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An Analytical Study of VaR through the Lens of Extreme Value Theory: A Comparative Study of G10 & Emerging Markets

by

Zarmina Ali Khan

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This thesis is dedicated to my parents & teachers, who are always a light for me in the dark and their unwavering support guided my Unfocused words into Coherent ideas.

CERTIFICATE OF APPROVAL

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Abstract

The purpose of the study is to investigate different risk forecasting models. This study apply different conventional and modern approaches to estimate the Value-at-Risk (VaR) forecast of one day for different stock markets of developed and emerging markets. Primarily, all conventional models are applied to daily returns data to capture the VaR of whole distribution. Secondly, extreme value theory VaR models are applied to estimate risk of only left tail of distribution to capture non-normality of financial data. The models of these two approaches are than evaluated using traditional and dynamic back testing techniques. The study implies daily returns of 23 countries (11 from developed market and 12 from emerging market) from 2000-2018. By comparing all conventional models, normal distribution out perform for both developed and emerging market. For estimation of extreme left tail risk, GPD static from conditional EVT perform well as compared with other models.

Keywords: Extreme value theory (EVT), Generalized Pareto distribution (GPD), back testing, Risk forecasting, Value-at-risk (VaR).

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Abbreviations

VaR	Value at Risk
ES	Expected Shortfall
GARCH	Generalized Autoregressive Conditional Heteroscedasticity
HS	Historical Simulation
EWMA	Exponential Weighted Moving Average
EVT	Extreme Value Theory
BMM	Block Maxima Model
GPD	Generalized Pareto Distribution
GEV	Generalized Extreme Value

Chapter 1

Introduction

The following chapter includes theoretical background of the study, identified research gap, problem statement, research objectives and questions, the significance of the study and overall plan of the study.

1.1 Background

Investment is very important for a country either economic or financial and investor choose investment on the basis of expected return, and their risk tolerance. Identified factors that directly influence investment may, includes demographics, cognitive biases, past records, risk, bonuses and accounting information however the less influencing factors may include inflation, taxes, trade opportunities, ethics (Shafi, 2014).

Pointing out the similarities of global crisis of 1929 with 2007-2008, the study reveal linkage between these two, like just because crisis, the global economy went through a boom session period with the fast economic growth rate 2001 and 2007 than in any other period in the past thirty year (McKenna and Metcalfe, 2013). Many analyst agreed that the crisis is triggered because of subprime mortgage bubble in the United States. Nevertheless Bernanke et al. (2010) has commented on many factors like losses are faced by primary market because of housing bubble burst, the exposed system as well as less attention or government responses to shortfalls explain the intensity of the crisis.

Another study by Shahrokhi (2011) recommend that crisis is not an outcome of calamity, but due to elevated risk, complicated products, unrevealed clashes between agency credit ratings and straight failure of regulators. These recent extreme market conditions raise a question on existing risk management models. All these criticised models give researchers the opportunities to find more appropriate and better models to be created, to deals with these rare events that creates disasters (heavy losses). The increasing financial uncertainties have challenged the financial market participants to develop and improve the existing methodologies used in measuring risk (Omari et al., 2017).

One of the basic and widely used method for financial risk measurement is Value at Risk. It is defined as the maximum loss expected on a portfolio over a certain holding period at a given confidence level (Berkowitz et al., 2011). VaR is defined as the lowest or bottom line expectation of loss because of change in value of the asset or portfolio of financial assets at a given confidence level over a specific time horizon under the assumption of normal market conditions (Omari et al., 2017)

Several studies Isik et al. (2016) Saddique and Khan (2015) uses various distributional assumptions like student-t distribution and normal distribution, but the concentration is mostly on central observations or, for stating in terms of financial market, concentration on returns under normal market conditions. Similarly, historical simulation, the non-parametric model make no assumptions related to the nature of the empirical distribution. For example, out-of-sample quantile may not be solved by these VaR models. The problems stays same for model that put same weight on all the observations, remains unsolved.

A definite quantity of substitute risk estimators have been advocate to overcome the problem of deficiency of sub additivity feature in VaR and it headline more information about shape of tail. Such measures typically summarize the entire tail of the distribution as a single-risk measurement. The most preferred option for risk measure is expected shortfall (ES), also known as tail VaR, or conditional VaR (Danielson, 2011) VaR is related as lower bound for conditional VaR or expected shortfall. Rockafellar et al. (2000) Coined conditional value at risk as famous risk estimator. VaR is very similar to risk measure Conditional VaR as both are the percentiles of extreme distribution of loss.

The measurement or estimation of the intense losses is the basic need to survive in financial markets. After the estimation of distributional risk, a proper risk model technique is designed to account for probability of risky events in normal market. A tool is required to assess the probabilities of rare financial events; like the recent global financial crisis (2007 to 2008). An Extreme value theory is appeared to be the most important statistical disciplines for the applied sciences over the last fifty years, and for other fields in recent years. In many fields of modern science, engineering and insurance, extreme value theory is well established (Embrechts et al., 1999) Recently, many research studies like Berkowitz et al. (2011) and Omari et al. (2017) have investigate extreme variations in financial markets, because of currency crises, stock market crashes and large credit defaults.

In some conditions, the investors are more concern about extreme probability of losses or risk. For such rare events, the most advance theory of EVT is used for risk estimation (Danielson, 2011). Its focal point is to analyse explicitly the regions of uncommon events. The attractive feature of EVT is that it is free from assumptions of return distribution, because the result follow any one of these three distributional shape like, Gumbel, Frchet or Weibull.

EVT is more successful in other fields like engineering, where it may be helpful in designing. Hence the concept was first familiarise with financial set up by (Gilli et al., 2006). The distinguishing feature of EVT is to quantify stochastic behaviour of a process mostly for large and sometimes for small levels. Specifically, EVT usually requires estimation of the probability of events that are more extreme than any other that has been previously observed.

In panoramic terms, the EVT adopted mostly, two considerable ways of obtaining models, like BMM (block maxima model) and POT (peak over threshold model). In block maxima method, the data consisted of maximum return for each block to compute generalised extreme value (GEV) (Fernández et al., 2003). In other words, it is the asymptotic distribution of a series of maxima (minima) observations, modelled and the distribution of the standardized maximum is shown to follow extreme value distributions of Gumbel, Frchet or Weibull distributions. The generalized extreme value distribution (GEV) is a standard form of these three distributions.

To analyse extreme market events, it is not always recommended to follow maxima or minima of observations, rather than to analyse all large exceedances over a given threshold. The peak over threshold (POT) models a distribution of explicitly excess over a given threshold. EVT represents that the generalized Pareto distribution or GPD is the limiting distribution of exceedances (Singh et al., 2011).

As compared with traditional approaches used for risk management, EVT models accommodate extreme quantile for heavy tails. This method provides more accessible framework, that deal separately with tail distribution. Considering the fact that most financial return series are asymmetric (Levich, 1985). The EVT approach is advantageous over models which assume symmetric distributions such as t-distributions, normal distributions, ARCH, GARCH-like distributions except E-GARCH which allows for asymmetry (Nelson, 1991).

The two different slots of markets like developed and emerging markets are used for risk analysis. A developed markets refers to a country with lessor rate of poverty, high per capita income of its individuals, less unemployment or under employment, operating capacity of infrastructure, intense industrialization and thin income differences. The emerging markets are headed to become developed markets. All features are aligned to developed markets, but at their earlier stage. Because of increase in chances of growth, the emerging markets are considered more preferred and favourable to investors as compared to developed markets, which already achieved its level.

1.2 Research Gap

One of the important and less explored domain of risk management is risk measurement. The risk profile varies from country to country, over the period of time.

Because of difference in risk profile of both developing and emerging market, number of methods exist for risk estimation. But, unfortunately consensus do not support any one single model or method for risk estimation. Past studies suggest that people may go for empirical distribution analysis or to study the tails of distribution. A detailed investigation is needed in this risk management domain for secure future.

1.3 Problem Statement

The dynamics of emerging and developing markets are different, so that the methods adopt for forecasting of risk may differs. This studies the nonlinear estimation and forecasting of the tails of return distributions in developed, and emerging. Instead of forcing a single distribution for the entire sample, it is possible to investigate only the tails of the return distributions using limit laws, given that only the tails are important for extreme values. It contributes to the literature in a way that it suggest different risk forecasting models with different distributional assumptions to be followed, that provides more accurate risk analysis.The conventional models use empirical distribution for estimation of VaR but these models ignored the tail behaviour which is most important for addressing extreme situations, that requires attention of academicians and practitioners. Furthermore, the study provide a guideline to investors and regulator, that investor can manage their portfolio in a better way and regulators get an idea to maintain capital reserve to save from future default. Moreover, the non-parametric and fully parametric modelling of the tails is convenient for the extrapolation of probability.

1.4 Research Questions

- What are VaR estimates under non-parametric and parametric distribution assumptions?
- What are VaR estimates under time varying volatility models?

- What are expected shortfall estimates under non-parametric and parametric distribution assumptions?
- What are expected shortfall (ES) estimates under time varying volatility models?
- What are VaR estimates in extreme environments?
- How VaR estimates vary under different distributional assumptions?
- What are expected shortfall estimates under extreme environment?
- Which is the most appropriate model for VaR estimation?
- Is VaR model global or country specific in nature?
- Are emerging markets are riskier than developed markets?

1.5 Research Objectives

- To investigate VaR estimates for developed and emerging markets under various distributional assumptions.
- To study the tail behavior of the returns using EVT (extreme value theory) in developed and emerging markets.
- To identify and recommend the most appropriate model for estimation of the risk for developing and emerging market.
- To estimate expected shortfall (ES) for developed and emerging markets under various distributional assumptions.

1.6 Significance

Measurement of risk is the first requirement for risk management. The financial markets has become more volatile over the period of time. Because of this increased volatility, the risk for investor has increased. In domain of risk management, more consensus does not exist for risk measurement. Once a model is suggested to be used for risk measurement, is only applied for a specific period of time. The risk estimators becomes weak over the period of time because of change in volatility dynamics.

Risk measurement is a continuous monitoring process. Risk management tools cannot be applied properly if risk is not correctly measured. Theoretically, it contribute to the literature in a way that it provides a guideline to different markets in future, that which is the appropriate and best suited method of risk measurement. Secondly, it may help the decision maker or the investor in resource allocation i.e. to identify which market offer higher risk in extreme events, so he/she can manage portfolio in a better way. It also provides a guideline to the regulatory body to maintain the capital requirements to the optimum level.

1.7 Plan of Study

This study is composed of five main chapters. First three chapters focus on theoretical area of relevant topic, whereas last two chapters covers the empirical aspects of the study.

Chapter 1: It focus on the fundamental idea of the study. This section introduces topic by providing basic information, problem statement, and gap analysis, research question and significance of work.

Chapter 2: This chapter narrates deep investigation of topic including theoretical as well as empirical arguments from past researches.

Chapter 3: This chapter includes different methodologies adopted for investigation of conventional and modern methods to estimate risk.

Chapter 4: It elaborates the outcomes from empirical results and explain the finding. On the basis of thesis objectives, the findings are filtered through back testing techniques.

Chapter 5: This chapter summarize research outcomes and recommend different risk forecasting models according to market conditions

Chapter 2

Literature Review

Value at risk is a tool used to measure the risk faced by any investment or market. This literature explains that VaR models are tested and adopted by financial institutions to forecast or to estimate risk with different distributional assumptions. After the financial crisis of 2007-2008, all risk estimating models were tested with different interval to save the investor from loss in future.

Gilli et al. (2006) stated that during hard times, risk estimation is much difficult and the forecasted returns may be not reliable as compared to forecasted returns in normal period. Another study revealed that VaR estimates were on higher side during global crisis in different countries (McKenna and Metcalfe, 2013).

The previous studies didnt favour the estimation of VaR by using single method because it might over or under estimate risk. It was always recommended to follow more than one method for risk forecasting. In case of risk averse organizations, they might have used historical simulation method as it provides higher value for VaR. The historical simulation and Monte-Carlo simulation performed better in risk averse organizations, as returns were normally distributed, (Saddique and Khan, 2015). But the risk takers preferred to use methods that provide smaller VaR estimation.

Another study compared two basic conventional models of risk forecasting i.e, Monte-Carlo and Historical simulation on Greek bonds and stocks. The reported results suggested the Monte-Carlo estimate were more accurate risk factor in bond market as compared to stock market, based on back testing techniques (Andersen and Bollerslev, 1998).

Another study conducted by Orhan and Köksal (2012) compared class of GARCH models to estimate VaR for both emerging and developed market for global crisis time period. The results favoured for ARCH (1,1) model for risk forecasting. Ragnarsson (2011) also evaluated GARCH models on 1% and 5% level, with three streams of sample period like Full sample, before crisis and after crisis. The concluding remarks were not preferable to choose one model of risk forecasting for all three different behavioural sample. As GARCH (1, 1) reported best for full sample time period, EWMA perform well for before crisis time, whereas GARCH (1, 2) provide better results for after crisis sample.

To compare the characteristics and performance of emerging and developed stock market, VaR was estimated using KE (Kernel estimator) approach with all traditional time series models. The results stated that most recent events or shock effect the tail of distribution more. For this purpose, moving average window is used, and results are evaluated with Kupiec back testing technique (Abad et al., 2014).

Results from previous studies showed that financial markets suffered extreme losses or discrepancies because of currency crises, stock market crashed and large credit defaults. The behaviour of both tails(right & left) of financial series had, among others, been discussed in (Koedijk et al., 1990; Müller et al., 1997; Loretan and Phillips, 1994; Longin, 1996; ; Kuan and Webber, 1998; Renier et al., 1998; Jondeau and Rockinger, 1999; Neftci, 2000; Diebold, 1998).

McNeil (1999) studied the role of extreme value theory (EVT) for risk management. He use peaks-over-threshold (POT) model for the estimation of tail risk in a general context. The study further showed that POT model provides more accurate results for the estimation of Value-at-Risk (VaR) and expected shortfall.

A study by Fernández (2005) concluded that Extreme value theory (EVT) had emerged as one of the most important statistical disciplines for the applied sciences over the last fifty years, and for other fields in recent years. They studied two important issues related to risk management: VaR computation and dependence of stock market specifically under extreme events. They worked on markets of United States, Europe, Asia, and Latin America. The findings clearly states that EVT provides better VaR estimates and stock markets dependency decreased when data was free of heteroscedasticity and serial correlation.

Many financial analyst applied different VaR models to identify risk. They capture different streams to analyse the behaviour of whole market. Gençay and Selçuk (2004) apply VaR models on daily stock market returns of emerging markets. They selected nine emerging markets to estimate VaR and to provide the tail forecasting at 0.999 percentile along with 95% confidence intervals for stress testing purposes using variancecovariance method, historical simulation method and extreme value theory (EVT). According to their results, EVT provided most appropriate results of VaR estimation as compared to other models. There results also suggested that some moments of return distribution did not exist in some of the countries in emerging markets as well as the behaviour of right and left tails differs.

While dealing with extreme financial events, the most reliable and suitable estimator was extreme value theory (EVT). It was appeared to be a natural statistical modelling technique for the computation of extreme risk estimators like the return level, value at risk and expected shortfall Singh et al. (2011) called these rare events as Black Swans in Talebs terminology. This indicated that there was not only a need to design proper risk modelling techniques which could predict the probability of risky events in normal market conditions but also a requirement for tools which could assess the probabilities of rare financial events; like the recent global financial crisis (2007 to 2008). The study applied univariate extreme value theory to model extreme market risk for the ASX-All Ordinaries (Australian) index and the S&P-500 (USA) Index. The results of the study explained that EVT could successfully applied to financial market return series for predicting static VaR, Conditional VaR or expected shortfall (ES) and expected return level and also daily VaR using a GARCH(1,1) and EVT based dynamic approach.

Another relevant study to EVT was conducted by (Mögel and Auer, 2018) . For the generalisation of study, they covered stock, commodity, bond and currency markets from 1986 to 2016. The purpose of study was to compare several modern EVT approaches for univariate VaR prediction and to provide some guidance for choosing the appropriate estimation strategy in practice. The study compared different approaches of EVT including generalised Pareto peak over threshold approach, BoxCox transformation, L-moment estimation and the Johnson system of distributions. The results clearly stated that the volatilities are highest for the commodity index and lowest for the bond index. The appropriate model was selected through back testing (violation ratio). The BoxCox method is the most promising unconditional approach directly followed by historical simulation. For conditional setting, historical simulation took the lead before the peak over threshold method indicating that return filtering had a stronger positive effect on historical simulation than on the EVT-based approaches. The results of this study were not in favour to follow EVT as it was not superior to simple historical simulation. Different researchers chose different markets to investigate EVT approach for VaR estimation.

EVT approach for VaR estimation was also applied to metal market as recently this market grasped a lot of attention because of its price volatility. A study by Zhang and Zhang (2016) examined the Value-at-Risk and statistical properties in daily price return of precious metals, including gold, silver, platinum, and palladium, from 2000 to 2016. They used two staged GARCH model, including VaR was estimated using GARCH family and EVT to capture the tail behaviour. In comparison with the dynamic VaRs of these precious metals, they found that gold had the steadiest and the highest VaRs, followed by platinum and silver, on the other hand the results showed that palladium had the most volatile VaRs. They also revealed that precious metals were characterized by fat tail distributed, volatility clustering and leverage effect behaviour.

VaR was empirically predicted by Zargar and Kumar (2018) in major Asian countries including Singapore, Malaysia, Hong Kong of China, Indonesia, South Korea, Philippines, Thailand, China, Taiwan of China and India with different competing models, for measuring and managing market risks. The VaR estimates are then back tested using unconditional coverage test, conditional coverage test and loss function to arrive at the best VaR model for each of the economies. The study shows mixed results because of two reasons. One reason is that VaR model uses historical stock market data to forecast future stock market performance, secondly the most important, the models rely on assumptions and approximations that do not necessarily hold in every situation. So, the outcomes of the back testing provided mixed results giving some indication of potential problems within the approaches.

The post-crisis financial system is bearing changes including disputed issues related to digital currencies and crypto currencies. Stavroyiannis (2018) examine the value-at-risk and related measures for the Bit coin and to compare the findings with Standard and Poors SP500 Index, and the gold spot price time series. The study implemented GJR-GARCH model with standardized Pearson type-IV distribution. The findings explains that Bitcoin is a highly volatile currency violating the value-at-risk measures more than the other assets. With respect to the Basel Committee on Banking Supervision Accords, a Bitcoin investor is subjected to higher capital requirements and capital allocation ratio.

Chapter 3

Research Methodology

In this chapter, different models for risk estimation are defined. Firstly, all conventional models like non-parametric, parametric and time varying volatility are discussed with their distributional assumptions. Secondly, the approaches of extreme value theory are discussed which are used to estimate, VaR of extreme left tail of distribution. The EVT uses its Generalised extreme value with Block maxima model, and generalised Pareto distribution with static and dynamic VaR forecasting.

3.1 VaR Estimation Via Historical Simulation (Non-parametric Method)

Non- parametric is a distribution where the main concern is not about data that whether it is normally distributed or not. It is said to be the empirical distribution. The method used to measure empirical data is Historical simulation (HS) under non-parametric approach. This method assumes that history will repeat itself, as the forecasting of risk will be on the basis of past returns. Its relative assumption is whatever trend of returns is in past, will continue in future as well.

Historical simulation give equal weightage to all past observation. This method provide better estimates in the absence of structural breaks. But the financial data is highly volatile, every time the trend may not be the same in future as in past this method is less responsive to odd outlier, which makes it better estimator as compared with parametric models. This is quiet helpful for portfolio investments because, as compared with other models, it captures non-aligned dependence directly.

3.1.1 Historical Simulation (Univariate)

The probability p for value at risk is the negative $T*P^{th}$ value, after the categorized returns series multiplied with financial or monetary value of whole portfolio.

The historical simulation model anticipate the VaR for the confidence level a, historical simulation forecasts the VaR in t + 1 via the factual (1-α) quantile, i.e.

$$VaR^{HS}_{t+1,\alpha} = quantile_{1-\alpha}(x_t, x_{t-1}....x_{t-T+1}) \tag{3.1}$$

Where x_t represent the actual returns in time t.

3.2 VaR Estimation through Parametric Model

Parametric model assume that the data is normally distributed. This may not the case all the time in a financial market as, because of increased volatility in financial markets, data may have fat tails. So, in case of kurtosis more than 3, another parametric model like student-t distribution may be followed for risk forecasting.

3.2.1 VaR Estimation through Normal Distribution Model

The first model under parametric approach is normal distribution model, where the returns are considered as normally distributed. The estimation of VaR under normal distributional assumption, with the confidence level, the forecasted VaR with time t+1 is:

$$VaR^{ND}_{t+1,\alpha} = \mu + \sigma z_{1-\alpha} \tag{3.2}$$

In the following equation, and represent mean and standard deviation of forecasted risk, with the moving window of time T. Whereas the z_1-α is the (1-α) quantile of the standard normal distribution (Vasileiou, 2017)

3.2.2 VaR Estimation through Student-T Distribution Model

Because of more volatility captured in financial markets, the returns are normally portrayed by considerable kurtosis. This model is better estimator of value at risk as compared to normal distribution, as the returns are explained adequately by student t distribution which is quiet helpful to estimate fat tail:

$$VaR^{ST}_{t+1,\alpha} = \mu + \sigma\sqrt{\frac{\upsilon-2}{\upsilon}}t^{\upsilon}_{1-\alpha} \tag{3.3}$$

Where μ represents means, whereas are defined as standard deviation. (1-α) quantile of the Student-t distribution with v degrees of freedom (Rachev et al., 2008). The fat tailed data or returns are usually modelled by estimating an optimal value of p (Campbell et al., 2001).

3.3 VaR Estimation Through the Time-dependent Volatility Models

In this section, different time varying volatility models are used for estimating value at risk. Two time dependent models used in this thesis are exponentially weighted moving average (EWMA) and generalised autoregressive conditional heteroscedasticity (GARCH).

3.3.1 VaR Estimation Using GARCH

Under the assumption of constant volatility over time, the volatility dynamics of financial assets are not taken into account and the estimated VaR fail to incorporate the observed volatility clustering in financial returns and hence, the models may fail to generate adequate VaR estimations. In practice, there are many generalized conditional heteroscedastic models and extensions that have been proposed in econometrics literature. The subsequent generalized conditional heteroscedastic (GARCH) model by (Bollerslev, 1986) are the most commonly used conditional volatility models in financial econometrics. This study focus on standard GARCH model.

The GARCH model specification has two main components: the conditional mean component that captures the dynamics of the return series as a function of past returns and the conditional variance component that formulates the evolution of returns volatility over time as a function of past errors. The conditional mean of the daily return series can be assumed to follow a first-order auto-regressive process,

$$r_t = \varphi_0 + \varphi_1 r_{t-1} + \varepsilon_t \tag{3.4}$$

The dynamic conditional variance equation of the GARCH (p, q) model can be characterized by

$$\sigma_t^2 = \alpha_o + \sum_{i=1}^{p} \alpha_t \varepsilon_{t-1}^2 + \sum_{j=1}^{q} \beta_j \sigma_{t-j}^2 \tag{3.5}$$

Where α_o >0, α_i >0 , $\alpha_{i=j}$ >0 are positive parameters with the necessary restrictions to ensure finite conditional variance as well as covariance stationary. Empirical studies within the financial econometrics literature have demonstrated that the standard GARCH (1,1) model works well in estimating and produce accurate volatility forecasts.

The GARCH models have been extensively used in modelling the conditional volatility in financial time series data and it assumes that good news and bad news shocks have the similar effect on future conditional volatility since it only depends on the squared past residuals.

For the GARCH model under the assumption of normally distributed innovations, the estimation of Value-at-Risk is computed as

$$VaR^{p}_{t+1/t} = \hat{\mu} + \hat{\varphi} r_t + \phi(p)\widehat{\sigma_{t+1}} \tag{3.6}$$

Where ϕ(p) used to represent p_{th} quantile of the normal distribution.

3.3.2 VaR Estimation Using EWMA

The exponential weighted moving average (EWMA) assumes that the most recent events happened in market have more effect as compared to old ones. This model assign weights to the most recent events or observations. This model is presented by (J.P. Morgan) to measure time varying volatility. The EWMA model distributional assumption assumes that rapid fluctuation in returns, will leads to more volatility in future (Danielson, 2011)

The formula used to estimate EWMA Value at risk:

$$\hat{\sigma}_{t,i,j} = \lambda \hat{\sigma}_{t-1,i,j} + (1-\lambda)_{yt-1,iyt-1,j} \tag{3.7}$$

3.4 Expected Short Fall Estimation

Expected shortfall is referred to the expected loss that incurred when VaR is being violated. Simply stating, expected shortfall is the expected loss incurred when losses exceeded VaR or beyond VaR. The expected shortfall measures more uncertainty than VaR. It is used to obtain the expectation of tails. It is suggested that expected short fall must be estimated with the VaR estimation.

This model works by discovering the VaR, and then estimating expectations of both left and right tail observations. As compared with Value at risk, the ES estimated with more unpredictability.

The function of Expected short fall is:

$$ES = -\int_{-\infty}^{-VaR(p)} x f_{VaR}(X)dx \tag{3.8}$$

Where, the expected short fall is:

$$ES = -\frac{\sigma^2 \phi(-VaR(P))}{P} \tag{3.9}$$

In the following equation, σ^2 represent the variance or standard deviation of the distribution, where ϕ represent the distribution like normal, t-distribution, EWMA, GARCH etc. Finally, the VaR is multiplied with minus to represent loss. The equation for expected short fall is same for all models, only the value of will be changed because of change in distribution.

3.5 VaR Estimation through EVT (Extreme Value Theory)

After applying the conventional VaR models, the next step is to apply Extreme value theory to estimate VaR for left tail of the distribution. Mostly, the two main approaches followed by EVT includes generalized extreme value distribution (GEV) which is captured under BMM (Block maxima model), while other one is said to be generalized Pareto distribution (GPD) which covers peak over threshold (POT) models. By comparing these two models, the block maxima model is traditional and old technique as compared with peak over threshold model. Here, in this study, although BMM may rarely use for estimation, still it is applied because of its applicability in literature.

The extreme value theory calculate three parameters like:

- *Shape parameter:* the eta is used to represent the shape of the distribution. For financial data, the value of eta is mostly positive, to show presence of fat tails.

- *Location parameter:* It is used to represent about location of the distribution, means if the value of location parameter is negative, than tail is on left side and vice versa.
- *Scale parameter:* The scale of the distribution is measured through standard deviation. It tells about is on higher side or on lower side.

3.5.1 The Generalized Extreme Value Distribution (GEV) and Block Maxima Method

Let X1, X2, X3Xn represent the independent variable. The term M represent the maximum value from the sample size T.The Fisher and Tippett (1928) and Gnedenko (1943) theorems are used to explain the type of distribution, whether it is relevant from Gumbel, Frechet or the Weibull. This model estimates by selecting the maximum value from sample of normally distributed variables are the fundamental results in EVT.

Theorem 1 (Fisher-Tippett-Gnedenko Theorem) states that, like constants are as well as some non-degenerate distribution function H is in following form:

$$\frac{M_n - b_n}{a_n} \to^d H$$

Now, the value of H may relate to any of these distributions:

$$Ferchet : \phi_\vartheta(x) = \begin{cases} 0 & \text{if} \quad x \leq 0, \quad \vartheta > 0 \\ exp(-x^{-\vartheta}) & \text{if} \quad x > 0, \quad \vartheta > 0 \end{cases} \tag{3.10}$$

$$Weibull : \psi_\vartheta(x) = \begin{cases} exp(-(-x^{-\vartheta})) & \text{if} \quad x \leq 0, \quad \vartheta > 0 \\ 1 & \text{if} \quad x > 0, \quad \vartheta > 0 \end{cases} \tag{3.11}$$

$$Gumbel : \wedge(x) = exp(-exp(-x)) \;\; \text{if} \;\; x \,\epsilon\, \Re \tag{3.12}$$

According to the theorem, M may follows any of the following distribution of Frechet, a Weibull or a Gumbel. If the value forξ =0, it means the distribution is

Gumbel. Whereas, if ξ <0, the shape is from Weibull distribution. Similarly, if ξ >0 means positive, the distribution is Frechet. Hence, the distribution is :

$$H_{\xi,\gamma,\partial}(x) = \begin{cases} exp\left(-(1+\xi\frac{x-y}{\partial})\right)^{\frac{1}{\xi}} & \text{if} \quad \xi \neq 0 \\ exp\left(-exp(-\frac{x-y}{\delta})\right) & \text{if} \quad \xi = 0 \end{cases} \tag{3.13}$$

For 1+ ξ $\frac{x-y}{\delta}$ >0, the location and scale parameters are represented by and are the location and scale parameters, which represents the limiting distribution of the extreme maxima. The following results reported by block maxima (BM) method can be obtained by inverting the following equation with any respective confidence level α i.e:

$$VaR^{BM}_{t+1,\alpha} = \begin{cases} \gamma - \frac{\delta}{\xi}(1-(-\ln(1-\alpha))^{-\xi}) & \text{if} \quad \xi \neq 0 \\ \gamma - \delta\ln(-\ln(1-\alpha)) & \text{if} \quad \xi = 0 \end{cases} \tag{3.14}$$

3.5.2 GPD & Peak Over Threshold (POT)

Another method used for extreme value theory VaR calculation is completely based on exceedances in threshold mostly called as peak over threshold that will be fitted to the exceeded distribution from GPD. This method have an advantage over BMM, as it uses the most available data efficiently. By comparing these two, in peak over threshold, we choose a point of threshold, and exceeding all data is to be account for. Whereas in case of BMM, only anyone maximum value is to be selected for estimation.

Hence, the generalized Pareto distribution uses the function of exceedances as:

$$F_u = Pr(X-u \leq y \mid X > u) = \frac{F(y+u)-F(u)}{1-F(u)}, 0 \leq y \leq x_F - u \tag{3.15}$$

Than GPD will be:

$$G_{\xi\sigma}(y) = \begin{cases} 1 - \left[\{1+\frac{\xi}{\sigma}\}^{-\frac{1}{\xi}}\right] & \xi \neq 0 \\ 1 - exp\left(\frac{-y}{\sigma}\right) & \xi = 0 \end{cases} \tag{3.16}$$

In the following equation of generalised Pareto distribution, the shape parameter is represented by ξ , whereas represents the scale parameter. If ξ >0, the distribution is said to be heavy-tailed distribution and if $\xi = 0$, the defined distribution is said to be light-tailed, similarly if ξ <0 the GPD is a short-tailed Pareto type II distributions. Generally all financial losses are heavy tailed (Gilli et al., 2006).

So, VaR for extreme events will be:

$$VaR_{t+1}^{P} = u + \frac{\hat{\sigma}}{\hat{\xi}} \left[[\frac{n}{N_u}(1-p)]^{-\xi} \right] \tag{3.17}$$

3.6 Backtesting

Back testing is the generalized method used to make comparison of various risk models. The motive is to select ex ante value-at-risk (VaR) forecasts from any particular model and to compare them with ex post realized return (i.e., historical observations). The back testing technique mostly compare the expectation of losses with the actual loss.

The technique is useful, as it points out and identify the weakness of risk estimation models, and give room for improvements in selection of risk forecasting models. If any models not performed well in process of back testing, this may question their distributional and parameter assumptions.

3.6.1 Violation Ratio

Violation ratio is the basic tool used to compare the expected number of violations with actual VaR. It is the conventional method of back testing the accuracy of forecasting models, as the models provide true forecasting of risk or not. In that case, if a model estimate minimum risk, but violation ratio suggest that the risk was under estimated. So that model may not be adopted for forecasting. The idea value for violations ratio will be equivalent to 1, explains number of expected violations are equal to number of observed violations. But in financial data, it is not always possible to get exactly 1.Danielson (2011) suggested a rule of thumb with range of acceptance of violation ratio (0.8 to 1.2). As for understanding, it means that VR¡0.5 or VR¿1.5 explains that respective model is defective in forecasting of risk. Most of times the results of violation ratio are considered as good forecasting technique, and decision will be made on violation ratio.

3.6.2 VaR Volatility

Volatility means instability. Another back testing technique is to estimate the volatility in any model. The parameter used to check volatility is standard deviation of returns. This method of back testing is adopted more for the normally distributed return series. One of the reason includes, the statistical properties of normal distribution are calculated by setting the bench mark with mean and standard deviation. Despite of this feature, the volatility in risk may not be applied to all other risk forecasting models except for normal distribution as it may not provide exact and appropriate volatility. The alignment of miscalculated volatility may also depend on unique applications.

When the motive is not to estimate the extreme conclusion, the volatility is the better estimator to check reliability of models as compared with other back testing techniques. This technique suggest that model with minimum volatility means minimum standard deviation should be selected.

3.6.3 Kupiec POF Tests

The Kupiec test is introduced in 1995 to investigate the fluctuation in binomial test, or it is the degree of failure. This test collaborate with binomial distribution approach. The test works and estimate the exceptions by comparing it with likelihood ratio. The LR suggests that whether the probability of exception matched with the probability P, at defined confidence level. The model said to be accepted or may provide true forecasting of risk if the LR is less than 3.84 for 95 percent confidence level and 6.67 for 99 percent confidence level, i.e χ^2 value of 1 degree of freedom.

The POF test statistic is

$$LR_{POF} = -2\log\left(\frac{(1-p)^{N-x}p^{x}}{(1-\frac{x}{N})^{N-x}(\frac{x}{N})^{x}}\right) \tag{3.18}$$

Where x represents the no of times a model failed, N is the number of observations and p = 1 VaR level (confidence level).

It is assumed that, if the chi square value does not exceed to critical value, the null hypothesis is accepted that model did true forecasting of risk.

3.6.4 Christoffersens Interval Forecast Tests

Christoffersens interval test is introduced in 1998. The basic motive attached to this test is to check the clustering effect. In simple words, this test estimate, whether the probability of any exception or extreme event on some specific time period has a long term effect, or effect to next or previous time period, or the event is of independent nature (Christoffersen, 1998). As compared with other traditional back testing approaches, this test specifically use to check dependence of events between connected days.

The independence test is:

$$LR_{CCI} = -2\log\left(\frac{(1-\pi)^{n00+n10}\pi^{n01+n11}}{(1-\pi_0)^{n00}\pi_0^{n01}(1-\pi_1)^{n10}\pi_1^{n11}}\right) \tag{3.19}$$

Where

- n00 represent time period with no failure, proceed by time period with no failure.
- n10 represent time period with failure, proceed by time period with no failure.
- n01 represent time period with no failure, proceed by time period of failure.

- n11 represent time period with failure, proceed by time period of failure.
- π_0 represent Probability of failure on period t, given that no failure occurred on period t 1 = n01 / (n00 + n01)
- π_1 represent Probability of failure on period t, given that a failure occurred on period t 1 = n11 / (n10 + n11)
- π represent Probability of failure on period t = (n01 + n11 / (n00 + n01 + n10 + n11)

The null hypothesis assumes to have no clustering, means the probability of violation of tomorrow does not depend on today's identified violation. Otherwise the null hypothesis is rejected and reported time period clustering between violations will be identified.

3.7 Data

For the analysis, the data samples forming the basis for analysis of this study is the daily closing stock market indices. The sample period is 2000-2018. The closing stock price indices consist of five working days. As this study is considering daily data, there is some missing observations in many stock market data. The data for stock indices is matched with each other in terms of dates in order to have daily analyses. The tail behavior is examined for the following sample.

The sample is selected on the basis of developed and emerging markets. G10 criteria is used for developed markets. The list of G10 countries include Belgium, Canada, France, Germany, Italy, Japan, the Netherlands, Sweden, Switzerland, the United Kingdom, the United States. Similarly, the emerging countries list includes Brazil, Russia, India, Bahrain, China, Colombia, Malaysia, Thailand, Argentina, Bangladesh, Pakistan and Sri Lanka.

Table 3.1 report the index of stock markets of developed and emerging markets. Many countries may have more than one stock indices, but only the defined stock indices are used in the study for risk estimation. The data of 18 years from

Table 3.1: Samples Details

Countries	Index	Period	No. Of Observations
	Developed Markets		
Belgium	BEL20	2000-2018	4835
Canada	S&P-TSX	2001-2018	4447
France	Cac40	2000-2018	4835
Germany	DAX	2001-2018	4555
Italy	FTSE MIB	2003-2018	3974
Japan	NIKKIE 225	2001-2018	4418
Netherland	AEX	2000-2018	4855
Sweden	OMX	2000-2018	4748
Switzerland	SMI	2001-2018	4515
UK	FTSE 100	2001-2018	4522
USA	S&P500	2006-2018	3247
	Emerging Markets		
Argentina	Marvel	2000-2018	4439
Bahrain	Share BAX	2010-2018	2112
Bangladesh	Dhaka Stock Exchange	2013-2018	1408
Brazil	Bo Vespa	2000-2018	4464
China	Shanghai	2000-2019	4580
Columbia	COLCAP	2008-2018	2645
India	Nifty 50	2000-2018	4704
Malaysia	FTSE	2010-2018	2108
Pakistan	KSE 100	2000-2018	4665
Russia	MOEX	2000-2018	4727
Sri Lanka	CSE	2000-2019	4424
Thailand	SET INDEX	2011-2018	1881

2000-2018 of respective indices is collected from web sources. After that, the returns are calculated by taking first difference of natural log for each series, $R_t = ln(p_t/p_(t-1))$, where R represents the return earned for the time T (mostly a day), p_t represent the price of index at time T, whereas $p_(t-1)$ represent the price of index at previous time T usually, the preceding day return.

3.8 Perceived Innovation / Application

EVT is discussed and investigated for currencies, stock, commodity, mutual funds with very less exposure to markets mostly comparison of 3 to 4 markets at once.

This study is conducted for the markets of G10 and emerging to provide broader acceptability of EVT estimation. The contribution to the literature is illustrated as follows. First, the study reviews the concepts of conventional techniques and also proposes the conditional EVT model that accounts for the time-varying volatility, asymmetric effects, and heavy tails in return distribution. Then, GARCH family of models with EVT is likely to generate more accurate quantile estimates for forecasting VaR. Secondly, compare the accuracy of the VaR forecast generated from the conditional-EVT model with the non-parametric and fully parametric approach. The estimated tail quantile of the competing model and the violation ratio with which the realized return violate these estimates give the preliminary measure of the model success. Finally, the out-of-sample predictive performance of the competing models is assessed through dynamic back testing using the Kupiec POF and TUFF Tests and Christoffersens Interval Forecast Tests The overall performance rating of the competing models is determined by ranking the top two models terms of the violation ratios and the passing both statistical back testing tests. In short, the procedure probably includes the following steps:

Value-at-Risk estimation under conventional models:

- Non-parametric Approach

  Historical simulation method

- Parametric Approach

  Normal distribution model

  Student-t distribution model

- Time varying volatility Approach

  EWMA

  GARCH

Value-at-Risk estimation under EVT approaches

- Generalized Extreme value

  BMM

- Generalized Pareto Distribution

  POT for static VaR

  POT for dynamic VaR

- Back Testing

  Violation Ratio

  VaR volatility

  Kupiec POF Test

  Christoffersens Interval Forecast Tests

Chapter 4

Data Analysis and Discussion

This chapter represents the result of the study to achieve the basic motive. The chapter starts by showing the descriptive statistics for developed and emerging markets. After that the VaR results is discussed and verified with the help of back testing for the analysis of whole distribution. Then, expected shortfall is reported if beyond VaR is to be calculated. Finally, results from Extreme value theory are reported for the analysis of extreme distribution or extreme conditions.

4.1 Descriptive Statistics

Table 4.1 shows the descriptive statistics of daily stock markets indices for developed markets (G10 Countries) and emerging markets. The mean value explains the return earned by any market. In developed markets, the mean value is highest for Italy and USA, which is 0.0002 in a day whereas, the maximum return earned by Argentina i.e 0.0010, followed by Pakistan (0.0007), Russia and Sri Lanka (0.0006) in emerging market. The overall comparison shows that Argentina earned highest mean return, and Nether land and Bahrain shows negative mean return of a day. The median shows the central value, which is nearest to zero in most of the cases except in Bahrain, which exhibits -0.0001. The maximum risk is reported by Bangladesh which is 0.0353. That trend is followed by Argentina and Italy, whereas, Bahrain, Malaysia and Thailand seems to be less risky stocks.

Table 4.1: Descriptive Statistics

	Mean	Median	S.D	Minimum	Maximum	Kurtosis	Skewness
			Developed Markets				
Belgium	0	0.0003	0.0123	-0.0832	0.0933	9.2636	-0.0177
Canada	0.0001	0.0007	0.0104	-0.0979	0.0937	14.1491	-0.6456
France	0	0.0003	0.0143	-0.0947	0.1059	8.1271	-0.034
Germany	0.0001	0.0007	0.0148	-0.0887	0.108	7.8352	-0.0559
Italy	0.0002	0.0005	0.0207	-0.1333	0.906	929.8717	21.0548
Japan	0.0001	0.0004	0.015	-0.1211	0.1323	9.5121	-0.3977
Netherland	-0.0001	0.0004	0.014	-0.959	0.1003	9.7425	-0.1121
Sweden	0	0.0005	0.0148	-0.088	0.0986	6.7827	0.0099
Switzerland	0	0.0004	0.0117	-0.0907	0.1079	10.0689	-0.1714
UK	0	0.0004	0.0117	-0.0926	0.0938	9.8378	-0.1593
USA	0.0002	0.0006	0.0121	-0.0947	0.1096	14.4228	-0.3765
			Emerging Markets				
Argentina	0.001	0.0013	0.0215	-0.1295	0.1612	7.1253	-0.1759
Bahrain	-0.0001	-0.0001	0.0046	-0.0284	0.0275	7.2915	-0.279
Bangladesh	0.0002	0.0001	0.0353	-0.528	0.5346	207.6837	0.1429
Brazil	0.0004	0.0006	0.0175	-0.121	0.1368	7.2788	-0.1156
China	0.000132	0.000641	0.0158	-0.0926	0.094	7.8236	-0.3509
Columbia	0.0002	0.0003	0.0105	-0.0892	0.0873	11.2277	-0.3671
India	0.0004	0.0009	0.0145	-0.1305	0.1633	12.115	-0.3059
Malaysia	0.0001	0.0002	0.0057	-0.0324	0.0332	5.9575	-0.4025
Pakistan	0.0007	0.001	0.0134	-0.0774	0.0851	6.7934	-0.266
Russia	0.0006	0.0009	0.0203	-0.2066	0.2523	18.6933	-0.2384
Sri lanka	0.0006	0.0001	0.0112	-0.1389	0.1829	38.7617	0.3352
Thailand	0.0003	0.0006	0.0095	-0.0581	0.0575	7.8252	-0.3256

The Nether land exhibits -0.9590 minimum loss incurred in a day as compare to other stocks, where the maximum return is earned by Italy which is 0.9060. In the case of normally distributed data, ideally the value for kurtosis is less than 3. But in this case, all kurtosis are more than 3 which shows fat tail distribution and non-normality of data. The leptokurtic return distribution is reported by Italy with the maximum Kurtosis value. In most of the cases the data is negatively skewed except for Italy, Bangladesh, Sweden, and Sri Lanka. The relationship of risk and return is inefficient in these markets, as the more risky stock is not able to gain highest returns.

4.2 VaR Estimation through Non Parametric and Parametric Models:

Table 4.2 exhibits VaR estimation by using non parametric model, like Historical simulation and parametric models, which includes normal distribution and student t distribution based models.

- Historical Simulation Model

VaR is used to express the minimum or expected potential loss suffered by any investment portfolio. The first two columns shows the expected loss suffered by developed and emerging markets by using Historical simulation model with 95% and 99% confidence interval. At 95% confidence interval, the historical simulation method reported highest loss of 3.3% in Argentina and Russia, whereas there is 95% chance that Bahrain may suffer minimum loss of 0.7%. Similarly with 99% confidence interval, the maximum expected loss reported by historical simulation is incurred in Argentina and Russia i.e 6.3%, whereas the minimum loss to the investor in Bahrain is 1.41%.

- Normal Distribution Model

The third and fourth column reports VaR by using normal distribution method with 95% and 99% confidence interval. The result shows that Bangladesh will suffer 5.8% of maximum loss with the 95% confidence, whereas Bahrain may suffer the minimum loss of 0.8% with normal distribution. And there is 99% chance that Bangladesh will suffer maximum loss of 8.2% and Bahrain loss will not exceed to 1.1%.

TABLE 4.2: VaR Estimation using Non-Parametric & Parametric Models

Value at Risk

	Historical Simulation		**Normal Distribution**		**t-Distribution**	
	95%	99%	95%	99%	95%	99%
			Developed Markets			
Belgium	-0.0204	-0.0347	-0.0203	-0.0286	-0.0183	-0.0354
Canada	-0.0163	-0.0314	-0.0171	-0.0241	-0.0149	-0.0288
France	-0.0231	-0.0411	-0.0236	-0.0333	-0.0216	-0.0401
Germany	-0.0237	-0.0454	-0.0243	-0.0343	-0.0222	-0.0424
Italy	-0.0244	-0.0460	-0.0340	-0.0481	-0.0223	-0.0434
Japan	-0.0238	-0.0413	-0.0247	-0.0349	-0.0228	-0.0405
Netherland	-0.0222	-0.0441	-0.0230	-0.0325	-0.0204	-0.0410
Sweden	-0.0242	-0.0424	-0.0244	-0.0344	-0.0227	-0.0419
Switzerland	-0.0182	-0.0347	-0.0193	-0.0273	-0.0173	-0.0329
UK	-0.0183	-0.0345	-0.0193	-0.0273	-0.0173	-0.0334
USA	-0.0185	-0.0374	-0.0199	-0.0281	-0.0168	-0.0382
			Emerging Markets			
Argentina	-0.0333	-0.0633	-0.0353	-0.0499	-0.0327	-0.0610
Bahrain	-0.0070	-0.0141	-0.0076	-0.0107	-0.0070	-0.0132
Bangladesh	-0.0127	-0.0248	-0.0581	-0.0820	-0.0144	0.0301
Brazil	-0.0281	-0.0460	-0.0289	-0.0408	-0.0273	-0.0458
China	-0.0251	-0.0520	-0.0260	-0.0367	-0.0236	-0.0471
Columbia	-0.0159	-0.0297	-0.0170	-0.0240	-0.0153	-0.0291
India	-0.0227	-0.0424	-0.0239	-0.0337	-0.0216	-0.0403
Malaysia	-0.0095	-0.0169	-0.0094	-0.0133	-0.0089	-0.0158
Pakistan	-0.0225	-0.0418	-0.0220	-0.0310	-0.0201	-0.0410
Russia	-0.0334	-0.0628	-0.0355	-0.0502	-0.0318	-0.0594
Srilanka	-0.0140	-0.0291	-0.0184	-0.0260	-0.0143	-0.0327
Thailand	-0.0147	-0.0276	-0.0157	-0.0221	-0.0144	-0.0264

- Student-t Distribution Model

By applying t-distribution model to last two columns, the result states that, with the confidence level of 95% and 99% Argentina is more risky because it may face the maximum loss of 3% and 6% in a day at 95% and 99% of confidence level. Whereas, Bahrain is the safest investment because the loss suffered in a day is just 0.7% with 95% of confidence level and 1.3% with 99% of confidence level, as compared with other markets.

The difference in the results is explained on the basis of change in assumptions of all three models. The maximum loss incurred in a country is even lesser if historical simulation is used for VaR estimation, as compare to normal distribution and t-distribution. Similarly, the VaR estimates of normal distribution are higher than the student-t distribution, which explains that historical simulation and t-distribution may underestimate the risk. Generally, the result shows that Bangladesh and Bahrain are less risky stocks as they face the minimum loss in a day. The markets like Argentina and Russia are more risky markets for an investor as their reported loss is more as compare to other markets.

4.3 VaR Estimate Via Time Varying Volatility (EWMA and GARCH)

In this section, table 4.3 report the VaR estimate by using time varying volatility models like EWMA(expected weighted moving average) and GARCH(Generalized autoregressive conditional heteroscedasticity) with the confidence interval of 95% and 99%. EWMA and GARCH reported the maximum loss incurred in a day or the more risky stocks valuation at different confidence interval.

- EWMA Model

At 95% confidence level, EWMA models report that maximum loss incurred is 4.1% in Argentina, followed by Brazil with 2.6% and in China and Russia with 2.4%. But the less riskier stock markets includes Bahrain with 0.5% chance of loss followed by Bangladesh with 0.9% and Malaysia with 1.0%.

For 99% confidence interval, the VaR estimates through EWMA model follows similar trend with 95% confidence interval. The value of maximum loss is more for

99% confidence interval as compare to 95%. In this case Canada is more riskier to invest with 7.2% of loss incurred in a day. This trend of maximum loss is followed by Sri Lanka with 6.3% and Argentina with 5.8%. Whereas, Bahrain reported to be the safest investment with 0.7% chances of loss, followed with 1.2% in Bangladesh and 1.4% for Malaysia.

TABLE 4.3: VaR estimates by using time varying volatility Models

	EWMA		**GARCH**	
Developed Markets				
Belgium	-0.0162	-0.0228	-0.0164	-0.023
Canada	-0.0121	-0.0717	-0.012	-0.0169
France	-0.0144	-0.0204	-0.0146	-0.0207
Germany	-0.0166	-0.0234	-0.0174	-0.0246
Italy	-0.0205	-0.0289	-0.0144	-0.0204
Japan	-0.0203	-0.0287	-0.0182	-0.0256
Netherland	-0.0138	-0.0195	-0.0142	-0.02
Sweden	-0.0165	-0.0233	-0.0173	-0.0244
Switzerland	-0.0129	-0.0182	-0.0133	-0.0188
UK	-0.0129	-0.0182	-0.0138	-0.0194
USA	-0.021	-0.0296	-0.0203	-0.0286
Emerging Markets				
Argentina	-0.0415	-0.058	-0.0366	-0.051
Bahrain	-0.0053	-0.0074	-0.0074	-0.0104
Bangladesh	-0.0086	-0.0122	-0.0097	-0.0137
Brazil	-0.0256	-0.0362	-0.0271	-0.0383
China	-0.0241	-0.034	-0.0234	-0.033
Columbia	-0.0185	-0.0261	-0.0197	-0.0279
India	-0.016	-0.0226	-0.0153	-0.0215
Malaysia	-0.0096	-0.0135	-0.0098	-0.0138
Pakistan	-0.0191	-0.027	-0.0145	-0.0204
Russia	-0.0241	-0.034	-0.0276	-0.0367
Sri lanka	-0.0115	-0.0632	-0.0085	-0.012
Thailand	-0.0136	-0.0192	-0.0131	-0.0186

- GARCH Model

Another measure for VaR estimation with time varying volatility GARCH is used. The reported results shows similarity with EWMA model. In GARCH model, Argentina, Russia and Brazil are more riskier for investment as the expected loss for a day is 3.7%, 2.8% and 2.7% respectively with 95% confidence level. The same trend is observed for 99% confidence interval as Argentina, Russia and Brazil shows 5.1%, 3.8% and 3.7% chances of loss may be faced by the investor, investing in these countries.

The minimum expected loss or the safest investment markets are Bahrain, Sri Lanka and Bangladesh for both 95% and 99% confidence interval. But the estimated minimum loss is 0.7%, 0.9% 1.0% for 95% confidence interval, and 1.0%, 1.2% and 1,4% for 99% confidence interval respectively.

Generally, the reported results shows that in EWMA and GARCH, Argentina is risky market for investment as compare to other markets, whereas Bahrain looks more safe choice available for risk averse investor.

4.4 Violation Ratio (VR):

Violation ratio is the basic tool used to compare the expected number of violations with actual VaR. Table 4.4 and 4.5 reported violation ration for Historical simulation, normal distribution, student t distribution, EWMA and GARCH models, with the confidence interval at 95% and 99%.

In historical simulation model most of the violation ratio are 1 or nearest to one (ranges from 0.80 to 1.20), Danielson (2011) for both developed and emerging markets, except for Bangladesh. This suggest that Historical simulation can be used by all emerging and developed markets for true VaR forecasting. In the case of Bangladesh, the violation ratio is 0.535 which states that historical simulation will not be used for Bangladesh market as it underestimate the risk. For developed markets, this model is best suited to be adopted by Belgium, Japan and Sweden, whereas India and Russia can also take the advantage of true forecasting of risk by using historical simulation.

Generally, historical simulation may report up to 96% better forecasting for developed and emerging markets with the confidence level of 95%.

TABLE 4.4: Violation Ratio at 95% of Confidence level

	Historical Simulation	Normal Distribution	t-Distribution	EWMA	GARCH
		Developed Markets			
Belgium	1.051	0.99	1.23	1.082	1.051
Canada	1.177	1.025	1.22	1.287	1.334
France	1.104	1.034	1.33	1.191	1.117
Germany	1.203	1.045	1.492	1.245	1.213
Italy	1.273	1.079	1.252	1.294	1.241
Japan	0.993	0.931	1.152	1.147	1.07
Netherland	1.102	1.065	1.316	1.203	1.125
Sweden	1.027	0.987	1.41	1.116	1.098
Switzerland	0.952	0.989	1.144	1.154	1.093
UK	1.091	0.974	1.203	1.259	1.17
USA	1.081	1.215	1.288	1.188	1.141
		Emerging Markets			
Argentina	0.979	0.945	1.274	0.993	0.979
Bahrain	0.859	0.87	0.762	0.924	0.827
Bangladesh	0.535	0.915	0.587	0.933	0.794
Brazil	1.049	1.001	1.044	1.134	1.077
China	1.09	1.025	1.313	1.173	1.039
Columbia	0.985	0.952	1.119	1.186	1.069
India	1.006	0.974	1.204	1.06	1.001
Malaysia	1.109	1.055	1.023	1.163	0.99
Pakistan	1.078	1.001	1.504	1.096	1.055
Russia	1.009	0.969	1.13	1.067	1.027
Sri Lanka	0.834	1.078	0.872	0.882	0.858
Thailand	1.067	1.079	1.411	1.263	1.288

In case of Normal distribution model, all violation ratio comes in range for all 23 countries, which clearly explain that expected violations are equivalent to the observed ones. Hence normal distribution may adopted by emerging and developed markets, as it provides the true forecasting of risk with the 95% confidence interval. Moreover, the normal distribution is best suited to Pakistan and Brazil as its violation ratio is exactly 1.00. Broadly, the normal distribution is better to be adopted as 100% of developed and emerging markets gets true risk forecasting by using this model.

For the student-t distribution model, in developed markets only 3 out of 11 reported true forecasting of risk under 95% confidence interval, in the case of emerging markets, only 5 markets out of 12 shows that expected violations are more or less equivalent to observed violations. As comparing with Historical simulation and normal distribution models, the student-t distribution is weaker model for risk forecasting as it is suited only to 27% to developed and 42% to emerging markets under 95% confidence interval.

In EWMA and GARCH models, 7 out of 11markets and 8 out of 12 markets shows true forecasting of risk under 95% level of confidence interval respectively for developed and emerging markets. For emerging markets, the reported violation ratio are much better as all are in range except for Sri Lanka and Thailand. The reported figures suggests that EWMA will be adopted to 64% of developed markets and 83% to emerging markets. Whereas, GARCH models is best suited to 73% to developed markets and 75% to emerging markets under 95% confidence interval.

For developed market, the normal distribution is better to be adopted as 100% countries gets true risk forecasting by using this model. The other models like GARCH and EWMA may also use for risk estimation, because the reported violation ratio in Belgium, France, Japan, Nether land, Sweden, Sri Lanka, UK and USA is in range of (0.80-1.20). For emerging market, the normal distribution is may adopted for risk forecasting in whole market. After Normal distribution, EWMA and GARCH reported violation ratio in range for Argentina, Bahrain, Brazil, China, Columbia, India, Malaysia, Pakistan and Russia.

TABLE 4.5: Violation Ratio at 99% of Confidence level

	Historical Simulation	Normal Distribution	t-Distribution	EWMA	GARCH
		Developed Markets			
Belgium	2.377	1.003	1.134	2.028	2.203
Canada	2.526	1.072	1.048	2.549	2.335
France	2.181	0.96	0.916	1.81	1.81
Germany	2.091	0.79	0.883	1.905	1.835
Italy	2.417	1.101	0.86	2.282	2.095
Japan	2.135	0.936	1.032	2.015	1.703
Netherland	2.28	1.064	1.086	2.063	1.976
Sweden	2.179	1	1.179	1.845	1.89
Switzerland	2.087	0.75	1.032	2.063	1.97
UK	2.341	1.007	0.96	2.317	1.966
USA	1.001	3.203	1.368	2.569	2.703
		Emerging Markets			
Argentina	2.148	0.836	1.241	2.196	1.958
Bahrain	1.504	0.644	0.644	2.363	2.041
Bangladesh	1.036	0.604	0.431	1.209	1.209
Brazil	1.614	0.759	0.427	1.637	1.4
China	2.217	0.855	1.285	2.171	2.009
Columbia	2.171	0.668	0.793	2.505	2.171
India	1.819	0.965	0.808	2.043	1.841
Malaysia	2.691	1.076	0.485	2.153	2.045
Pakistan	2.763	0.861	1.45	2.265	2.129
Russia	1.965	0.871	0.826	2.032	1.876
Sri Lanka	1.845	0.934	0.911	2.108	1.605
Thailand	2.391	1.165	1.227	2.146	2.514

The reported violation ratio in table 4.5 are more as compare to table 4.4, in historical simulation only USA from developed markets and Bangladesh from emerging market show true forecasting. Hence historical simulation model can be used for risk forecasting in USA and Bangladesh with 99% confidence interval.

Although normal distribution and student-t distribution models also reported weak forecasting of risk as, 73% from developed market and 58% from emerging market may use normal distribution for risk forecasting as it is better than historical simulation model. Similarly for student t distribution model, all developed market risks can be forecasted except for USA. Whereas, for emerging markets, this model may only be adopted by India, Russia and Sri Lanka as it reports less violation ratio.

For time varying volatility models like EWMA and GARCH, none of the markets from developed and emerging report true forecasting of risk as all violation ratio is more than 1.5. By comparing the violation ratio reported by 95% confidence interval with 99% confidence interval, the number of expected violations increased with the increase in confidence interval. The risk forecasting with 95% confidence interval, the models perform much better, as in many markets the violation ratio are equivalent to 1 explaining that the expected violations are equal to the observed ones.

In case of developed markets, normal distribution reported better forecasting of risk for all countries except for USA, Germany and Switzerland. The student-t distribution covers more countries than normal distribution to predict risk except for USA only. Although, historical simulation reported violation ratio as 1.01 for USA.

For emerging market, Normal distribution is used as risk estimator for Argentina, China, India, Malaysia, Pakistan, Russia, Sri Lanka, and Thailand. The historical simulation model covers only Bangladesh with violation ratio of 1.03, Bangladesh may use historical simulation for risk forecasting under 99% of confidence level.

4.5 VaR Volatility

Volatility refers to market uncertainty. It is used to measure risk, if volatility is lower, suggested model is reliable for VaR estimation. Table 4.6 and 4.7 reports VaR volatility at 95% and 99% confidence interval for non-parametric and parametric models.

With 95% confidence interval, in developed countries normal distribution and EWMA model are considered to be less volatile models as their volatility is 1%. The other models like historical simulation, t-distribution and GARCH reported more volatility in VaR for Italy i.e 2%. In emerging markets, Normal distribution and GARCH reported less volatility, even it is zero in Bahrain, Columbia, Malaysia and Thailand. Only three models like historical simulation, t-distribution and EWMA reported 2% -5% volatility for Bangladesh.

The reported VaR volatility shows that Normal distribution is best suited model for risk forecasting, as there are less volatility in VaR results for both developed and emerging markets with the confidence interval of 95%.

With the increase in confidence interval, the VaR volatility also increases. For developed markets, historical simulation and EWMA is best suited models for risk forecasting as the volatility is 1% except for Italy and USA. Whereas for emerging markets, same two models can be followed for VaR forecasting except for Bangladesh and Russia because there forecasted VaR volatility is more than 1%.by comparing all these models with the parameter of volatility, it is noticed that some of emerging market like Bahrain, Columbia, Malaysia and Thailand volatility is zero, explaining the fact that the volatility does not exist in these markets under all conventional VaR estimates.

Moreover, all the countries under the bracket of developed and emerging markets may follow Historical simulation and EWMA for risk forecasting under 99% confidence level, as the reported results are better in these two models.

TABLE 4.6: Volatility at 95% of confidence level

	Historical Simulation	**Normal Distribution**	**t-Distribution**	**EWMA**	**GARCH**
		Developed Markets			
Belgium	0.0075	0.0085	0.0078	0.0096	0.0099
Canada	0.0079	0.0085	0.0085	0.0092	0.0091
France	0.0085	0.0098	0.0084	0.0107	0.011
Germany	0.0092	0.0107	0.0091	0.0111	0.0114
Italy	0.0151	0.011	0.0151	0.0113	0.0162
Japan	0.0077	0.0089	0.0079	0.0103	0.0106
Netherland	0.0086	0.0092	0.01	0.0119	0.0121
Sweden	0.0088	0.01	0.0084	0.0107	0.0107
Switzerland	0.0072	0.0078	0.0054	0.009	0.0096
UK	0.0077	0.0093	0.0078	0.0094	0.0096
USA	0.0109	0.0095	0.0098	0.0113	0.0116
		Emerging Markets			
Argentina	0.0102	0.0111	0.0095	0.0138	0.0136
Bahrain	0.0006	0.0013	0.0023	0.0018	0.0017
Bangladesh	0.0499	0.0044	0.0504	0.04	0.0165
Brazil	0.008	0.0086	0.0085	0.0105	0.0096
China	0.0091	0.0123	0.0086	0.0111	0.0117
Columbia	0.0045	0.0051	0.0044	0.0045	0.0047
India	0.0088	0.0093	0.0088	0.0107	0.0108
Malaysia	0.0019	0.0027	0.0021	0.0034	0.0034
Pakistan	0.0063	0.0093	0.0059	0.0088	0.0095
Russia	0.0122	0.0128	0.0126	0.0159	0.0162
Sri Lanka	0.0083	0.0066	0.0079	0.0107	0.0136
Thailand	0.0044	0.005	0.0041	0.0056	0.0059

TABLE 4.7: VaR Volatility at 99% of Confidence Level

	Historical Simulation	**Normal Distribution**	**t-Distribution**	**EWMA**	**GARCH**
		Developed Markets			
Belgium	0.0106	0.0139	0.0144	0.0106	0.0139
Canada	0.0112	0.0182	0.0161	0.0112	0.0129
France	0.012	0.0152	0.0157	0.012	0.0155
Germany	0.0131	0.0154	0.017	0.0131	0.0161
Italy	0.0214	0.0159	0.0293	0.0214	0.023
Japan	0.011	0.0191	0.0146	0.011	0.015
Netherland	0.0139	0.0194	0.0186	0.0139	0.0176
Sweden	0.0125	0.0136	0.0156	0.0125	0.0151
Switzerland	0.0101	0.0151	0.0101	0.0101	0.0136
UK	0.011	0.0162	0.0146	0.011	0.0136
USA	0.0199	0.0134	0.0184	0.016	0.0164
		Emerging Markets			
Argentina	0.0145	0.0215	0.018	0.0145	0.0192
Bahrain	0.0008	0.0033	0.0044	0.0008	0.0023
Bangladesh	0.0706	0.2034	0.0974	0.0706	0.0233
Brazil	0.0113	0.0185	0.0161	0.0113	0.0136
China	0.0128	0.0207	0.0162	0.0128	0.0166
Columbia	0.0063	0.0098	0.0084	0.0063	0.0067
India	0.0124	0.0184	0.0166	0.0124	0.0152
Malaysia	0.0027	0.0045	0.0048	0.0027	0.0049
Pakistan	0.0089	0.0101	0.011	0.0089	0.0134
Russia	0.0173	0.0302	0.0236	0.0173	0.0229
Sri Lanka	0.0117	0.0243	0.0155	0.0117	0.0192
Thailand	0.0062	0.0111	0.0078	0.0062	0.0083

4.6 Kupiec POF Test-Unconditional Coverage Test for Non-parametric, Parametric and Time varying Volatility Models.

The table 4.8 and 4.9 reports results of unconditional coverage test by Kupiec with the confidence level at 95% and 99%. Kupiec explains that if the data suggests that the probability of exceptions is different than p, the VaR model is rejected. For 95% the value is 3.84, whereas it is 6.67for 99%confidence level. This test is used to compare the observed violations with the expected number of violations. The model said to be accepted or may provide true forecasting of risk if the LR is less than 3.84 for 95% confidence level and 6.67 for 99% confidence level.

The first table reports Kupiec test likelihood ratio at 95% confidence interval. In historical simulation model, most of the countries likelihood ratio is in range, which explains the historical simulation may be used for risk assessment except for Canada, France, Germany, Italy, USA , Bangladesh and Sri Lanka, as there likelihood ratio is more than 3.84. Hence, for these markets Historical simulation may not be used for VaR estimation.

For normal distribution model, the Kupiec test predicts that all markets from developed and emerging, it is the best model for risk estimation except for USA only because the LR is 148.09, which is quiet higher than 3.84 under 95% of confidence level.

The Kupiec test results looks worst for t-distribution, EWMA and GARCH model. For t-distribution model, only Switzerland from developed markets and Columbia, Brazil and Malaysia from emerging market can get true forecasting of risk, as there number of expected violation are less than the observed ones.

In case of EWMA and GARCH models, most of the markets null hypothesis is rejected for developed market except for Belgium, Sweden and Japan, which means that the number of expected violation are more or less equal to observed ones.

TABLE 4.8: Kupiec POF Test-Unconditional Coverage Test at 95% confidence level

	Historical Simulation	Normal Distribution	t-Distribution	EWMA	GARCH
		Developed Markets			
Belgium	0.6239	0.0233	11.9424	1.5742	6552.1184
Canada	6.9159	0.188	10.4389	17.2461	5479.3348
France	2.7216	0.3474	24.5888	535.0531	6934.5594
Germany	8.8142	0.4584	353.109	12.6675	48.6828
Italy	13.4801	1.2084	10.5752	15.5975	10.5752
Japan	0.0099	1.0711	4.5251	4.5251	1.0537
Netherland	1.7369	0.7305	20.9531	10.6173	6680.0754
Sweden	0.1727	0.0395	33.9709	3.0779	6533.73
Switzerland	0.5267	0.0251	3.1552	5.0557	209.8468
UK	1.8038	0.1558	8.7409	14.0259	6232.3968
USA	23.1796	148.087	112.8153	47.7769	42.2499
		Emerging Markets			
Argentina	0.1002	0.6706	15.3721	0.0106	0.1002
Bahrain	2.0332	1.7281	5.9938	0.5842	3.1063
Bangladesh	15.7192	0.4487	11.0376	0.2826	2.7613
Brazil	0.522	0.0004	0.8666	3.842	1.2961
China	1.7985	0.1459	18.5661	6.4927	6362.1375
Columbia	0.027	0.2951	1.7216	4.1178	0.5857
India	0.008	0.1548	9.1332	0.8208	5727.3543
Malaysia	1.1182	0.2897	0.0496	2.4608	0.0092
Pakistan	1.3852	0.0003	48.8779	2.2891	4758.4978
Russia	0.0207	0.226	4.0899	1.0499	6102.2891
Sri Lanka	6.4216	1.3083	4.044	3.1995	6058.9431
Thailand	0.3756	0.5241	12.882	5.5019	6.533

For emerging market, the likelihood reported results are much better as EWMA model can be used for risk estimation in Argentina, Bahrain, Bangladesh, India, Russia and Sri Lanka.

Whereas, the GARCH model may suited to Argentina, Bahrain, Bangladesh, Columbia Malaysia and China.Generally, comparing all these five models at 95% confidence level, the Kupiec test suggest that Normal Distribution is the best model to be adopted by developing and emerging markets for risk estimation, as 100% from emerging and 91% from developed market null hypothesis is accepted.

At 99% level of confidence, the decision is more or less similar with 95% level of confidence. For historical simulation model, the reported LR suggest that this model is good for true risk forecasting in Belgium, USA and Bangladesh, the likelihood ratio results are much better for normal distribution and student-t distribution.

The normal distribution model is suitable for all markets except for Belgium, as its LR is quiet high under 99% confidence level.

For t-distribution model the reported likelihood ratio is in range for many countries, except for Belgium, Sweden, USA, Brazil and Pakistan. The reported values give a sign that these countries may not use t-distribution for risk forecasting under 99% confidence level.

The Kupiec likelihood ratio report shows worst results for time varying volatility models. For developed market, only Belgium may use EWMA, and USA can use GARCH for risk estimation. In case of emerging market, EWMA is reliable model for Bangladesh whereas, GARCH is reliable for Bangladesh and Brazil only with 99% confidence level.

Kupiec test results suggest that Normal distribution is most reliable for risk forecasting in both developed and emerging markets with 99% confidence level as there is no significant difference between observed and expected risk.

The reported results showed that null hypothesis is accepted in most of the cases under 99% of confidence interval

Table 4.9: Kupiec POF Test-Unconditional Coverage Test at 99% confidence level

	Historical Simulation	**Normal Distribution**	**t-Distribution**	**EWMA**	**GARCH**
		Developed Markets			
Belgium	0.1003	14.0803	22.2104	0.2138	4895.8896
Canada	69.3464	0.2159	0.2159	71.2401	54.9094
France	48.3076	0.0764	0.336	24.5201	13790.765
Germany	39.3597	2.0711	0.623	28.1316	24.3236
Italy	54.0754	0.3713	0.782	45.3969	34.2671
Japan	40.9382	0.1779	0.0113	33.5292	17.2063
Netherland	55.9544	0.187	0.5194	40.2158	13380.9357
Sweden	47.2287	0	80.7805	25.9809	13227.7028
Switzerland	38.7491	2.9402	0.0101	37.2673	31.5749
UK	56.3199	0.0018	0.0123	54.6019	31.4374
USA	6.4322	1.02	13.7289	6.8385	4.5783
		Emerging Markets			
Argentina	41.9975	1.2125	2.2891	45.1484	30.3234
Bahrain	4.134	2.7198	2.7198	25.2669	15.6591
Bangladesh	0.0152	2.1311	4.7993	0.4789	0.4789
Brazil	13.518	2.6879	17.7969	14.5024	6.06
China	48.1201	0.9739	2.9418	44.9287	34.4565
Columbia	24.8618	3.0185	0.6971	38.6561	24.8618
India	24.2683	0.0544	1.77	37.6051	25.4935
Malaysia	36.6935	0.107	6.1623	18.7539	15.7438
Pakistan	93.7034	0.9081	7.1797	52.5322	10233.8395
Russia	32.884	0.7879	1.8639	37.0994	12445.4127
Sri Lanka	24.0829	0.1858	0.8362	39.2742	12076.0953
Thailand	22.9394	0.4256	1.2489	16.2871	26.5865

4.7 Christoffersens Independence Test for VaR Conventional Models

It is a conditional coverage test, developed specifically to check clustering. The main focus is to check whether violations happen one after the other to make cluster at one point of time, or the violations behave independently. The null hypothesis assumes to have no clustering, means the probability of violation of tomorrow does not depend on today's identified violation. Otherwise the null hypothesis is rejected and reported time period clustering between violations will be identified.

The following table 4.10 reported dependence test at 95% of confidence level on parametric, non-parametric and time varying volatility models. In historical simulation and normal distribution the likelihood ratio is more than 3.84 except for Thailand, which states that null hypothesis is rejected in all markets related to developed and emerging except for Thailand. In Thailand the reported value shows clustering trend (probability of tomorrows violation depends upon today violations) under 95% of confidence level.

In t-distribution model, no clustering is found in developed and emerging markets null hypothesis is accepted. In the case of time varying volatility models, like EWMA and GARCH, the market responded more in future because of past volatility as compare to parametric and non-parametric models.

In EWMA model, 5 out of 11 and 7 out of 12 markets reported to accept null hypothesis. For GARCH, France from developed and 5 countries from emerging market reported likelihood ratio less than 3.84, as no clustering is recorded and return series are independent of previous day volatility.

By comparing the parametric, non-parametric and time varying volatility, the reported likelihood ratio supports parametric and non-parametric models for risk forecasting as minimum or no clustering is found in their case.

Table 4.10: Christoffersens Independence Test at 95% confidence level

	Historical Simulation	**Normal Distribution**	**t-Distribution**	**EWMA**	**GARCH**
		Developed Markets			
Belgium	82.9629	68.7575	81.832	32.9433	1.0871
Canada	30.6948	25.6804	29.2492	7.4866	0.0186
France	21.7205	18.9394	22.8386	2.0429	5.7606
Germany	27.2977	27.6529	19.1243	2.4635	0.4656
Italy	18.9016	17.6887	24.7569	0.7987	0.0088
Japan	8.177	9.4439	8.3355	0.1334	0.1036
Netherland	32.2846	38.0704	35.0599	9.3779	0.1658
Sweden	18.3104	36.2615	20.3617	10.9413	0.4918
Switzerland	26.5792	25.7669	32.5694	2.4083	3.1763
UK	19.8114	17.78	15.8589	10.9938	0.9709
USA	10.1395	8.6094	7.7069	0.0885	0.0463
		Emerging Markets			
Argentina	14.0324	14.0943	16.7867	8.0729	3.377
Bahrain	7.041	4.7005	4.8864	3.5536	0.012
Bangladesh	10.837	9.2399	15.6788	2.1398	0.0169
Brazil	5.7023	9.112	7.5297	0.8545	0.1428
China	7.4153	13.947	9.9725	0.0007	0.0327
Columbia	34.5672	27.216	35.6811	13.568	6.614
India	24.7776	20.5206	41.6991	6.7029	21.7817
Malaysia	17.3054	17.1842	21.5225	4.898	2.4843
Pakistan	100.723	63.3725	88.1577	30.9912	65.9781
Russia	57.695	50.5074	61.5649	5.071	7.0606
Sri Lanka	107.6725	115.8385	123.7306	72.4873	106.8091
Thailand	3.6807	2.1037	8.4292	0.9851	0.2456

TABLE 4.11: Christoffersens Independence Test at 99% confidence level

	Historical Simulation	**Normal Distribution**	**t-Distribution**	**EWMA**	**GARCH**
		Developed Markets			
Belgium	26.9793	2.8936	13.3361	26.5307	1.6997
Canada	34.1966	2.7572	2.5544	0.5488	2.5485
France	16.1129	0.5319	0.6397	0.155	7.8203
Germany	15.1268	1.0314	0.7762	0.2402	0.1942
Italy	4.8666	2.9766	4.3526	0.0019	0.0799
Japan	8.6676	12.5928	21.9571	7.0309	4.2147
Netherland	37.3896	14.5064	9.27	8.3021	0.1799
Sweden	13.1818	15.9407	13.2787	5.1954	1284.7553
Switzerland	18.9683	1.3701	6.6671	4.0002	0.3127
UK	14.968	16.3543	11.0994	9.2652	4.6569
USA	10.8012	8.9153	5.2342	6.1737	5.2695
		Emerging Markets			
Argentina	22.0644	0.9921	21.5304	5.4611	1.0111
Bahrain	11.8275	3.42	8.8421	2.619	3.9397
Bangladesh	2.2577	4.1366	5.0135	1.9922	1.7552
Brazil	4.7984	1.2571	3.0797	0.0247	0.0243
China	10.1977	0.8175	4.084	0.679	0.3927
Columbia	29.2006	2.3582	18.1007	15.2691	0.5748
India	23.1616	16.7437	7.1928	8.8874	1.1951
Malaysia	26.1193	5.6782	3.9488	3.4493	3.9297
Pakistan	42.9152	13.4273	13.4426	6.7961	70.575
Russia	33.0125	0.8614	9.0326	1.9753	7.412
Sri Lanka	43.3815	24.0794	19.7046	27.025	111.7996
Thailand	0.9768	1.5237	4.3429	0.078	0.001

Table 4.11 report maximum likelihood ratio with 99% of confidence level. In historical simulation the null hypothesis is rejected except for Italy, Bangladesh and Brazil. This explains that the effect of last day volatility will be transferred to next day in most of the markets except for these three. For normal distribution model, 6 out of 11 and 9 out of 12 markets show no clustering trend, where null hypothesis is accepted. The likelihood ratio under dependence test reported clustering in India, Pakistan, Sri Lanka, Japan, the Nether land, Sweden, UK and USA.

The less effect of todays volatility on tomorrow return series is reported by t-distribution as 55% from developed market, 42% from emerging market reported no clustering , as null hypothesis is accepted at 99% of confidence level.

The time varying volatility models like EWMA and GARCH reported minimum likelihood ratio as less clustering is reported by these two models as compared to parametric and non-parametric models

4.8 ES Estimation through Non-parametric and Parametric Models

Expected shortfall is referred as the expected loss that incurred when VaR is being violated. Simply stating, expected shortfall is the expected loss incurred losses exceeded VaR or beyond VaR. The expected shortfall measures more uncertainty than VaR. It is used to obtain the expectation of tails. Or it is said to be the sub additive risk measure.

Table 4.12 reports expected shortfall at confidence interval 95% and 99% under parametric and non-parametric models. At 95% confidence level, the historical simulation reports maximum potential for loss ranges from 4% to 5% (mostly 4% for developed market and 5% for emerging market). But the potential minimum loss incurred in a day is reported as 3% in 7 countries out of 11. Whereas, Bahrain and Malaysia reported 1% of average expected shortfall in emerging market.

TABLE 4.12: Expected Short Fall with Non-Parametric and Parametric Models

Expected ShortFall						
	Historical Simulation		**Normal Distribution**		**t-Distribution**	
	95.0%	99.0%	95.0%	99.0%	95.0%	99.0%
Developed Markets						
Belgium	-0.0301	-0.0468	-0.0254	-0.0328	-0.0235	-0.0504
Canada	-0.0259	-0.0451	-0.0214	-0.0276	0.0182	0.0403
France	-0.0344	-0.0538	-0.0296	-0.0381	-0.0264	-0.0540
Germany	-0.0357	-0.0560	-0.0304	-0.0393	-0.0282	-0.0594
Italy	-0.0366	-0.0585	-0.0426	-0.0551	-0.0289	-0.0624
Japan	-0.0359	-0.0601	-0.0310	-0.0400	-0.0270	-0.0515
Netherland	-0.0346	-0.0569	-0.0289	-0.0373	-0.0274	-0.0618
Sweden	-0.0350	-0.0525	-0.0306	-0.0395	-0.0275	-0.0551
Switzerland	-0.0287	-0.0475	-0.0242	-0.0312	-0.0219	-0.0460
UK	-0.0285	-0.0473	-0.0242	-0.0312	-0.0222	-0.0477
USA	-0.0307	-0.0539	-0.0249	-0.0322	-0.0274	-0.0696
Emerging Markets						
Argentina	-0.0508	-0.0818	-0.0443	-0.0572	-0.0411	-0.0830
Bahrain	-0.0111	-0.0184	-0.0095	-0.0122	-0.0087	-0.0183
Bangladesh	-0.0410	-0.1380	-0.0728	-0.0941	0.0201	0.0478
Brazil	-0.0400	-0.0631	-0.0362	-0.0467	-0.0312	-0.0543
China	-0.0397	-0.0647	-0.0326	-0.0421	-0.0316	-0.0707
Columbia	-0.0251	-0.0412	-0.0213	-0.0275	0.0187	0.0401
India	-0.0352	-0.0574	-0.0299	-0.0386	-0.0272	-0.0554
Malaysia	-0.0143	-0.0214	-0.0118	-0.0152	-0.0107	-0.0204
Pakistan	-0.0339	-0.0477	-0.0275	-0.0355	-0.0281	-0.0626
Russia	-0.0526	-0.0906	-0.0445	-0.0575	-0.0398	-0.0812
Srilanka	-0.0253	-0.0496	-0.0231	-0.0298	-0.0232	-0.0601
Thailand	-0.0230	-0.0377	-0.0197	-0.0254	-0.0178	-0.0351

For 99% confidence level, the average minimum loss reported is 5% for developed market and 2% for emerging market, which is quiet high as compare to 95% of confidence level. Whereas, the maximum expectation of loss is reported is 14% by Bangladesh (the emerging market) and 6% by Germany, Italy, Japan and Nether land (developed market).

For 99% confidence level, the average minimum loss reported is 5% for developed market and 2% for emerging market, which is quiet high as compare to 95% of confidence level. Whereas, the maximum expectation of loss is reported is 14% by

Bangladesh (the emerging market) and 6% by Germany, Italy, Japan and Nether land (developed market).

For normal distribution model, the maximum loss incurred in a day is faced by Italy like 4% with 95% confidence level and 6% under 99% confidence level. Whereas, the minimum shortfall reported as 2% by Canada, Switzerland, UK and USA with 95% of confidence interval. The same countries show minimum pattern of expected shortfall in a day as 4% under 99% of confidence level. The emerging market looks safer as the minimum reported expectation of loss is recorded as 1% in Bahrain for both 95% and 99% of confidence interval. The maximum shortfall is reported by Bangladesh like 14% under 95% of confidence interval and 6% with 99% of confidence level respectively.

The t-distribution model follows the same pattern like normal distribution, as 4 out of 11 countries reported the expected average shortfall in a day as 2%. The reported chances of maximum loss is 3%, reported by 6 out of 11 countries under the shadow of developed market. The reported results show that chances of loss increased in 99% of confidence level as compare to 95% of confidence level, as 4% minimum loss and 7% maximum loss recorded for developed market.

In case of emerging market, the minimum expected loss is reported by Bahrain and Malaysia which is 1%, whereas maximum expected loss is incurred in Argentina and Russia as 4% under 95% of confidence interval and 8% with 99% of confidence interval respectively.

Table 4.13 report the estimated figure for expected shortfall under time varying volatility models, like EWMA and GARCH at 95% and 99% of confidence level. In EWMA model, 8 out of 11 countries reported that there is only 2% expectation of loss under 95% of confidence level. Whereas, the maximum average expected loss is reported by 3 out of 11 countries which is approximately 3% in Italy, japan and USA from developed market. In case of emerging market, the maximum expected shortfall is reported by Argentina as 5% under 95% of confidence level. The minimum expectation of loss in a day 1%, reported by Bahrain, Bangladesh, Malaysia and Sri Lanka.

With 99% of confidence level, the minimum and maximum expected loss in a day is reported by 5 out 0f 11 countries i.e 2% and 6 out of 11 countries i.e 3% respectively for developed market. Whereas in emerging market, only Argentina reported as more risky because the its maximum average expected shortfall is 7%. Only 2 out 11 countries report minimum expected shortfall of 1% (in Bahrain and Bangladesh).

Table 4.13: Expected Shortfall Estimation through Time Varying Volatility Models

	EWMA		**GARCH**	
	95.00%	99.00%	95.00%	99.00%
	Developed Markets			
Belgium	-0.0203	-0.0262	-0.02053	-0.0262
Canada	-0.01521	-0.0196	-0.01504	-0.0194
France	-0.01811	-0.0232	-0.01837	-0.0237
Germany	-0.02079	-0.0268	-0.02183	-0.0282
Italy	-0.02565	-0.0331	-0.0181	-0.0233
Japan	-0.02549	-0.0329	-0.02277	-0.0294
Netherland	-0.01729	-0.0223	-0.01779	-0.0229
Sweden	-0.02072	-0.0267	-0.02166	-0.0279
Switzerland	-0.01622	-0.0209	-0.0167	-0.02157
UK	-0.01621	-0.0209	-0.01727	-0.0223
USA	-0.02628	-0.03395	-0.0254	-0.03282
	Emerging Markets			
Argentina	-0.052	-0.067	-0.04586	-0.059
Bahrain	-0.00664	-0.0085	-0.00924	-0.0119
Bangladesh	-0.01084	-0.014	-0.01219	-0.0157
Brazil	-0.03213	-0.0415	-0.03404	-0.04398
China	-0.03022	-0.039	-0.02931	-0.0378
Columbia	-0.02323	-0.03	-0.02477	-0.0319
India	-0.02005	-0.0259	-0.01914	-0.0247
Malaysia	-0.01198	-0.0154	-0.01224	-0.0158
Pakistan	-0.02397	-0.0309	-0.01816	-0.0234
Russia	-0.03019	-0.039	-0.03458	-0.0446
Sri Lanka	-0.01448	-0.0187	-0.01067	-0.0137
Thailand	-0.01709	-0.022	-0.01646	-0.0212

The other time varying volatility model GARCH also applied for minimum and maximum expected shortfall estimation at 95% and 99% of confidence interval. With 95% of confidence level, GARCH reported more safer estimation of expected shortfall for developed market, as only USA have a maximum loss of 3%, all other countries show the minimum expectation of loss as 2% only. For emerging market, the minimum loss is reported by Bahrain, Bangladesh, Malaysia and Sri Lanka i.e 1%. Whereas Argentina reported maximum expected shortfall of 7% in a day.

The expectation of loss increases in GARCH model under 99% of confidence level, as 6 out of 11 and 5 out of 11 countries reported 2% minimum expected loss and 3% maximum expected loss estimated in a day for developed market stream respectively. In case of emerging market, only the countries like Bahrain and Sri Lanka reported minimum expected loss of 1%. Whereas Argentina shows 6% of maximum average expected shortfall at 99% confidence interval.

By comparing these two time varying volatility models, under developed market, GARCH reported best estimated figures for expected shortfall at 95% and 99% confidence level. Whereas, for emerging market, ideally EWMA models should be adopted for expected shortfall estimation under 95% and 99% confidence level.

4.9 VaR Estimation Via Extreme Value Theory (EVT) Models

The financial markets are highly volatile, and the extreme movement may happen. The investors are not concerned with all distribution, either they are more interested about tails. The focus of extreme value theory is to analyse the tail region or the differential events. The distinctive feature of extreme value theory as compared to previous parametric and non-parametric models, it estimate the extreme events happened on tail extremes, instead of estimation of whole distribution. The main concern of extreme value theory is to study behaviour of extreme outcomes on both left and right tail. For risk analysis, only the left tail is analysed. To estimate extreme market risk, the BMM, POT and the dynamic POT method is implemented to return series of developed and emerging market. The distribution of minima (left tail) is reported in table 4.10 with negative sign for 95% and 99% of confidence level.

- BMM (Block Maxima Model)

In case of block maxima model under GEV approach, the results are generated only for left tail of return distribution (VaR) as the research motive is to estimate expected extreme loss. In this approach, the data consisted of maximum return for each block to compute GEV. The BMM suggest that the value of (shape parameter is >0, which states that data follows Frechet distribution (Danielson, 2011)

TABLE 4.14: VaR estimates using extreme value theory models

	Block Maxima		**GPD (Static)**		**GPD (Dynamic)**	
	95% VaR	99% VaR	95% VaR	99% VaR	95% VaR	99% VaR
			Developed Markets			
Belgium	-0.0496	-0.0779	-0.0203	-0.0345	0	-0.0001
Canada	-0.041	-0.0634	-0.0163	-0.0308	-0.0003	-0.0003
France	-0.0557	-0.081	-0.0237	-0.042	-0.0004	-0.0005
Germany	-0.0586	-0.0907	-0.0233	-0.045	-0.0001	-0.0001
Italy	-0.0612	-0.0942	-0.0232	-0.0443	-0.00001	-0.0001
Japan	-0.0602	-0.0913	-0.031	-0.055	-0.0008	-0.0006
Netherland	-0.0579	-0.1003	-0.0225	-0.0437	-0.0006	-0.0007
Sweden	-0.0585	-0.087	-0.0247	-0.0427	-0.0002	-0.0003
Switzerland	-0.0492	-0.084	-0.0268	-0.0462	-0.0006	-0.0007
UK	-0.0482	-0.0803	-0.0179	-0.0326	-0.0002	-0.0003
USA	-0.0524	-0.0897	-0.0185	-0.0364	0	0
			Emerging Markets			
Argentina	-0.0913	-0.1406	-0.0333	-0.063	-0.0017	-0.0023
Bahrain	-0.0211	-0.0337	-0.007	-0.0139	-0.0002	-0.0002
Bangladesh	-0.0771	-0.2578	-0.0127	-0.0238	-0.0007	-0.0007
Brazil	-0.0652	-0.092	-0.0282	-0.0459	-0.0013	-0.0015
China	-0.0717	-0.1139	-0.0331	-0.0603	-0.0006	-0.0004
Columbia	-0.0449	-0.0713	-0.0114	-0.0261	-0.0005	-0.0006
India	-0.0624	-0.107	-0.0246	-0.0442	-0.0001	-0.0001
Malaysia	-0.0257	-0.0398	-0.005	-0.0118	-0.0003	-0.0004
Pakistan	-0.053	-0.0719	-0.0232	-0.042	-0.0001	-0.0002
Russia	-0.0961	-0.1566	-0.0391	-0.0727	-0.0002	-0.0005
Sri Lanka	-0.0961	-0.1566	-0.0134	-0.0275	-0.0005	-0.0004
Thailand	-0.0411	-0.0626	-0.0081	-0.0132	-0.0001	-0.0002

The expected potential minimum loss under BMM is reported by Canada and Bahrain under 95% and 99% of confidence level. The minimum loss for developed market like Canada reported 4.10% with 95% confidence level, and 6.34% under 99% of confidence interval, which is quiet higher as compare to minimum loss for emerging market like Bahrain (reported as 2.11% and 3.37% for 95% and 99% of confidence level respectively). Whereas, the maximum loss in a extreme event is reported by Italy i.e 6.12% with 95% of confidence and Nether land i.e 10.03% with 99% of confidence level from, developed markets.

In case of emerging market, the maximum potential loss is suffered by Russia and Sri Lanka with 9.61% of chances for Russia and 15.66% chances for Sri Lanka for both 95% and 99% of confidence level.

- POT (Peak Over Threshold) with Static EVT VaR

After applying BMM, same daily return data is used to estimate static and dynamic VaR for POT method. The threshold u is selected by using rule of thumb at 95% and 99%. The exceedances above than threshold u will be fitted to GDP for static and dynamic VaR estimation under 95% and 99% of confidence level.

With 95% of confidence level, the predicted minimum and static loss is reported by Canada and Japan as 1.63% and 3.10% respectively, for developed market. Whereas, the minimum prediction of loss cannot exceed to 0.5% in Malaysia, the maximum expected loss is reported by Malaysia as 3.91% from emerging market.

With 99% of confidence level, the minimum expected loss will stay at 0% in Belgium, Italy and USA, but the maximum expectation of loss is 0.08% reported by Japan. Whereas, in emerging market 3 out of 11 markets like India, Pakistan and Thailand reported 0.1% of minimum expected loss. The maximum static risk of 7.27% is reported by Russia in a day.

- POT (Peak Over Threshold) with Dynamic EVT VaR

The dynamic EVT is used to predict or to estimate the time varying VaR. For dynamic POT, a moving window of last 500 days is used of log returns series. The dynamic POT forecast 1 day ahead VaR with 95% and 99% of confidence level. For developed market, the minimum expectation of loss under GPD dynamic will not exceed from 0% at 95% and at 99% of confidence level. Whereas, the maximum forecasted loss is 0.08% reported by Japan, and 0.07% reported by the Nether land and Switzerland at 95% and at 99% of confidence level. For emerging market, the minimum expected risk is 0.01% reported by 3 out of 11 markets and 1 out of 11 under 95% and 99% of confidence level. Whereas, the maximum expected dynamic GPD VaR is reported by Argentina only as 0.17% and 0.23% at 95% and at 99% of confidence level respectively.

4.10 Violation Ratio of Extreme Value Theory Models

Violation ratio is the back testing measure used to check the reliability of any model. Ideally the violation ration must be 1, which indicates that the expected number of violations are equal to the observed one. But the range from 0.80-1.20 reported violation ratio can also be used for the validity of any model under extreme value theory debate.

Table 4.15 reported violation ratio for VaR calculation using extreme value theory with 95% of confidence level. In BMM, only 3 out of 11 countries show significant violation ratio, which means that expected violations are equivalent to observed ones. Instead of these 3 countries like Canada, UK and USA, all other countries underestimate the risk for long position. Likewise no country from emerging market reported violation ratio in range of (0.8-1.2), as all reported violations under block maxima model underestimate the expected loss on extreme left tail.

The GPD approach is also used for EVT static VaR estimation, show that 9 out of 11 countries expected violation are equal to the observed ones, except for Japan and Switzerland. In case of emerging market, 5 out of 11 reported violation ratio prescribed range, which provide evidence that GPD approach under EVT may be used for true forecasting of extreme risk.

The reported results for GPD approach under dynamic value at risk estimation reported weaker risk forecasting under extreme value theory. The dynamic VaR shows that this approach usually overestimate the expected risk in long run position. By comparing all these models for estimation of EVT VaR, the POT (peak over threshold model) is the best suited for risk forecasting in fat-tails as 82% of the developed market and 42% from emerging market shows that observed violations are equal to the expected ones.

TABLE 4.15: Violation Ratio of Extreme value theory VaR at 95%

	Block Maxima	**GPD (Static)**	**GPD (Dynamic)**
	Developed Markets		
Belgium	0.0611	0.9987	8.8705
Canada	0.081	0.9957	8.3421
France	0.0654	0.9248	8.9902
Germany	0.0511	1.0037	8.4665
Italy	0.0645	1.198	8.8477
Japan	0.0672	0.4608	8.7833
Netherland	0.0738	0.9687	8.8923
Sweden	0.0489	0.8761	8.924
Switzerland	0.061	0.4034	8.8133
UK	0.089	0.9927	8.9232
USA	0.0801	1.0748	9.1121
	Emerging Markets		
Argentina	0.0334	0.9499	7.8807
Bahrain	0.0215	0.891	9.0714
Bangladesh	0	0.604	8.6799
Brazil	0.0712	0.9632	8.7212
China	0.0514	0.5746	8.9372
Columbia	0	1.7195	8.8147
India	0.0404	0.7276	8.2596
Malaysia	0.0215	2.6925	8.8314
Pakistan	0.0136	0.8926	7.3675
Russia	0.067	0.5897	8.3181
Sri Lanka	0.0192	1.0832	8.277
Thailand	0.0368	2.7117	10.0736

Table 4.16 report violation ratio for extreme value theory VaR estimation at 99% of confidence level. In case of BMM, none of the countries from developed and emerging market report true forecasting of extreme risk or risk of left tail,

under 99% of confidence level. It is noticed that with the increase in confidence level, the dependence and reliability of model decreases.

In GPD (Generalised Pareto distribution), the risk forecasting is better as compared to BMM , because 9 out of 11 from developed market and 5 out of 12 from emerging market shows the VaR violations in range (0.8 to 1.2), which states that observed violations are equivalent to expected , and model is more preferable to be adopted for risk forecasting. The exact violation ratio of 1 is reported by Belgium, Canada, Germany, Nether land and UK for developed market. Whereas, Sri Lanka reported 1.13 from emerging market.

TABLE 4.16: Violation Ratio of Extreme value theory VaR at 99%

	Block Maxima	**GPD (Static)**	**GPD (Dynamic)**
Developed Markets			
Belgium	0.0218	1.0031	44.0689
Canada	0.1429	1.0243	41.3768
France	0.0436	0.9815	44.5365
Germany	0	1.0223	42.0539
Italy	0.0269	1.155	43.379
Japan	0.12	0.456	43.2925
Netherland	0	1.0209	43.788
Sweden	0.0222	0.9117	44.353
Switzerland	0.0235	0.3518	43.5038
UK	0.0468	1.0068	44.1011
USA	0.1001	1.1015	45.5607
Emerging Markets			
Argentina	0	0.9308	38.4964
Bahrain	0	0.7515	45.2496
Bangladesh	0	0.1726	43.9172
Brazil	0.0949	0.949	43.1079
China	0	0.5606	44.8727
Columbia	0	0.8765	43.7396
India	0.0449	0.7186	40.7815
Malaysia	0	3.231	44.0495
Pakistan	0.0227	0.8609	36.3616
Russia	0.0223	0.6031	40.7639
Sri Lanka	0	1.1263	41.0256
Thailand	0	5.6442	50.9816

The last column reported EVT VaR calculation by using GPD dynamic approach. None of the countries from developed and emerging markets reported true forecasting of risk by using GPD dynamic model. By comparing all three EVT approaches, the GPD static reported better forecasting of risk as compare to others, i.e 82% from developed market and 42% from emerging market may use this approach to forecast risk.

In both the intervals 95% and 99%, the GPD static may be used by most of developed and emerging market as it provides true forecasting of extreme risk.

4.11 Kupiec POF Test-Unconditional Coverage Test for Extreme Value Theory Models

The Kupiec POF test is used for back testing of EVT models results of forecasted risk. Two basic approaches of extreme value theory are used for value at risk estimation, which includes generalised extreme value (GEV) and generalised Pareto Distribution (GPD). Under GEV approach the block maxima model is used, whereas for GPD approach, the static and dynamic VaR are calculated under 95% and 99% of confidence level.

The table reports Kupiec test likelihood ratio at 95% of confidence level. For block maxima model, all countries reported maximum likelihood ratio as the results are nor significant except for Germany from developed countries. But in case of emerging market, none of the countries reported significant results. The extreme value theory VaR estimation can only be followed by Germany as the BMM is suitable for risk forecasting for Germany only.

The other approach used for EVT VaR estimation is GPD static model. Under this model, all countries from developed market reported significant likelihood ratio, which states that generalized Pareto distribution is best suited for extreme left tail estimation. For emerging market, all countries reported significant likelihood ratio, as GPD static is more reliable estimator for extreme tail risk except for Bangladesh and Columbia.

Under GPD dynamic model, none of the likelihood ratio is significant, which states that this model is not reliable to be used for risk estimation at extreme left tail under 95% of confidence level. From all these extreme value theory models, only generalised Pareto distribution is best suited for estimation of static value at risk of extreme left tail.

Table 4.17: Kupiec POF Test-Unconditional Coverage Test for EVT at 95%

	Block Maxima	**GPD(STATIC)**	**GPD(DYNAMIC)**
	Developed Markets		
Belgium	362.6849	0.0003	6150.5982
Canada	309.4328	0.0036	5023.6716
France	357.067	0.1809	6298.0115
Germany	0.0027	0.337	5830.6083
Italy	291.0342	0.5341	4941.1186
Japan	322.5805	0.4528	5509.8337
Netherland	348.1277	0.0026	6199.8796
Sweden	371.9422	1.7182	6097.0415
Switzerland	337.5024	0.3402	5634.3754
UK	306.4381	0.4608	5762.571
USA	277.5805	0.8614	4215.9779
	Emerging Markets		
Argentina	367.4488	0.5577	4534.3328
Bahrain	171.4511	1.1952	2590.721
Bangladesh	108.5761	11.0376	1490.2241
Brazil	321.543	0.2997	5450.8696
China	355.5461	0.0109	5809.1955
Columbia	234.0219	3118.3444	3156.0644
India	380.2608	2.0877	5216.8281
Malaysia	171.0494	0.0496	2469.3879
Pakistan	420.8236	0.6697	4237.0032
Russia	346.7998	3.0234	5318.1903
Sri Lanka	388.1531	0.2659	4947.1046
Thailand	141.2009	1.4995	1909.1896

Under 99% of confidence level, the BMM reported none of the likelihood ratio is significant, from both developed and emerging markets. This reported likelihood ratio explains that this method is not suitable to be adopted for risk forecasting under extreme value theory.

For GPD static model, 9 out of 11 developed markets and 10 out of emerging markets reported significant likelihood ratio. Hence, this model provides best static VaR estimates using extreme value theory. In case of GPD dynamic model, the reported likelihood ratio suggest very less reliability over this model. None of the likelihood ratio is significant, which explains that this model may not be used for risk forecasting under extreme value theory.

By comparing all three models of extreme value theory, only GPD static model provides true forecasting of risk under 99% of confidence level.

TABLE 4.18: Kupiec POF Test-Unconditional Coverage Test for EVT at 99%

	Block Maxima	**GPD(STATIC)**	**GPD(DYNAMIC)**
	Developed Markets		
Belgium	82.4909	38.5623	4606.0179
Canada	48.9081	0.0253	10337.7186
France	75.5933	0.0005	12557.3248
Germany	76.9888	0.0261	10819.6123
Italy	65.6003	0.0827	9811.6006
Japan	52.4793	0.1779	10951.7165
Netherland	82.8843	0.0823	12359.8561
Sweden	80.7805	0.0893	12246.8846
Switzerland	76.2034	0.3248	11328.1876
UK	69.5847	0.0709	11467.9634
USA	221.581	138.4845	4215.9779
	Emerging Markets		
Argentina	74.7118	0.2061	9324.2456
Bahrain	29.5594	1.2666	5202.5668
Bangladesh	16.3588	12.2153	3086.6657
Brazil	57.79	0.1117	10995.7086
China	77.4797	10.362	5765.7663
Columbia	39.7695	6.064	3118.3444
India	73.0761	0.7265	10740.1412
Malaysia	29.4833	0.0185	5023.2457
Pakistan	79.1494	0.2326	9092.0591
Russia	80.3874	1.8639	10799.9161
Sri Lanka	74.4174	0.038	10192.0952
Thailand	25.1812	1.2666	3956.0137

4.12 Christoffersens Independence Test for EVT Models:

The Christoffersen's test is used to measures the dependency between consecutive days. The back testing approach will help to find out the clustering effect of an event. That is the effect prolongs to more than a day or not.

TABLE 4.19: Christoffersens Independence Test for EVT Models at 95% confidence level

	Block Maxima	**GPD(STATIC)**	**GPD(DYNAMIC)**
	Developed Markets		
Belgium	11.1924	77.9144	4.763
Canada	16.7808	23.5218	0.7504
France	10.6697	13.5176	2.6353
Germany	5.0231	27.8212	0.4738
Italy	4.4206	24.1128	0.836
Japan	11.6691	6.7933	7.0569
Netherland	3.7679	28.1983	2.0302
Sweden	4.9469	17.9446	0.0025
Switzerland	12.3905	42.3041	0.5628
UK	3.2008	23.7621	0.5238
USA	4.3221	7.8293	10.6185
	Emerging Markets		
Argentina	15.5432	22.5558	24.0646
Bahrain	8.748	6.1358	0.9813
Bangladesh	10.5663	2.5964	46.9922
Brazil	3.9629	19.006	0.1131
China	12.7958	19.165	0.2163
Columbia	12.0184	22.4382	11.0977
India	6.2733	49.556	25.3636
Malaysia	9.4201	11.0585	4.4238
Pakistan	9.792	107.9955	95.4512
Russia	19.887	41.998	17.8826
Sri Lanka	8.6726	153.107	162.163
Thailand	7.807	2.3963	2.4111

Table 4.19 report dependence test used to examine whether the estimated value at risk under extreme value theory face clustering or not. At 95% of confidence level, the BMM under EVT value at risk estimation reported clustering in 9 out of 11 developed markets, and in all emerging market. Only the likelihood ratio

reported by UK and Nether land show that the impact of happening of an extreme event does not travel to the next day return prices.

In GPD (static) model, all countries under developed market reported likelihood ratio more than the value of χ^2 , which states that developed market face clustering of an extreme event by using GPD static model for extreme value theory VaR estimation under 95% of confidence level. Whereas, in emerging market, only Bangladesh and Thailand reported significant likelihood ratio so, null hypothesis of no clustering is accepted in Bangladesh and Thailand. All other countries under emerging market reported insignificant likelihood ratio, so null hypothesis is rejected and the reported GPD static model face clustering effect, if adopted by these emerging markets, under 95% of confidence level.

Another model GPD dynamic is used for EVT VaR estimation. The dependence test reported 8 out of 11 countries null hypothesis is accepted in developed market, except for Belgium, Japan and USA. This explains that an effect of an extreme event will travel from one day to another in the markets of Belgium, japan and USA. Whereas, in emerging market, 4 out of 12 reported significant likelihood ratio of χ^2, as the null hypothesis of no clustering is accepted for Bahrain, Brazil, China and Thailand. All other countries from emerging market reported insignificant likelihood ratio, states that extreme events are of independent nature.

By comparing these three models of EVT, the GPD dynamic model reported less chances of clustering, if adopted by developed and emerging market. The reported results explains 52% chances of null hypothesis to be accepted, if GPD dynamic model is selected for EVT VaR estimation. Whereas, there are only 9% chances of no clustering under block maxima model and GPD static model.

Under 99% of confidence level, the block maxima model (BMM) for the EVT VaR estimation reported insignificant likelihood ratio for both developed and emerging market. So, in this case, null hypothesis is accepted, that extreme risk of left tail follows clustering effect under BMM.

For generalised Pareto distribution of static VaR estimation, 4 out of 11 developed markets and 4 out of 12 emerging markets reported significant likelihood ratio. The result explain that extreme events on left tail distribution follows in dependency as the effect does not prolong for more than 1 day, because of significant value of χ^2. But all other countries of developed market like Belgium, Canada, Germany, Nether land, Switzerland, UK and USA may suffer clustering effect of extreme events by following GPD static model. This trend is also followed by countries of emerging markets like Argentina, Bahrain, Bangladesh, Brazil, India, Pakistan and Sri Lanka under 99% of confidence level.

The reported likelihood ratio suggest less clustering effect under GPD dynamic risk estimation model. In case of developed markets, 9 out of 11 markets reported significant likelihood ratio, as extreme events are of independent nature except in Belgium and USA. For emerging market, the dependence of extreme events prolong in 7 out of 11 countries, as there reported likelihood ratio is insignificant. Whereas, Bahrain, Brazil, China, India. And Thailand reported that null hypothesis of no clustering between extreme events is accepted.

The model recommended to eliminate clustering effect is GPD dynamic model as 82% of developed market and 42% of emerging market reported no clustering effect.

4.13 Expected Shortfall Estimation through EVT Models

The following table reported expected shortfall in extreme value theory at 95% and 99% of confidence level. In block maxima model, the minimum expectation of loss is reported by Canada (from developed market) and Bahrain (from emerging market) at 95% and 99% of confidence level. Whereas, the maximum average expected loss may face by Nether land and Bangladesh from developed and emerging market stream respectively. The maximum expected loss reported by emerging market is more as compare to the maximum loss reported by developed market under BMM.

Table 4.20: Christoffersens Independence Test for EVT Models at 99% confidence level

	Block Maxima	**GPD(STATIC)**	**GPD(DYNAMIC)**
		Developed Markets	
Belgium	11.2249	39.8274	6.026
Canada	6.9346	16.1894	0.6856
France	10.5462	2.8936	1.9233
Germany	13.191	7.0943	0.8172
Italy	12.9002	3.3041	1.4876
Japan	7.8687	3.675	0.6426
Netherland	13.3257	10.161	1.8887
Sweden	13.2778	0.5619	0.0296
Switzerland	13.1715	18.2848	0.5545
UK	11.0831	12.0008	0.284
USA	9.0184	12.5957	10.6185
		Emerging Markets	
Argentina	13.1365	12.63	26.1528
Bahrain	11.5152	8.4844	0.7736
Bangladesh	10.5663	8.4768	46.0455
Brazil	8.2913	7.5164	0.1394
China	13.2022	0.4857	0.4663
Columbia	12.0184	3.5801	12.3405
India	12.2117	7.0052	0.1231
Malaysia	11.5109	1.7357	17.0776
Pakistan	13.2406	29.8151	93.4291
Russia	13.2689	26.8958	19.7524
Sri lanka	13.1293	47.8955	160.5048
Thailand	11.2506	2.8694	3.2004

In GPD (static) VaR estimation, the maximum expectation of loss is reported by Japan as 4.6% at 95% confidence level, and 7.4% at 99% confidence level. Whereas, Canada reported minimum expected loss in left tail distribution as 2.6% chances at 95% confidence level and 4.5% chances at 99% confidence level from developed market. The minimum expected loss beyond VaR is reported by Malaysia (1%) and Bangladesh (1.9%) at 95% and 99% confidence level respectively. Whereas Russia reported maximum average expected shortfall as 6% at 95% confidence level, and 10.1% at 99% confidence level.

Table 4.21: Expected Short Fall or tail VaR

	Block Maxima		GPD (Static)		GPD (Dynamic)	
	95.00%	99.00%	95.00%	99.00%	95.00%	99.00%
Developed Markets						
Belgium	-0.06146	-0.09658	-0.03006	-0.04678	-0.00058	-0.00058
Canada	-0.04995	-0.07727	-0.02601	-0.04529	-0.0004	-0.0004
France	-0.06271	-0.09116	-0.03506	-0.05451	-0.00047	-0.00047
Germany	-0.07288	-0.11287	-0.03528	-0.05557	-0.00068	-0.00068
Italy	-0.0746	-0.11476	-0.03526	-0.05697	-0.00063	-0.00063
Japan	-0.07252	-0.1099	-0.04604	-0.07412	-0.00058	-0.00058
Netherland	-0.08179	-0.14172	-0.03506	-0.05738	-0.00047	-0.00047
Sweden	-0.06744	-0.10029	-0.03555	-0.05294	-0.00052	-0.00052
Switzerland	-0.06838	-0.11674	-0.03835	-0.05836	-0.00046	-0.00046
UK	-0.06483	-0.10786	-0.02809	-0.04662	-0.00035	-0.00035
USA	-0.07139	-0.12214	-0.03074	-0.05367	-0.00065	-0.00065
Emerging Markets						
Argentina	-0.11251	-0.17334	-0.05079	-0.0818	-0.00131	-0.00131
Bahrain	-0.02733	-0.0438	-0.01106	-0.01847	-0.00012	-0.00012
Bangladesh	-0.31647	-1.05778	-0.04766	-0.01368	-0.0011	-0.0011
Brazil	-0.07329	-0.10343	-0.04005	-0.06302	-0.00066	-0.00066
China	-0.09048	-0.14367	-0.0478	-0.07171	-0.0002	-0.0002
Columbia	-0.05731	-0.09097	-0.01975	-0.03574	-0.00034	-0.00034
India	-0.08668	-0.14871	-0.03739	-0.06003	-0.00083	-0.00083
Malaysia	-0.03192	-0.04944	-0.01015	-0.01731	-0.0002	-0.0002
Pakistan	-0.05328	-0.07218	-0.03444	-0.04805	-0.00115	-0.00115
Russia	-0.12421	-0.20242	-0.06047	-0.10105	-0.00108	-0.00108
Sri Lanka	-0.12421	-0.20242	-0.02459	-0.04825	-0.00028	-0.00028
Thailand	-0.04898	-0.07459	-0.01592	-0.02678	-0.00054	-0.00054

In case of GPD dynamic model, the difference in minimum and maximum expectation of loss is very less, like 0% expected loss and 0.1% expectation of loss for both developed and emerging market with same confidence level of 95% and 99%. In this model, mostly all countries face same minimum and maximum expected loss in left tail distribution.

By comparing the reported expectation of loss estimated by all three models of extreme value theory, the GPD dynamic reported minimum expectation of loss in both developed and emerging markets. Almost 50% of market expected loss is 0.1%, whereas 50% of the market shows no loss (0%) of expected loss.

TABLE 4.22: Model Selection or Recommended Model

Market	Conventional VaR Model		EVT VaR Model	
	95%	**99%**	**95%**	**99%**
	Developed Market			
Belgium	Norma Dist. & Historical Simu.	Historical Simu. & EWMA	GPD(Static)	NIL
Canada	Normal Dist.	Normal Dist. & T-Dist.	GPD(Static)	GPD(Static)
France	Normal Dist.	Normal Dist. & T-Dist.	GPD(Static)	GPD(Static)
Germany	Normal Dist.	Normal Dist. & T-Dist.	GPD(Static)	GPD(Static)
Italy	Normal Dist.	Normal Dist. & T-Dist.	GPD(Static)	GPD(Static)
Japan	Norma Dist. & Historical Simu.	Normal Dist. & T-Dist.	GPD(Static)	GPD(Static)
Netherland	Norma Dist. & Historical Simu.	Normal Dist. & T-Dist.	GPD(Static)	GPD(Static)
Sweden	Norma Dist. & Historical Simu.	Normal Dist.	GPD(Static)	GPD(Static)
Switzerland	Norma Dist. & Historical Simu.	Normal Dist. & T-Dist.	GPD(Static)	GPD(Static)
UK	Norma Dist. & Historical Simu.	Normal Dist. & T-Dist.	GPD(Static)	GPD(Static)
USA	NIL	Normal Dist. & EWMA	GPD(Static)	NIL
	Emerging Market			
Argentina	Norma Dist. & Historical Simu.	Normal Dist. & T-Dist.	GPD(Static)	GPD(Static)
Bahrain	Norma Dist. & Historical Simu.	Normal Dist. & T-Dist.	GPD(Static)	GPD(Static)
Bangladesh	Normal Dist. & EWMA	Norma Dist. & Historical Simu.	NIL	NIL
Brazil	Norma Dist. & Historical Simu.	Normal Dist.	GPD(Static)	GPD(Static)
China	Norma Dist. & Historical Simu.	Normal Dist. & T-Dist.	GPD(Static)	NIL
Columbia	Norma Dist. & Historical Simu.	Normal Dist. & T-Dist.	NIL	GPD(Static)
India	Norma Dist. & Historical Simu.	Normal Dist. & T-Dist.	GPD(Static)	GPD(Static)
Malaysia	Norma Dist. & Historical Simu.	Normal Dist. & T-Dist.	GPD(Static)	GPD(Static)
Pakistan	Norma Dist. & Historical Simu.	Normal Dist.	GPD(Static)	GPD(Static)
Russia	Norma Dist. & Historical Simu.	Normal Dist. & T-Dist.	GPD(Static)	GPD(Static)
Sri Lanka	Normal Dist. & EWMA	Normal Dist. & T-Dist.	GPD(Static)	GPD(Static)
Thailand	Norma Dist. & Historical Simu.	Normal Dist. & T-Dist.	GPD(Static)	GPD(Static)

The box table reported the best model suited for risk forecasting for whole distribution (parametric, non-parametric and time varying volatility models) and risk forecasting for left tail (BMM, GPD Static & GPD Dynamic). The model are selected by using back testing techniques of violation ratio and Kupiec test.

For both developed and emerging markets, normal distribution is recommended to use for risk forecasting of whole distribution at 95% and 99% of confidence interval. In case of risk estimation of left tail distribution, GPD static report more accurate forecasted figures for 99% and 99% of confidence level in both markets.

Chapter 5

Conclusion and Recommendation

In recent years, the financial markets have experienced exponential growth coupled with significant extreme price movements such as recent global financial crisis, currency crisis and extreme default losses. Value-at-risk is widely used as a risk forecasting tool. The financial markets uses VaR for risk estimation. It is the worst estimated loss, may be the change in asset valuation or a portfolio at a given confidence level. Different VaR models are adopted for risk forecasting with different distributional assumptions. After risk estimation, different back testing techniques are used to check accuracy of VaR models.

Firstly, VaR has been estimated for developed and emerging markets by using non-parametric (historical simulation), parametric (normal distribution, t-distribution) and time varying volatility models (EWMA, GARCH) at 95% and 99% of confidence level. The forecasted risk estimated by each model is compared with each other, to find the best suited model for risk estimation in both developed and emerging markets. The descriptive analysis reported non normality of data, which indicates that returns follow fat tails distribution.

According to all VaR models, the highest forecasted risk is reported by t-distribution and normal distribution at 95% and 99% of confidence level respectively. Whereas the lowest or minimum risk was reported by EWMA model under both 95% and 99% of confidence level. For developed markets, the risk is highest in Italy, and lowest in case of Canada. But for emerging market, Argentina reported to be the more risky market, as less risky market is Bahrain. To check the validity that VaR models are providing true forecasting or not, different back testing approaches like violation ratio, volatility, Kupiec test and Christoffersens test are applied.

According to violation ratio, the normal distribution model reported minimum number of violations under 95% and 99% of confidence level, for both developed and emerging market. The normal distribution model reported 100% suitability to all markets at 95%, whereas, the models seems suitable to 73% of developed markets and 67% of emerging market.

The next step is to account for the VaR volatility reported by all VaR models. At 95% of confidence level, volatility also indicates that normal distribution VaR results are less volatile as 100% of developed market reported 1% of volatility, whereas, 4 emerging markets even reported 0 volatility. At 99% of confidence level, EWMA reported minimum volatility in VaR, as 83% developed market and 67% emerging market reported volatility 1 or less than 1.

In the next section, to check the accuracy of models point of failure test and independence test has been applied. The used test are Kupiec (1995) and Christoffersen (1998) test. In Kupiec test, the number of expected violations are compared with observed violations. If the difference in both violations is insignificant, it explains that model is good risk estimator. Generally, comparing all these five conventional models at 95% and 99% of confidence level, in Normal Distribution 100% from emerging and 91% from developed market case, null hypothesis is accepted for 95% of confidence level. The results at 99% of confidence interval also favour normal distribution model to adopt for risk forecasting, as the behaviour of developed market and emerging market is same, the null hypothesis accepted, which clearly states no difference between actual and expected violations. The worst likelihood ratio is reported by EWMA and GARCH models, as Kupiec test reject these two models.

The Christoffersens test reported the number of exceptions are totally independent of violation of previous day returns. This test observe the volatility clustering in developed and emerging market. The clustering effect is reported by parametric and non-parametric models in almost all markets except for Thailand at 95% of confidence, whereas GARCH and EWMA models reported no clustering effect. For 99% of confidence level, only historical simulation reported clustering effect, whereas all other models reported independent violations.

VaR has some of the observations as coherent risk measure as it ignore tails. To overcome this issue, expected shortfall or Conditional VaR is estimated. In developed market, Historical simulation and normal distribution reported maximum expectation of loss as 4% and 6% for both 95% and 99% confidence level, the maximum expectation of loss in emerging market is reported more by respective models as ranges from 5% to 14%. The minimum expectation of risk is reported by GARCH model with sane 1% to 2% chances in most of the countries of emerging and developed markets.

The next step is to investigate specifically the extreme left tail behaviour of risk. The investors are more likely to be interested in downside risk, for that purpose extreme value theory (EVT) is applied to the return series of 23 countries. The distinguishing feature of EVT is that it provides quantification of the stochastic behaviour of a process at unusually large or small levels. Specifically, EVT usually requires estimation of the probability of events that are more extreme than any other that has been previously observed. The risk is estimated by using two approaches of EVT, the generalised extreme value (GEV) and generalised Pareto distribution (GPD). After that same procedure of VaR is applied, as back testing techniques are used to check the validity of extreme value theory VaR results.

The maximum risk on extreme left tail is reported by BMM under GEV approach in both developed and emerging market. At 95% of confidence level, the risk is 6.12% in developed market and 9.61% in emerging market. At 99% of confidence level, the risk increased to 10.03% in developed market and 15.66% in emerging market. Whereas, the minimum loss or risk in left tail distribution because of extreme events is reported by GPD dynamic model under GPD approach.

After the forecasting of EVT value at risk, the violation ratio is checked, as comparison of the expected number of violations with actual VaR. The GPD static model under generalised Pareto distribution reported less violations as the expected violations are equivalent to the old one. This model is suitable to 62% of the total markets as there are no violation reported. Whereas, the violation ratio results show that GPD dynamic approach is not reliable for EVT risk forecasting as there are more violations.

Moving on to next step, Kupiec test of the number of expected violations are compared with observed violations in extreme value theory VaR. The Kupiec results are significant for GPD static model for EVT value at risk calculations, which report no change in expected and observed violation in extreme left tails of distribution. 92% of total market shows significant likelihood ratio at 95%, whereas 82% of total market reported significant results for 99% of confidence level. The test clearly reject GPD dynamic model as for all countries, the likelihood ratio is insignificant, so this model may not be used for EVT VaR estimation as it will not provide the true forecasting.

After that the clustering effect is checked by applying Christoffersens test to all countries return data under extreme value theory risk forecasting. By comparison of all three models of EVT, the GPD dynamic model reported less chances of clustering as 52% chances at 95% of confidence level, 62% chances at 99% of confidence level.

5.1 Recommendation

The findings indicate that the normal distribution method has highest accuracy in risk estimation under 95% and 99% of confidence level. Hence the results are more satisfactory at 95% of confidence level, the value at risk of whole distribution should be estimated at 95% of confidence interval for both developed and emerging market. In case of extreme events, EVT static value at risk can be estimated by using generalised Pareto distribution by both emerging and developed markets because this model provide more true forecasting of risk in extreme left tail of distribution.

From conventional VaR models, mostly normal distribution and historical simulation outperform under 95% of confidence interval, whereas normal distribution and student-t distribution report better forecasting under 99% of confidence interval, for both developed and emerging market. To understand the behaviour of extreme left tail, GPD static perform well as compared with other extreme value theory models, under 95% and 99% of confidence level.

The selection of risk forecasting models, specifically from developed and emerging market, under 95% of confidence interval, other than normal distribution (which suitable for all countries except for USA) historical simulation can also adopt for risk forecasting in the markets of Belgium, Japan, Nether land, Sweden, Switzerland, Argentina, Bahrain, Bangladesh, Brazil , China, Columbia, India, Malaysia, Pakistan, Russia and Thailand. Other than these two models, Sri Lanka, Bangladesh can also use EWMA for risk fore casting of distribution. The model selection is more or less same for markets under 99% of confidence interval as 96% of the market is covered by normal distribution. Other than using normal distribution as risk fore casting tool, most of the markets like Canada, France, Germany, Italy, Japan, Nether land, Switzerland, UK, Argentina, Bahrain, Bangladesh, China, Columbia, India, Malaysia, Russia, Sri Lanka and Thailand can also use student- t distribution for risk estimation. Although, EWMA is also suitable risk forecaster in markets of USA and Belgium.

Similarly, for estimation of risk on extreme left tail of distribution, generalised Pareto Distribution with static VaR should be adopted by all countries of developed and emerging except for Bangladesh and Columbia under 95% of confidence level, and USA, Bangladesh and China under 99% of confidence level. No model successfully forecast risk for USA from all conventional at 95% of confidence level, as the disturbance wave of 2007-2008 started from USA, and stay for longer time.

The reported results explains that all risk forecasting models perform well at 95% of confidence interval as compare to 99% of confidence level. As the confidence level increases the performance of model decreases, and more difference in observed and expected risk is noted in both developed and emerging markets.

The reported results show that VaR estimates are neither country nor market specific, the models for risk estimation are global is nature as normal distribution from conventional approach and Generalised Pareto distribution (static) for EVT can be applied to both developed and emerging markets, to forecast risk behaviour of whole distribution or left tail respectively.

The risk profile of developed an emerging market is more or less similar, as there is no significant difference of high or low risk found in developed and emerging markets.

5.2 Limitations

Because of few implication, VAR is not supposed to be the best risk estimator, like, it is not able to measure the maximum case loss which may lie in 1% uncovered area (may be 2-3 days in a year) (Uylangco and Li, 2016). The VaR approach has been subject to numerous criticisms, Jorion (1996) states that the majority of the parametric methods use a normal distribution approximation in VAR. Using this approximation, the risk of the high quantile is underestimated, especially for the fat tailed series, which are common in financial data. Some studies have tried to solve this problem using more appropriate distributions (such as the Student-t or mixture of normal), but all the VaR methods focus on the central observations or, in other words, on returns under normal market conditions. Similarly, the Non-parametric methods make no assumptions concerning the nature of the empirical distribution. For example, they cannot be used to solve for out-of-sample quantile; also, the problem of putting the same weight on all the observations remains unsolved.

In case of EVT, because extreme events are by definition uncommon, applications of EVT usually demand larger sample sizes than the other methods.

In case of expected shortfall, the study estimated only the expected shortfall of value at risk and extreme value theory. The back testing of expected shortfall is not done in this study by different back testing techniques like violation ratio, volatility, Kupiec test and Christoffersens test.

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