & McNeil, 2005).

3.2.3 The Student t-distribution

In order to forecast the risk well of the returns of time series that are leptokurtic, usually the student-t distribution is the natural choice. The standardardized student t distribution has mean equal to zero whereas the degree of freedom is used to create variance. McNeil & Frey (2000) and Embrechts et al., (2005) presented the Student-t distribution expressions for the VaR as well as for the ES.

$$\mathrm{VaR}_\alpha = \mu + \sigma t v^{-1}(\alpha)$$

Where tv represent the distribution function of student t-distribution.

3.2.4 EWMA

Volatility forecasts can be done more effectively by applying the EWMA model. In this model more weight is applied to the most recent dates.

$$\hat{\sigma}_{t,ij} = \lambda\hat{\sigma}_{t-1,ij} + (1-\lambda)y_{t-1,i}y_{t-1,j}$$

and

$$\hat{\sum_{t}} = \lambda \hat{\sum_{t-1}} + (1-\lambda)y'_{t-1}y_{t-1}$$

Where λ is called the decay factor having the value of 0.94. It is very simple to implement this univariate model of the EWMA model. The unconditional volatility on day 1 is σ_1. The burn time considers the error embedded into the model through fixing it to an arbitrary value $\sum_t$.

3.2.5 The GARCH

The volatility dynamics are captured by the GARCH models which give more refined volatility movements, as well as providing estimation model measures for each set of data. Resultantly, the GARCH model provides volatility forecasts in a better way as compared to the other parametric models. The GARCH (1, 1) model can be written as follows,

$$\sigma^2_{t+1} = \omega + \alpha Y_t^2 + \beta\sigma_t^2$$

While executing VaR forecasts from the above GARCH model we take the last estimate of volatility $\hat{\sigma}_t$ and the parameter to get the VaR forecast for day t+1. In this respect $\hat{\sigma}_(t+1)^2$ is calculated manually.

3.3 Backtesting

Backtesting is termed as a statistical tool where in actually obtained profits as well as losses are categorically compared to their related estimates of VaR. In this backtesting process we can statistically investigate the alignment of frequency exceptions of a certain time interval with the related confidence level. Such tests are called unconditional coverage tests. These tests are quite simple tests in regard to implementation as occurrences of the exceptions are not taken into account (Jorion, 2001).

3.3.1 Violation Ratios

The main tools used in backtesting are violation ratios, where the actual numbers of VaR violations are compared with the expected value.

For the elimination of the waiting time the backtesting investigates the VaR forecasting by evaluating the performance of the VaR forecast over a past period .When all the returns of a certain day exceed the forecasted value of VaR, then VaR limit is deemed to get violated. A judgment can be made on the corresponding number of exhibited violations; this technique is termed as violation ratios.

In this technique, the violations are recorded as t, which obtains value 1 upon occurrence of violation and 0 otherwise. The observed numbers of violations are gathered in the variable termed as v, whereas v_1 shows the number of exhibited violations while v_0 is the number of days which are without any violations. This is added up to coin the period of testing.

Generally it is the rule of thumb is that if Violation ratio ranges between 0.5-1.5 it is considered as a good model to forecast and if the value of Violation Ratio is less than 0.5 or is greater than 1.5, the model is said to be imprecise. These limits shall narrow with the increasing lengths of testing window. Backtesting usually laid focus on the violation ratios but it is likely probable that different VaR estimation methodology may give the same results of violation ratios but have differences in their values of forecasted VaR. Therefore, in that case, it shall be quite be useful if the volatility (the standard deviation also computed in this study) pertaining to the risk forecasts is considered. Evidently, the one with the lesser value of standard deviation is preferred on other models.

3.4 Backtesting of the VaR and ES Methodologies

The study compares the performance of different Value at Risk and Expected Shortfall proposed models through their daily returns of fifteen stocks of emerging and frontier markets. These VaR models are validated through the Kupiec test (conditional coverage test) as well as Christoffersen test (Independence test). In the process of this two stage Backtesting, the outperforming model must be accepted in the Christoffersen test as well as Kupiec.

3.4.1 Christoffersen Test

The conditional coverage test is introduced by Christoffersen (1998). The probability exhibited by the Christoffersen test of independence explains the dependence of today's exception on the previous day outcomes. Log likelihood ratio is used in this test involving the independence of exceptions statistics which is then compared with the chi square value.

The null hypothesis states that if $LR > \chi^2$, then the model will be deemed to be invalid. According to this null hypothesis, over the period of time, the occurrence of violation shall be independent.

The likelihood ratio test shall be expressly in the following formula.

$$\mathrm{LR}_{UC} = -2\ln\left[\frac{(1-p)^{T_0}p^{T_1}}{(1-p)^{T_0}\pi^{T_1}}\right]$$

Where p is termed as the probability level of 1 percent or 5 percent as the case maybe, π shows the observed violations, T_0 represents the observed number of days in which Value at risk does not get violated and T_1 show the actual number of violations exhibited.

The independence test is likely to investigate the clustering of violations through comparison of the probability of occurrence of a violation and then followed by the non-violation having the assumption that same value will be obtained for two independent probabilities whereas there will be clustered violations in case of higher probability of having two combined violations. Independence test has the following LR statistic,

$$\mathrm{LR}_{IND} = -2\ln\left[\frac{(1-\pi)^{T_0}\pi^{T_1}}{(1-\pi_{01})^{T_{00}}\pi_{01}^{T_{01}}(1-\pi_{11})^{T_{10}}\pi_{11}^{T_{11}}}\right]$$

Where

$$\pi_{01} = \frac{T_{01}}{T_{00}+T_{01}}$$

And

$$\pi_{11} = \frac{T_{11}}{T_{10}+T_{11}}$$

When there will be no consecutive violations T_{11}, then LR shall be computed using the following test statistic,

$$\mathrm{LR}_{IND} = -2\ln\left[\frac{(1-\pi)^{T_0}\pi^{T_1}}{(1-\pi_{01})^{T_{00}}\pi_{01}^{T_{01}}}\right]$$

Christoffersen aids to investigate the reasons behind the inaccuracy due to clustered violations, invalid coverage or may be both. Campbell, Lo and Mackinlay (1997) recommend the application of both the independence test and the coverage separately as the model may not pass the joint test sometimes.

3.4.2 Kupiec Test (POF)

Kupiec is said to be the conditional coverage technique which validates the VaR models. The Kupiec's test is validated by the values of χ^2 distribution at degree of freedom equal to 1. If the calculated value of likelihood ratio is lesser than that of χ^2 value, the model shall be accepted. However, if LR has greater value than that of the critical value, the decision about the inaccuracy of the model will be made. Similarly, at the 5% significance level the model shall be rejected if LR value is greater than 3.84.

Kupiec POF test takes into account the exceptions that occur; therefore the calculation of total number of exceptions is very significant. For this purpose we compute the daily losses of the sample stock returns and its comparison is performed with the forecasted value of Value at Risk. The POF test is run after the calculation of the numbers of exceptions observed for each level of confidence. It is generally seen that the validity of the test is directly proportional to the size of sample. The model has the loophole that it categorically ignores the loss period occurrence. This is very reasons of its failure in times of violation clustering. This is the strongest reason behind application of the Christoffersen test to resolve any of the shortcomings observed in the model.

Chapter 4

Results and Discussion

4.1 Descriptive Statistics

Table 4.1 indicates the descriptive statistics of daily returns of fifteen stocks listed in different emerging and frontier countries. The negative mean of stocks shows that these countries experience negative returns. Pakistan, Philippines and Vietnam show positive average returns. Maximum average return 0.000721 is exhibited by Pakistan and thus can be regarded as best return however minimum return -0.000643 is reported by Indonesia. The skewness for India, China, Brazil, Russia, South Africa, Egypt, Indonesia, South Korea, Turkey and Vietnam is positive while Pakistan, Bangladesh, Mexico and Nigeria are negatively skewed. The high excess kurtosis of each stock reports the fat tail distribution of stock returns. The leptokurtic return distribution is reported by Bangladesh by maximum kurtosis value. In order to check the normality of distribution, Jarque Bera Test has been performed. The extreme fat tail of returns shows the non-normality of the data. A considerable positive approach is given by these tails for VaR Model Estimations. Bangladesh stock market reports the maximum risk of 0.038343 and is termed as riskiest market whereas South African market shows the minimum risk of 0.008744. Therefore; it can be regarded as least risky market.

TABLE 4.1: Descriptive Statistics.

	Mean	**Median**	**Max**	**Min**	**Std. Dev.**	**Skew**	**Kurt**	**Jarque-Bera**
				EMERGING MARKETS				
IND	-0.000388	-0.0005	0.0612	-0.037035	0.009657	0.167386	5.030307	299.3947
CHINA	-0.000196	-0.0007	0.09256	-0.094008	0.015945	0.350013	7.837156	4340.669
BRAZIL	-0.000381	-0.0006	0.12096	-0.136782	0.017696	0.118103	7.320345	3308.188
RUSSIA	-0.000556	-0.0009	0.20657	-0.252261	0.020668	0.223006	18.22901	43503.47
SOUTH_AFRICA	-0.00043	-0.0005	0.03622	-0.041593	0.008744	0.201262	4.502935	152.1095
				FRONTIER MARKETS				
PAK	0.000721	0.00041	0.08507	-0.077414	0.013067	-0.277546	7.014285	3211.989
BANGLADESH	-0.000362	-0.0002	0.52797	-0.534623	0.038343	-0.116963	177.2482	1501679
EGYPT	-0.00047	-0.001	0.11117	-0.073143	0.015044	0.585732	8.678609	2578.852
INDONESIA	-0.000643	-0.0012	0.10954	-0.076234	0.01342	0.673499	10.16275	9313.6
SOUTH_KOREA	-0.000175	-0.0001	0.05469	-0.042467	0.008919	0.121512	5.39795	367.9176
MEXICO	-0.000508	-0.0008	0.07266	-0.104407	0.012127	-0.045481	9.05657	6454.437
NIGERIA	-0.000418	-0.0002	0.04353	-0.079848	0.010277	-0.267407	8.348847	1763.871
PHILLIPINES	0.000234	0	0.06244	-0.128354	0.013007	-1.366542	15.8009	9930.16
TURKEY	-0.000417	-0.0008	0.19979	-0.177736	0.021312	0.073114	10.7127	11194.77
VIETNAM	0.0000739	-0.0000634	0.13332	-0.105926	0.013383	0.482274	10.97367	5155.402

4.2 Non Parametric Approach

Table 4.2 represents the results of VaR estimates under Non-Parametric Assumptions based on Historical simulation model.

TABLE 4.2: VaR Estimates (Historical Simulation Method).

Markets	**Confidence level 95%**	**Confidence level 99%**
EMERGING		
India	0.01678423	0.02629884
China	0.02463231	0.04169115
Brazil	0.02654845	0.04614596
Russia	0.02922103	0.05201286
South Africa	0.01378825	0.02165377
FRONTIER		
Pakistan	0.02205888	0.04184988
Bangladesh	0.01527692	0.02811821
Egypt	0.02211887	0.04132374
Indonesia	0.01966165	0.03376304
South Korea	0.01431366	0.02328062
Mexico	0.0184315	0.03374059
Nigeria	0.0170414	0.03134128
Philippines	0.01980263	0.04750284
Turkey	0.03251151	0.05885777
Vietnam	0.02017539	0.03169936

At 95% confidence level, the Historical simulation method reports the highest risk of 3.25% in Turkey. It means that there are 95% chances that the loss will not exceed 3.25%. Historical simulation reports that South Africa has the lowest risk of 1.37%. The potential loss for one day to the investor is lowest in this stock. It means that Turkey is the riskiest stock in the portfolio and South Africa is the least risky stock. At 99% confidence level, the Historical simulation method reports the highest risk of 5.88% for Turkey again. It means that there are 99% chances that the loss will not exceed 5.88%. Historical simulation reports that South Africa has the lowest risk of 2.165%. The potential loss for one day to the investor is lowest in this stock. It means that Turkey has the riskiest stock in the portfolio and South Africa is the least risky stock at the 99% level of confidence.

Table 4.3 represents the results of Expected Shortfall estimates under Non-Parametric Assumptions based on Historical simulation model.

Table 4.3: Expected Shortfall Estimates (Historical Simulation Method).

Markets	**95% Confidence level**	**99% Confidence level**
	EMERGING	
India	0.02181218	0.03039566
China	0.03545162	0.05668079
Brazil	0.03859548	0.06093308
Russia	0.04537279	0.07929394
South Africa	0.01896785	0.02700431
	FRONTIER	
Pakistan	0.03368305	0.04737832
Bangladesh	0.04687274	-0.1685751
Egypt	0.03285058	0.05368465

Markets	**95% Confidence level**	**99% Confidence level**
Indonesia	0.02950784	0.04742047
South Korea	0.02020498	0.0295965
Mexico	0.02794097	0.04728468
Nigeria	0.0257597	0.03999264
Philippines	0.03449344	0.06568643
Turkey	0.0490306	0.08149287
Vietnam	0.02857969	0.04118228

At 95% confidence level, Historical simulation method reports that average expected shortfall is 4.9% in Turkey. It means that the maximum potential for loss is 4.9%. Historical simulation reports that South Africa has the lowest risk of 1.8%. The potential loss for one day to the investor is lowest in this market. It means that Turkey is the riskiest stock in the portfolio and South Africa is the least risky market.

At 99% confidence level, the historical simulation method reports the highest risk of 8.14% at Turkey. It means that there are 1% chances that the average loss will be 8.14%. Historical simulation reports that Bangladesh has the lowest risk of 16.8%. The potential loss for one day to the investor is lower in this market. It means that Turkey is the riskiest market and Bangladesh has the least risky market.

4.3 Parametric Approach

Table 4.4 reports the results of VaR calculation under parametric assumptions based normal and t-distribution models at 95% and 99% confidence intervals.

Table 4.4: Value at Risk–Parametric Approach.

Markets	Normal distribution 95%	t-distribution 95%	Normal distribution 99%	t-distribution 99%
EMERGING				
India	0.01588356	0.01534818	0.02246443	0.02540503
China	0.02622645	0.02374967	0.03709257	0.04780656
Brazil	0.02910802	0.02746304	0.04116802	0.04640106
Russia	0.03399622	0.02934737	0.04808151	0.05728099
South Africa	0.01438222	0.01397443	0.02034105	0.02253462
FRONTIER				
Pakistan	0.02149272	0.01943494	0.03039756	0.04235308
Bangladesh	0.06306805	0.01495921	-0.0891983	-0.0326507
Egypt	0.02474541	0.02263694	0.0349979	0.04132456
Indonesia	0.02207325	0.01987904	0.03121863	0.03760158
South Korea	0.01467084	0.0140232	0.02074925	0.0241576
Mexico	0.01994773	0.0181512	0.02821245	0.0335142
Nigeria	0.01690486	0.0151926	0.02390887	0.0311497
Philippines	0.02139535	0.01800838	0.03025985	0.04640404
Turkey	0.03505434	0.03170227	0.04957802	0.05889214
Vietnam	0.02201257	0.02060756	0.0311328	0.03507567

At the 95% confidence level, the risk of Bangladesh market is highest at 6.3% when returns follow normal distribution followed by Turkey 3.5% and then Russia 3.3%. South Africa is diagnosed as a least risky stock at a value at risk of 1.43% followed by South Korea 1.46% and then India having 1.58The student t model considers the Turkey as the riskiest market at 3.17% followed by Russia at 2.93% and Brazil at 2.7% whereas least risky stock diagnosed by the model is South Africa in this case at 1.39%. The maximum risk diagnosis by the model is 3.17% of Turkey and minimum risk calculated by the model is 1.39% of South Africa followed by South Korea at 1.40% and Bangladesh at 1.49%.

At the 95% level, the VaR estimates of the normal distribution VaR are higher than the student- t distribution. The difference in result is explained on the basis of difference of the assumptions of the two models. The results at 95% confidence level show that VaR estimates of Normal distribution are higher than the student-t distribution which explicitly means that normal VaR always overestimates the risk at 95% confidence interval. Roccioletti (2015) figured out that normal VaR is higher than the student-t VaR at 95%.

At the 99% confidence level, the risk of Turkey stock is highest at 4.9% when returns follow normal distribution. The second highest value at risk is exhibited by Russia at 4.8% and then Brazil at 4.11%. Bangladesh is diagnosed as a least risky stock at a value at risk of -8.9%. The second least Value at risk is exhibited by South Korea at 2.0% and then India at 2.2%.

At the 99% confidence level, the student t model considers the Turkey as the riskiest stock at 5.88% followed by Russia at 4.6% and then Philippines at 4.6%. The least risky stock market diagnosed by the student t model is Bangladesh in this case at -3.2. It is observed that at the 99% confidence level, the VaR estimates of the student t distribution are higher than the VaR calculated under normal distribution. This difference in the results is explained on the basis of difference of the assumptions of the two models. The results at 99% confidence level show that VaR estimates of Normal distribution are lower than the student-t distribution which explicitly means that normal VaR always underestimates the risk at 99%

confidence interval. Roccioletti (2015) figured out that normal VaR is lower than the student-t VaR at 99% confidence interval.

Table 4.5 reports the results of Expected Shortfall under parametric assumptions based on normal and t-distribution models at 95% and 99% confidence interval.

At 95% confidence level, Normal distribution method reports the value of expected shortfall at 95% confidence level at 7.9% in Bangladesh. It means that the maximum potential for loss is 7.9%. The potential loss for one day to the investor is lowest in South Africa and is 1.8%. It means that Bangladesh is the riskiest market and South Africa as the least risk market.

At the 95% significance level, student t model reports Turkey to be the riskiest market with a maximum risk of 3.9% and South Africa, the least risky stock with minimum risk of 1.6%.

At 99% confidence level, Normal distribution method reports that there are 99% chances that the loss will not exceed from 10.2% in Bangladesh. It means that the maximum potential for loss is 10.2%. The potential loss for one day to the investor is lowest in the South Africa and is 2.33. It means that Bangladesh is the riskiest market and South Africa is the least risky market.

At the 99% significance level, student t model reports the Philippines to be the riskiest stock with a maximum value of 10.27% and South Africa, the least risky stock with minimum risk of 2.5%.

TABLE 4.5: Expected Shortfall-Parametric Approach.

Markets	Normal distribution 95%	t-distribution 95%	Normal distribution 99%	t-distribution 99%
EMERGING				
India	0.01991863	0.01753804	0.0257367	0.02963347
China	0.03288903	0.03218955	0.04249564	0.07240641
Brazil	0.03650263	0.0314941	0.04716474	0.05528352
Russia	0.04263263	0.03861773	0.05508528	0.08333019
South Africa	0.01803589	0.01612242	0.02330402	0.02582037
FRONTIER				
Pakistan	0.02695274	0.02998798	0.03482541	0.07266111
Bangladesh	0.07908988	0.02242641	0.1021914	0.05543747
Egypt	0.03103174	0.02795603	0.04009585	0.05497679
Indonesia	0.02768075	0.02563139	0.03576607	0.05272054
South Korea	0.01839783	0.01616935	0.02377168	0.02939904
Mexico	0.02501525	0.02255714	0.032322	0.04517964
Nigeria	0.02119938	0.02092418	0.02739155	0.04828481
Philippines	0.02683063	0.03580968	0.03466764	0.1027723
Turkey	0.04395956	0.03902778	0.05679978	0.07945123
Vietnam	0.02760465	0.02342799	0.03566775	0.04187516

Emerging countries show lesser value for expected shortfall at 95% confidence level under t distribution as compared to Normal Distribution. Whereas at 99% confidence level higher values of expected shortfall are reported under t distribution. However, among the frontier markets, Pakistan has value of 2.69% under normal distribution and 2.99% under t distribution at 95% confidence level and at 99% confidence level it shows 3.4% and 7.2% under normal and t distribution. Philippines shows similar trend as that of Pakistan. Bangladesh results report that higher values of expected shortfall are obtained for Normal Distribution at both 95% and 99% confidence levels. It is observed in other frontier markets like Egypt, Indonesia, South Korea, Mexico, Nigeria, Turkey and Vietnam that at 95% confidence level higher values are obtained under normal distribution and at 99% confidence level t distribution shows higher values than normal distribution for these markets.

4.4 Value at Risk-Time Varying Volatility Approach

Table 4.6 reports the results of Value at Risk estimation under parametric assumptions based on EWMA and GARCH models at 95% and 99% confidence intervals.

TABLE 4.6: Value at Risk Estimation-Time Varying Volatility Approach.

Markets	VAR at 95% confidence level		VAR at 99% confidence level	
	EWMA	GARCH	EWMA	GARCH
		EMERGING		
India	0.02132142	0.02016375	0.03015529	0.02851797
China	0.04158489	0.04077697	0.05881431	0.05767165
Brazil	0.03775606	0.03779964	0.05339911	0.05346075

Markets	VAR at 95% confidence level		VAR at 99% confidence level	
	EWMA	**GARCH**	**EWMA**	**GARCH**
Russia	0.06249601	0.07574444	0.0883893	0.1071268
South Africa	0.01804658	0.02038689	0.02552362	0.02883357
FRONTIER				
Pakistan	0.01752255	0.01746709	0.02478248	0.02470405
Bangladesh	0.02119705	0.02165986	-0.02997939	0.03063395
Egypt	0.0289879	0.06162054	0.04099814	0.08715111
Indonesia	0.01604692	0.01636258	0.02269546	0.02314191
South Korea	0.03421698	0.02897457	0.04839373	0.04097929
Mexico	0.02409485	0.02397643	0.0340778	0.03391032
Nigeria	0.01103923	0.01093462	0.01561299	0.01546504
Philippines	0.02472392	0.03881937	0.03496751	0.05490298
Turkey	0.0668148	0.06612268	0.09449745	0.09351857
Vietnam	0.02721328	0.04003428	0.03848825	0.05662124

At 95% confidence level, the EWMA method reports that there are 95% chances that the loss will not exceed from 6.68% in Turkey. It means that the maximum potential for loss is 6.68%. The potential loss for one day to the investor is lowest in the Nigeria stock and is 1.1%. It means that Turkey is the riskiest market under EWMA method at 95% confidence level and Nigeria is the least risky stock market. The results indicate that all models do not identify similar results. At the 95% significance level, The GARCH model reports Russia to be the riskiest stock with a maximum value at risk of 7.57% and Nigeria to be the least risky stock with minimum risk of 1.09%.

At 99% confidence level, the EWMA method reports that there are 99% chances that the loss will not exceed from 8.8% in Russia. It means that the maximum potential for loss is 8.8%. The potential loss for one day to the investor is lowest in the Bangladesh is -2.9%. It means that Russia is the riskiest market under EWMA method at 99% confidence level whereas Bangladesh being the least risky stock shows a negative value of -2.9%. At the 95% significance level, The GARCH model reports Turkey to be the riskiest stock with a maximum value at risk of 10.7% and Nigeria to be the least risky stock with minimum risk of 1.5%.

Therefore, it can be concluded from the results that estimated by EWMA are higher than GARCH at a particular confidence level. It can be said that EWMA overestimates the risk as compared to GARCH. Moreover, as the confidence level increases higher values for VaR are reported under both EWMA and GARCH.

Table 4.7 reports the results of Expected Shortfall calculation under parametric assumptions based on EWMA and GARCH models at 95% and 99% confidence intervals.

Table 4.7: Expected Shortfall-Time Varying Volatility Approach.

Markets	**VAR at 95% confidence level**		**VAR at 99% confidence level**	
	EWMA	**GARCH**	**EWMA**	**GARCH**
		EMERGING		
India	0.02673792	0.02528615	0.03454784	0.03267203
China	0.05214913	0.05113597	0.06738146	0.06607237
Brazil	0.04734762	0.04740227	0.06117746	0.06124808
Russia	0.07837252	0.09498658	0.1012645	0.1227314

Markets	VAR at 95% confidence level		VAR at 99% confidence level	
	EWMA	GARCH	EWMA	GARCH
South Africa	0.02263113	0.02556599	0.0292415	0.0330336
FRONTIER				
Pakistan	0.02197399	0.02190444	0.02839241	0.02830255
Bangladesh	0.02658195	0.02716233	0.03434632	0.03509623
Egypt	0.03635199	0.07727464	0.04697011	0.09984593
Indonesia	0.02012348	0.02051933	0.02600138	0.02651286
South Korea	0.02897457	0.03633528	0.05544298	0.04694851
Mexico	0.03021591	0.03006741	0.03904173	0.03884985
Nigeria	0.01093462	0.01371245	0.01788725	0.01771774
Philippines	0.03100479	0.04868106	0.05490298	0.0629004
Turkey	0.08378846	0.08292051	0.1082624	0.1071409
Vietnam	0.03412655	0.0502046	0.04409463	0.06486895

At 95% confidence level, the EWMA method reports about the ES values at 95% confidence level is 8.3% in Turkey followed by Russia with 7.8%. The potential loss for one day to the investor is lowest in the Nigeria stock and is 1.09%. It means that Turkey is the riskiest market under EWMA method at 95% confidence level and Nigeria is the least risky market. At the 95% significance level, The GARCH model reports Russia to be the riskiest stock with a maximum value at risk of 9.4% followed by Turkey at 8.29% and Egypt at 7.72%. Nigeria to be the least risky stock with minimum risk of 1.37%.

At 99% confidence level, the EWMA method reports that the average loss is 10.1% in Russia. The potential loss for one day to the investor is lowest in the Nigeria stock and is 1.7%. It means that Russia is the riskiest market under EWMA method at 99% confidence level and Nigeria is the least risky stock. At the 95% significance level, the GARCH model reports Russia to be the riskiest stock with a maximum value at risk of 12.2% and Nigeria to be the least risky stock with minimum risk of 1.7%.

4.5 Backtesting

Table 4.8 reports the results of Violation Ratio computed in Backtesting under various assumptions based normal, t-distribution, EWMA and GARCH models at 95% confidence interval.

Table 4.8: Violation Ratio at 95% confidence level.

Violation Ratio at 95% confidence level					
	HS	**N.DIST**	**T.DIST**	**EWMA**	**GARCH**
		EMERGING			
India	1.169591	1.336675	-	1.269841	1.152882
China	1.098161	0.963481	-	1.113701	0.973841
Brazil	1.112002	0.978348	-	1.218925	1.090617
Russia	1.255628	1.110555	-	1.175588	1.08054
South Africa	0.8928571	0.8531746	-	1.170635	0.9722222
		FRONTIER			
Pakistan	1.001431	1.03958	-	1.111111	1.001431

	HS	N.DIST	T.DIST	EWMA	GARCH
Bangladesh	0.003142829	0.03994287	-	0.0721675	0.1424152
Egypt	0.8053691	0.7158837	1.148397	1.073826	0.8351976
Indonesia	1.073355	0.8683927	1.197411	1.18123	1.111111
South Korea	1.313725	1.196078	-	1.215686	1.137255
Mexico	1.171413	1.085438	-	1.289629	1.16604
Nigeria	0.8911917	0.8704663	1.07772	1.305699	1.056995
Philippines	0.9427609	0.7631874	0.52974	1.032548	0.8305275
Turkey	1.215442	1.105853	-	1.165629	1.13076
Vietnam	1.269394	1.170663	-	1.12835	1.100141

In the EWMA model, the observed violation ratio has value greater than 1 in the case of all the countries except for Bangladesh that clearly under forecast the risk at 95% confidence level for this country. The stocks for other countries are a clear representation of perfect modeling. The model of normal distribution violation ratio in case of seven countries stock is fairly modeled except the stock of that is underestimated by the model indicated by the Violation ratios having less than 1 value. The forecasting under historical simulation is a clear indication of perfect modeling better than normal distribution. The model of GARCH under forecasted the risk for Bangladesh. There is not a single model that overestimated the risk of countries stocks at 95% confidence level. While evaluating these models, 95% confidence level is better for calculation of the risk for all stocks as 100% of the emerging markets and 90% of the Frontier countries perform well in risk estimation indicated by their violation ratios within the recommended range.

At the 95% confidence level, all the models perform better than the other models estimated at 99% confidence level for all the markets except for Bangladesh.

Table 4.9 exhibits the Violation Ratio computed under parametric assumptions based normal, t-distribution, EWMA and GARCH models at 99% confidence interval.

TABLE 4.9: Violation Ratio at 99% confidence level.

Violation Ratio at 95% confidence level					
	HS	**N.DIST**	**T.DIST**	**EWMA**	**GARCH**
EMERGING					
India	1.503759	2.088555	-	2.255639	2.088555
China	1.098161	0.963481	-	1.113701	0.973841
Brazil	1.256349	1.817696	-	1.897888	1.470195
Russia	1.850925	2.276138	-	2.051026	1.8009
South Africa	0.8928571	1.388889	-	1.785714	1.686508
Bangladesh	1.892285	2.911208	-	2.620087	2.183406
FRONTIER					
Pakistan	1.025274	2.718169	-	2.312828	2.145923
Egypt	0.9694258	1.342282	1.49142	1.565996	1.342282
Indonesia	1.240561	1.806904	0.21575	2.130529	1.860841
South Korea	1.470588	2.54902	-	2.156863	2.254902
Mexico	1.316497	2.256851	-	2.391188	2.095648
Nigeria	0.4145078	1.139896	0.145078	2.072539	1.761658
Philippines	1.346801	2.020202	1.234568	3.142536	2.469136

	HS	N.DIST	T.DIST	EWMA	GARCH
Turkey	1.295143	1.668742	-	1.843088	1.743462
Vietnam	1.410437	1.480959	-	1.622003	1.410437

At the 99% confidence level, violations are observed at EWMA, Normal and GARCH models indicated by high values of violations ratios whereas violation ratio values appear in the recommended range of 0.5-1.5 for Historical simulation model.

Under Historical simulation method, most of the Emerging Markets fall under the recommended range while rests of the 20% clearly overestimate the risk whereas similar outcomes are found in Frontier markets following this method when back tested.

Under normal distribution method, only 40% countries among the emerging markets estimate the risk accurately whereas only 60

EWMA reports that, only 20% of the Emerging Markets fall under the recommended range while rests of the 80% clearly overestimate the risk whereas similar outcomes are found in Frontier markets.

Countries do not perform well in risk estimation under GARCH model at 99% confidence level as 60% countries from Emerging markets and 90% countries from Frontier markets overestimate risk under this model indicated by their violation ratios.

Therefore, it can be concluded that at the 99% confidence level, each of these models underestimates the risk except the Historical simulation method. The backtesting values for t-test cannot be computed as the data is not leptokurtic in nature for these countries.

4.6 VaR Volatility

Table 4.10 presents volatility ratio of VaR under parametric assumptions based on normal distribution, t-distribution, EWMA and GARCH models at 95% confidence interval.

Table 4.10: Volatility of VaR at 95% confidence level.

Volatility of VaR at 95% confidence level					
	HS	**N.DIST**	**T.DIST**	**EWMA**	**GARCH**
EMERGING					
India	0.0018	0.0011	-	0.0044	0.0037
China	0.0058	0.0071	-	0.0109	0.0105
Brazil	0.0054	0.0067	-	0.0108	0.0106
Russia	0.0091	0.0123	-	0.0172	0.0184
South Africa	0.0014	0.0014	-	0.0040	0.0036
FRONTIER					
Pakistan	0.0086	0.0055	-	0.0088	0.0087
Bangladesh	0.0031	0.0399	-	0.0722	0.1424
Egypt	0.0024	0.0022	0.0034	0.0079	0.0084
Indonesia	0.0046	0.0053	0.0054	0.0090	0.0092
South Korea	0.0012	0.0011	-	0.0040	0.0031
Mexico	0.0056	0.0060	-	0.0087	0.0087
Nigeria	0.0032	0.0029	0.0028	0.0069	0.0067

	HS	N.DIST	T.DIST	EWMA	GARCH
Philippines	0.0020	0.0016	0.0015	0.0084	0.0139
Turkey	0.0100	0.0104	-	0.0157	0.0153
Vietnam	0.0044	0.0043	-	0.0078	0.0081

Volatility is regarded as an appropriate risk measure. It shows that lower volatility values reports the reliable and fair VaR model. At 95% confidence level, the GARCH forecasted the maximum value of volatility in the stock of Bangladesh. It means that GARCH is a weaker method for the risk assessment of stock at 95% confidence level in Bangladesh.

EWMA model also forecasted the high values for volatility in the Bangladesh stock while others stocks have relatively lower volatility and model is considered to be stable for them. The volatility forecasted by the Historical simulation method is lower as compared to the EWMA, GARCH and Normal distribution. It is therefore considered a stable method. GARCH volatility is also high as compared to the other models and it is considered as a weaker method. GARCH forecasted highest volatility in the stock of Bangladesh means that it is the riskiest market for investment. The method is not stable for the risk estimation.

The appropriate model observed at the 95% confidence level on the basis of volatility is suggested as the Historical Simulation method.

From emerging markets India shows least volatility values under Normal distribution whereas under China, Brazil and Russia, Historical Simulation Method shows the least value of volatility forecasting. In South Africa HS method and normal distribution report the same least values for volatility forecasting as compared to EWMA and GARCH. Therefore in can be concluded that Historical Simulation method is the most appropriate model for volatility forecasting for emerging markets at 95% confidence level.

From the frontier markets, the volatility forecasting for Pakistan, Egypt, South Korea, Nigeria and Vietnam have least values under normal distribution whereas other frontier markets like Bangladesh, Indonesia, Mexico and Turkey show minimum volatility forecasts under historical simulation method. It shows that 50% of frontier markets show minimum volatility forecasting under normal distribution whereas 40% of frontier markets show least values under HS at 95% confidence level.

Table 4.11 presents Volatility ratio of VaR calculated under parametric assumptions based on normal distribution, t-distribution, EWMA and GARCH models at 99% confidence interval.

TABLE 4.11: Volatility of VaR at 99% confidence level.

Volatility of VaR at 99% confidence level					
MARKETS	**HS**	**N.DIST**	**T.DIST**	**EWMA**	**GARCH**
		EMERGING			
India	0.0032	0.0016	-	0.0063	0.0053
China	0.0132	0.0101	-	0.0154	0.0149
Brazil	0.0142	0.0096	-	0.0153	0.0150
Russia	0.0286	0.0175	-	0.0243	0.0260
South Africa	0.0029	0.0020	-	0.0057	0.0051
		FRONTIER			
Pakistan	0.0087	0.0078	-	0.0125	0.0124
Bangladesh	0.0073	0.0565	-	0.1021	0.2014
Egypt	0.0069	0.0032	0.0065	0.0112	0.0119
Indonesia	0.0118	0.0075	0.0104	0.0128	0.0130
South Korea	0.0032	0.0015	-	0.0056	0.0043

MARKETS	HS	N.DIST	T.DIST	EWMA	GARCH
Mexico	0.0056	0.0059	-	0.0087	0.0087
Nigeria	0.0055	0.0041	0.0061	0.0098	0.0095
Philippines	0.0073	0.0022	0.0028	0.0120	0.0197
Turkey	0.0228	0.0146	-	0.0222	0.0217
Vietnam	0.0057	0.0060	-	0.0110	0.0115

The volatility of VaR estimated through EWMA is generally higher than the volatility of VaR estimated under assumptions of time varying volatility. The similar pattern is also observed in GARCH based estimates.

The volatility of VaR is minimum for VaR estimates calculated under normal distribution except for Bangladesh at 99% confidence level. The historical simulation method also indicates lower volatility in VaR estimates.

The t-distribution is ignored as the results are not comparable across the sample.

From emerging markets India shows least volatility values under Normal distribution whereas all other emerging markets like China, Brazil and Russia and South Africa show the same trend. It reveals that 100% of the emerging countries show least values for volatility forecasts under normal distribution method. Therefore in can be concluded that normal distribution method gives the most appropriate volatility forecasting for emerging markets at 99% confidence level.

From the frontier markets, the volatility forecasting for Pakistan, Egypt, Indonesia, South Korea, Nigeria, Philippines and Turkey have least values under normal distribution whereas other frontier markets like Bangladesh, Mexico and Vietnam show minimum volatility forecasts under historical simulation method. It shows that 70% of frontier markets show minimum volatility forecasting under normal distribution whereas 30% of frontier markets show least values under HS at 99%

confidence level. Therefore, it can be concluded that normal distribution shows better volatility forecasting at 99% confidence level.

4.7 Kupiec POF Test-Unconditional Coverage Test

Table 4.12 reports the results on unconditional coverage test prepared by Kupiec at 95% confidence level. The table reports the LR statistics of χ^2 values.

Table 4.12: Kupiec's-POF test 95% Confidence level.

Kupiec's-POF test					
95% Confidence level					
MARKETS	**H.S**	**N.DIST**	**EWMA**	**GARCH**	χ^2 **values**
EMERGING					
India	6.488813	4.242029	-	1.722401	3.84
China	3.847314038	174.0266655	2.537803845	0.038211956	3.84
Brazil	2.387181944	269.7088484	3.563118	1.57253464	3.84
Russia	-	80.37578	6.156467	1.331568	3.84
South Africa	0.630812	1.201007	1.46792672	0.0413	3.84
FRONTIER					
Pakistan	0.000452	90.21354	2.634524	0.000452	3.84
Bangladesh	20.39962	5.109001	0.636060221	0.210151	3.84
Egypt	2.856134	6.296645	0.376019783	2.025835	3.84

MARKETS	**H.S**	**N.DIST**	**EWMA**	**GARCH**	χ^2
Indonesia	1.026665	351.0357316	6.073076012	2.329236	3.84
South Korea	4.829832	1.94744	2.343631	0.970306	3.84
Mexico	1.392953	-	-	5.468615	3.84
Nigeria	0.623177	0.889512	4.347703677	0.162098	3.84
Philippines	2.85384	0.049176	-	0.156501	3.84
Turkey	-	74.19014	5.516733	3.472978	3.84
Vietnam	5.009163	2.065661	1.182603866	0.725876	3.84

The likelihood ratio test is developed by Kupiec in order to figure out if the certain value at risk model is validated or rejected. Kupiec test checks about the observed values of violations in comparison to the expected number of percentage violations.

At 95% level of confidence, the likelihood ratio calculated by the normal model is highest for a stock return of Indonesia is 351 due to which this rejects the model. It implies that the Normal distribution model is not reliable for the certain markets like Pakistan, India, China, Brazil Russia & Indonesia risk assessment. In the present case, the normal distribution model does not attempt to perform well on account of abnormally high violation ratios that clearly imply this model rejection. The highest likelihood ratio calculated for the EWMA distribution model is 6.07 of Indonesia. The model is not reliable for the risk assessment of countries like Pakistan, India, China, Brazil Russia & Indonesia because of their greater values of likelihood ratios than that of the critical value of 3.84.

The Kupiec POF test predicts that Historical Simulation model is not reliable for the risk assessment of the India, Bangladesh, South Korea, and Vietnam.

The Kupiec POF test predicts that at 95% confidence level, the GARCH model is reliable for the risk assessment of all of the stock returns except for Mexico.

GARCH is the model that is validated at 95% confidence level for most of the stocks. It shows that it is a reliable model for risk assessment for emerging and frontier markets.

At 95% confidence level, only 20% markets among the emerging markets and 40% from frontier markets could perform well under normal distribution. 60% of the emerging markets fall below 3.84 whereas only 50% of the frontier markets under observation have their likelihood ratio within the specified threshold under EWMA. The Kupiec test conducted under Historical simulation shows similar performance from both emerging and frontier markets as in both groups, 60% of markets have their LR within the critical value. GARCH has exhibited best performance among all the models at 95% confidence level for 100% emerging and 90% frontier markets as indicated by their Kupiec Test results. Therefore, it can be concluded that for most of the markets GARCH outperforms other models at 95% confidence level.

Table 4.13 reports the results on unconditional coverage test prepared by Kupiec at 99% confidence level. The table reports the LR statistics of χ^2 values.

Table 4.13: Kupiec's-POF test 99% Confidence level.

Kupiec's-POF test					
99% Confidence level					
MARKETS	**H.S**	**N.DIST**	**EWMA**	**GARCH**	**χ^2 values**
EMERGING					
India	2.657592	10.90741	14.05684	10.90741	6.6
China	0.404722204	18.49660049	23.41455595	17.343131	6.6
Brazil	2.296551625	20.34283158	24.11091202	7.29714038	6.6
Russia	23.37474	48.3119	34.21544	20.93304	6.6

MARKETS	H.S	N.DIST	EWMA	GARCH	χ^2
South Africa	0.121252	1.373533	5.096489924	3.97854	6.6
			FRONTIER		
Pakistan	0.026838	85.12844	53.27676	41.88099	6.6
Bangladesh	4.377833	16.73785	12.59861429	7.264155	6.6
Egypt	0.012792	1.433246	3.70138902	1.433246	6.6
Indonesia	2.013549	19.68092	36.14701	22.14033	6.6
South Korea	1.992727	17.30538	10.35924	11.96584	6.6
Mexico	3.620523	44.55569	53.20479	34.98449	6.6
Nigeria	4.28804	0.18253	8.563510524	4.609377	6.6
Philippines	0.976415	7.229107	26.3578497	13.78542	6.6
Turkey	3.231976	15.09918	23.0826	18.34692	6.6
Vietnam	2.140152	2.886163	4.663969179	2.140152	6.6

At 99% level of confidence, the likelihood ratio calculated by the normal model is highest for a stock return of Pakistan is 85.12 due to which this rejects the model. It implies that the Normal distribution model is not reliable for the most of stocks like Pakistan, India, China, Brazil, Russia & Indonesia, South Korea, Mexico, Philippines, Turkey risk assessment. In the present case, the normal distribution model does not attempt to perform well on account of high violation ratios that clearly imply this model rejection. The highest likelihood ratio calculated for the EWMA distribution model is 53.27 for Pakistan. The model is not reliable for the risk assessment of countries like Pakistan, India, China, Brazil, Russia, Indonesia, and South Korea and Vietnam because of their greater values of likelihood ratios than that of the critical value of 3.84.The Kupiec POF test predicts that Historical Simulation model is reliable for the risk assessment of the majority of stock returns except for Russia & Nigeria. As for their results, it can be said that the risk is underestimated by the VaR estimation.

The Kupiec POF test predicts that at 99% confidence level, the GARCH model is not that reliable for the risk assessment of all of the stock returns except for Mexico. GARCH is the model that is rejected at 99% confidence level for most of the stocks. It shows that it is not a reliable model for risk assessment of the stocks for emerging and frontier markets at higher level of confidence of 99%. For this test, Historical Simulation model is found to be the reliable model for the purpose of risk assessment of market stocks at 99% confidence level having less violation. At the higher level of confidence, more violations have occurred and the models that were found reliable at 95% are ultimately rejected at the 99% level.

At 99% confidence level, only 0% markets among the emerging countries were able to lie within limit and 40% from frontier markets could perform well under normal distribution and GARCH. 0% of the emerging markets fall below 3.84 whereas only 10% of the frontier markets under observation have their likelihood ratio within the specified threshold under EWMA. The Kupiec test conducted under Historical simulation shows better performance from both emerging and frontier markets as 60% of emerging markets and 80% of frontier markets have their LR within the critical value. HS has exhibited best performance among all the models at 99% confidence level. Therefore, it can be concluded that for most of the markets Historical simulation model outperforms other models at 99% confidence level.

4.8 Christofferson's Test-Independence Test

Table 4.14 reports the results of Christoffersen Test conducted to evaluate the violation clustering. The null hypothesis is the violation and independence. The results report LR statistics and values of χ^2 values at 95% confidence level.

Table 4.14: Christofferson's test 95% Confidence interval.

Christofferson's test					
95% Confidence interval					
MARKETS	**H.S**	**N.DIST**	**EWMA**	**GARCH**	χ^2
EMERGING					
India	0.538658	0.303256	1.960061	0.211463	3.84
China	340.5621	265.4095	207.4705349	201.7878	3.84
Brazil	171.7425	154.874	141.5184	123.5021	3.84
Russia	359.8311	333.6667	255.1936	162.0403	3.84
South Africa	0.719887	0.532173	2.740682	1.173216	3.84
FRONTIER					
Pakistan	555.1743	607.8288	405.6981	271.856	3.84
Bangladesh	0.009529	3.631806	0.283163	0.497016	3.84
Egypt	7.655479	4.598532	1.142084	0.056473	3.84
Indonesia	268.4152992	20.85877	271.5010687	161.2194336	3.84
South Korea	1.339693	0.15666	0.371395	0.288779	3.84
Mexico	337.2155	256.1775	-	301.5464	3.84
Nigeria	12.62505	17.11866	0.87933	1.794133	3.84
Philippines	0.355222	1.242537	0.062343	0.000179	3.84
Turkey	329.2352	304.2184	212.0117		3.84

MARKETS	H.S	N.DIST	EWMA	GARCH	χ^2
Vietnam	12.56832	4.859481	0.501644	0.022951	3.84

The Christoffersen Test provides that the null hypothesis of violation and independence is rejected for VaR Estimates obtained under the assumption of historical distribution and normal distribution. The results are constant for estimates of VaR calculated by using EWMA and GARCH for Pakistan.

EWMA model fails to assess the risk of Mexico stock. Christoffersen test at 95% confidence holds good for all the models for countries like India, South Africa, Bangladesh, South Korea & Philippines. The test shows that volatility clustering is present in the EWMA, normal, and HS model for the rest of the countries. That is why; these models do not pass the Christoffersen test except GARCH.

In emerging markets, only India and South Africa pass Christoffersen test which means that only 40% of the emerging markets pass the Christoffersen test under non parametric HS model. These two countries show similar trend under other models. Rests of the emerging markets reject the models. Among the frontier markets, only Bangladesh, South Korea and Philippines only pass the Christoffersen test for HS model. Under Normal distribution similar trend is observed by countries like Bangladesh, South Korea and Philippines at 95% confidence level. However, under time varying volatility models of EWMA and GARCH, it is observed that 50% of the frontier countries pass the Christoffersen Test.In rest of the markets high volatility clustering is observed. It is reported that Christoffersen test explicitly rejects all models on the basis of high volatility clustering for the emerging markets like China. Brazil, Russia and Pakistan, Indonesia, Mexico and turkey from the frontier markets group.

Table 4.15 reports the results of Christoffersen Test conducted to evaluate the violation clustering. The null hypothesis is the violation and independence. The results report LR statistics and values of χ^2 values at 99% confidence level.

Table 4.15: Christofferson's test 99% Confidence interval.

Christofferson's test					
99% Confidence interval					
MARKETS	**H.S**	**N.DIST**	**EWMA**	**GARCH**	χ^2
EMERGING					
India	1.21506	0.362068	2.122767	0.362068	6.6
China	6.783385	11.06451	0.372906633	2.354427	6.6
Brazil	0.200728	0.054237	0.314134	0.040136	6.6
Russia	20.52847	17.29329	0.879293	1.708883	6.6
South Africa	3.194035	1.644025	0.815102	0.966062	6.6
FRONTIER					
Pakistan	6.701946	46.28578	6.906472	0.002487	6.6
Bangladesh	1.155628	0.263309	0.477401	0.771243	6.6
Egypt	2.246466	1.221182	0.925344	1.221182	6.6
Indonesia	2.248441	14.04439	0.058684	0.088483	6.6
South Korea	0.570278	0.139112	0.015313	2.41076	6.6
Mexico	0.143715	1.873782	0.008332	0.331756	6.6
Nigeria	17.6256	23.12339	0.624808	1.068996	6.6
Philippines	1.809747	0.795946	0.003501	0.245161	6.6
Turkey	1.769696	4.690278	0.269959	0.057836	6.6

MARKETS	**H.S**	**N.DIST**	**EWMA**	**GARCH**	χ^2
Vietnam	4.707002	4.349639	3.702106	1.004672	6.6

The results of Christoffersen test at 99% confidence level show that under Historical simulation method 60% of the emerging markets and 70% of the Frontier markets pass the test. Whereas under normal distribution, 60% emerging markets and only 50% Frontier markets were able to pass the test. EWMA performs better than HS and Normal Distribution as 100% of the emerging markets pass the test 90% of the frontier markets pass the Christoffersen test.

At 99% confidence level, GARCH is reported to show no volatility clustering as for all of the as 100% markets from emerging as well Frontier markets pass the Christoffersen test under GARCH model. It means that under GARCH model, a number of violations today are independent of the previous day violations in 100% of emerging and frontier markets. Under EWMA, 100% of the emerging markets and 90% of the frontier markets show significant values. It means that volatility clustering is not reported in these markets under EWMA at 99% confidence level. Under HS and Normal distribution, only 60% emerging markets were able to show significant values for Christoffersen Test whereas among the frontier markets 70% and 50% of the markets showed no volatility clustering under HS and normal distribution models at 99% confidence level. The rest of the markets reject the models evaluated under Christoffersen test.

Chapter 5

Conclusion and Recommendations

VaR is one of the most famous methods in estimating market risks. The VaR models usually take historical data from market to predict the portfolio performance in future. Additionally, these models are based on assumptions and approximations that are not necessarily validated in all situations and scenarios. As none of the methods is ideal, therefore it provides a valid reason to question the performance of estimated VaR levels.

In the study, Value at risk has been analyzed under various distributional assumptions such as non-parametric approach including Historical Simulation method and parametric approaches like Normal Distribution and Student-t distribution. Furthermore, it estimates VaR under the assumption of time varying volatility. The models under this assumption include EWMA and the conventional GARCH model. For all the models under consideration, a rolling window of 500 days is used to compute new estimate of value of VaR or ES as risk prediction for the following trading day. Backtesting is done to test the predictability of these methods. Violation ratios and volatility are also computed to evaluate the performance of the aforementioned methods of risk forecasting Finally, Kupiec test & Christoffersen test are used to check the unconditional coverage and independence of violations.

What so ever the frame work is coined for backtesting in future, the most important learning from this study is to comprehend the shortcomings underlying the VaR calculation. As evident from empirical research, VaR estimates may never be taken to be cent percent accurate, no matter how organized the systems may seem to operate. But if the flaws attached with VaR are taken up by users, the method can emerge as a very efficient measure in risk management, especially due to non-existence of any other tool to be taken as serious contender as alternative for VaR.

While evaluating these models, the results indicate that the violation ratios at 95% confidence level is better for calculation of the risk for all stocks as 100% of the emerging markets and 90% of the Frontier countries perform well in risk estimation indicated by their violation ratios within the recommended range. Violation Ratios reveal that at the 95% confidence level, all the models perform better than the other models estimated at 99% confidence level for all the markets except for Bangladesh as shown in the results. At 99% confidence level, most of the Emerging Markets fall under the recommended range while rests of the 20% clearly overestimate the risk whereas similar outcomes are found in Frontier markets following this method when back tested under Historical simulation method.

At 95% confidence level, the volatility forecasted by the Historical simulation method is lower as compared to the EWMA, GARCH and Normal distribution. Therefore, historical simulation is considered a stable method. GARCH volatility is also high as compared to the other models and it is considered as a weaker method. Based on the findings and analysis, it is recommended that Historical simulation is still the better method of risk estimation as compared to other methods for risk assessment at 95% confidence level.

The volatility of VaR is least for VaR estimates calculated under normal distribution except for Bangladesh at 99% confidence level. The historical simulation method also indicates lower volatility in VaR estimates. The appropriate model observed at the 99% confidence level on the basis of volatility is suggested as the Historical Simulation method.

Kupiec test propose that LR statistics to the violation ratio. Kupiec test is explicitly based on the null hypothesis that the observed and expected number of violations in VaR forecasting is same. Each model is evaluated and accepted or rejected on this null hypothesis. The Kupiec test conducted under Historical simulation reveal at 95% confidence level that from both emerging and frontier markets, 60% of markets have significant values of Likelihood Ratio. Kupiec POF test reveals HS is accepted among all the models at 99% confidence level. Therefore, it can be concluded that for most of the markets Historical simulation model outperforms other models at 99% confidence level.

Christoffersen independence test provides the evidence about volatility clustering. This test is applied to validate whether the violations are clustered or are found uniformly over a certain period. At the 95% confidence level, all of the models pass the Christoffersen test while, at 99% confidence level, only GARCH model passes the test which shows that clustering is not found under this model.

Therefore it is concluded that the VaR models have limited scope, as they can produce different predictions due to marketing fluctuation. The outcomes of the back tests give some sign of potential flaws such as underestimation risk particularly for value at risk despite of the fierce market condition at high confidence levels such as 99%.

5.1 Recommendations

The findings indicate that the Historical Simulation method has highest accuracy in risk estimation in emerging as well as frontier markets at 95% confidence level which is a clear indication of perfect modeling. Therefore, the results imply that Historical simulation method is recommended to be used at 95% confidence level for emerging as well as frontier markets. However, higher confidence level of 99% comes out with over estimation of risk.

5.2 Future Research Arenas

It is a future direction for the scholars to perform the Backtesting of the Expected short fall and enrich the literature. It will help to compare the VaR and ES models and to recommend the best model for the world markets. Moreover different methods like Monte Carlo simulation, Variance, and covariance methods for VaR and the Expected shortfall can be taken up for assessment of the risk. Lastly, sample data can be enriched like the index returns of more stock exchanges in comparison with other stock markets of the world can be taken up in order to get a holistic view of performance of these models. Moreover GARCH can be combined with its extensions for risk assessment.

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