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Extreme Tails Behavior in Asian Currency Markets

by

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This thesis is dedicated to my teachers, family and friends who helped and motivated me to complete my thesis.

CERTIFICATE OF APPROVAL

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Abstract

This study examines extreme tail behavior of Asian currency market for the period of 2005-2018. Value-at-Risk (VaR) is estimated through conventional and EVT approaches to forecast losses incurred in a day in Asian currencies. Initially all conventional methods are applied on daily returns at 95% and 99% confidence interval to estimate VaR and expected shortfall. Secondly, EVT approach is used to estimate extreme losses on the left tail of the distribution. The estimation of these two approaches are back tested through traditional and advance back testing methods to a certain the accuracy of the models used. Results indicate that in all conventional methods, EWMA (Exponentially Weighted Moving Average) method performed better at 95% confidence intervals and the performance of historical simulation is better at 99% level of significance. However, the estimation of GPD static model is best for extreme risk forecasting in EVT approach at both 95% and 99% confidence intervals. Above different methods are recommended to use by many market players.

Key words: Value-at-Risk (VaR), Extreme value theory (EVT), back testing, risk forecasting

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Abbreviations

BMM	Block Maxima Model
ES	Expected Shortfall
EVT	Extreme Value Theory
EWMA	Exponentially Weighted Moving Average GARCH
GARCH	Generalized Autoregressive Conditional Heteroscedasticity
GEV	Generalized Extreme Value
GPD	Generalized Pareto Distribution
HS	Historical simulation
VaR	Value-at-Risk
VR	Violation Ratio

Chapter 1

Introduction

1.1 Background of the Study

Exchange rate risk is a key aspect of international trade because fluctuation in exchange rates between home country and the country in which an individual or company operates can have major influence on profit margin of all companies with limited liquidity. This risk has also a significant impact on individual investor who used to trade the products and services in international market. It is one of the most important factor for investors and companies to capture the uncertain fluctuation in currency exchange rate. If they unable to measure appropriate exchange rate risk can cause heavy losses.

Measurement and management of exchange rate risk is important to reduce an investors and institution's vulnerabilities from high movements in exchange rate, which could badly affect the profitability and assets value of any company (Papaioannou, 2006). Depreciation in currency over a period of time creates major issues for any countrys economy. It can cause to increase inflation and interest rates. Resources must be diverted from economic development and put into financial payments much of which could be sent overseas.

In global financial market is increasing currency volatility and exchange rates variations direct effect to any companies financial operations and its profitability. Volatility in exchange rates highly influence not only multinational companies but also large corporations, medium and small enterprises. Even the companies who only operates in their local country. It actually affects the whole country financial stability (Benita and Lauterbach, 2007).

Bloomberg compiled 13 Asian currencies in current year and analyze that Pakistani Rupee performed worst in Asia in 2018. The Pakistani Rupee devaluated approximately 20% in this year, followed by Indian Rupee about 11%, Russian Ruble with 15%, Venezuelan Bolivar with 99%, Argentine Peso with 53% and Turkish Lira with 38%. However, Brazilian Real decreased by 20%, Swedish Krona with 10%, and the Philippines Peso with 8%. Big countries like Chinese Yuan Renminbi has experienced 5% devaluation and Euro has declined by 3% (Official Forex Rate).

Currency devaluation and instability leads us the choices of risk measurement. After 1990, Value-at-Risk (VaR) is a method which is mostly used for the measurement of risk in financial sectors. Value-at-Risk is generally dened as the capital sucient to cover, in most instances, losses from a portfolio over a holding period of a fixed number of days. (Gilli et al., 2006). In other words, VaR is the maximum expected loss over a specific period of time with a specific level of significance (Jorion, 1995).

The main purpose for VAR estimation is to quantify market risk and economic capital allocation, most commonly helping the regulators, investors and the firm itself. Previously different approaches used to estimate VaR for one day to forecast the risk and return of exchange rates for a portfolio (Omari et al., 2017). Historical simulation is a non-parametric method which uses real data in the calculation of VaR so it captures the unexpected variations and correlations which are not predicted by other theoretical models.

Another method which is mostly used to estimate VaR GARCH (Generalized Auto Regressive Conditional Heteroskedasticity) to estimate the volatility of any financial series data and its correlation. This method is similar to Risk Metrics also called Exponentially Weighted Moving Average (EWMA), which describes the behavior of the daily volatility estimator generate by GARCH (1,1) volatility model with normal turbulences. Although simple GARCH model can cover volatility clustering with tails leptokurtic behavior of the underlying nancial return time series distribution but it failed to model volatility asymmetries regarding the sign of previous shocks. Negative sign shows the bad news in simple GARCH model has the same effect on the volatility as good news. The leverage eect can be estimate by using the GARCH extensions, like a threshold GARCH (TGARCH) or exponential GARCH (EGARCH). However, there are still some limits to apply these GARCH models because these methods are based on the error distribution assumption (Zhang and Zhang, 2016).

Einhorn and Brown (2008) has criticized VaR that it ignores the remaining side of distribution which are tails and only focuses on risk related to the middle of the distribution that is more controllable. VaR and conditional VaR methods are using by different financial sectors like banking but these moments provide lower threshold on 95% confidence interval. VaR has been failed to estimate extreme tails behavior. With the passage of time, financial uncertainties challenged the financial market participants to create and improve the current methodologies used in measuring risk (Omari et al., 2017). In past few years, major crises in international markets like in currency market, stock market, commodity market and bond market helped institutions and regulators for the identification of these risks which ultimately can cause to crash the financial markets (Mögel and Auer, 2018).

With the time in the worldwide nancial markets, evaluating the extreme events probability, has become main concern in the management of nancial risks. Current market conditions required the quantication of worst losses in all types of nancial markets. EVT provides a wide theoretical base on which the statistical models explaining extreme situations can be formed. The EVT has unique feature of stochastic behavior quantication of a process at abnormally large or small levels. However, EVT generally requires the probability estimation of more extreme events than any other method (Singh et al., 2013).

Extreme value theory (EVT) has developed as one of the most important statistical approach for the applied sciences from almost last fifty years and now using in other fields like finance, in recent years. EVT provides the more accurate estimation of VaR than other traditional methods, tail dependence decreases when filtering out heteroscedasticity and serial correlation by multivariate GARCH models (Fernandez, 2005).

The generalized Pareto distribution (GPD) is another EVT approach which is mostly used to estimate extreme tails behavior. This method does not only take a maximum value but also capture all extreme values above the threshold. Econometricians argue that a specific market returns show a distribution with innite fourth moment. GPD can be used to estimate this kind of phenomena behavior when the normal distribution failed to model this kind of behavior.

1.2 Problem Statement

Risk management is an important issue in many markets. During last decades, currency market has seen high volatility. The currencies of Iran, Iraq, Turkey and Pakistan have reported sudden falls for one or the other reason. The conventional risk measurement methods like VaR have been criticized that these are unable to capture extreme conditions. Therefore, investor do not have awareness about the possibility of maximum loss that they may face in certain condition. This domain need further exploration in changing landscape of currency market.

1.3 Research Questions

1. What is VaR in currency markets if returns follow empirical distribution?
2. What is VaR in currency markets if returns follow normal distribution?
3. What is VaR in currency markets if volatility is time varying?
4. What is behavior of returns on tails?
5. Which VaR model is appropriate for forecasting risk of Asian currencies?
6. How do EVT based VaR model perform in currency market?

1.4 Research Objectives

1. To estimate the VaR using conventional parametric and non-parametric VaR methods.

2. To study the tail behavior using EVT in Asian currency market.

3. To identify most appropriate model for estimation of risk in Asian currency market.

1.5 Significance of the Study

This study is focus on the exploration of risk profile of the Asian currency markets. The estimation is important for portfolio theory and other fields of finance, like hedging, credit analysis and derivatives valuation. Taking into account asymmetry and volatility clustering in the currency market behavior, return of any financial time series with combining ltering process such as extreme value approach is important in improving risk management assessments and hedging strategies.

At investor point of view, it is very important to identify the appropriate risk for effective risk management. Investor portfolio also contain foreign investment and gain or loss is not only associated with stock market but with also currency exchange rate. Managers of multinational company need to analyze the appropriate exchange rate risk when they go for international projects and to determine the gain or loss from inflows and outflows of domestic currency with international currency.

Economies in which currencies are more stable can increase foreign direct investment due to low variation in currency rates. Recently, the currencies of Turkey, Argentine, Iran and Pakistan have big variations. So it increases the importance of the currency risk management. Todays currency market is highly volatile and new techniques have introduced to measure the risk but with the passage of time out dated. Using different techniques can help the investor and institution to measure the appropriate risk so they can manage it. Under high economic and political pressure, financial institution tries to manage the associated risks effectively.

1.6 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

Traditional VaR models make specic assumptions about the returns distribution and thus estimate the maximum loss of an asset under normal market conditions. Thus, the VaR measures may provide inaccurate estimates of actual losses during highly volatile periods corresponding to nancial crises (Martins-Filho and Yao, 2006). In contrast, a recent strand of literature focuses on the distributions of extreme returns instead of the distribution of all returns such that the corresponding VaR estimates have higher potential to provide good predictions of catastrophic market risk during extraordinary periods (Mögel and Auer, 2018).

Exchange rate plays a vital role in the development of any economy. That fact also applied on Brazilian economy. A study by Ogawa et al. (2018) explained the volatility of Brazilian currency market with the comparison to other currency markets by estimating VaR. Two groups of currencies are used for VaR estimation: emerging market currencies include Brazilian Real (BRL), Argentine Peso (ARG), Chilean Peso (CLP), New Peruvian Sun (PEN), Mexican Peso (MXN), Chinese Yuan (CNY), Indian Rupee (INR), and South Korean Won (KRW) and developed market currencies are Australian Dollar (AUS), Euro (EUR), Swiss Franc (CHF), Pound sterling (GBP) and Japanese Yen (JPY). These currency markets are used to estimate VaR and compare emerging, developed and Asian currency markets.

It is a fact that for foreign exchange transactions, the currencies of developed countries are easily convertible and acceptable at the global financial market.

Whereas, the emerging countries currencies are not freely acceptable and conversable in other countries. This parameter is also applied on the classification of these two group.

EVT theory is applied to calculate VaR of each group through parametric method to capture the extreme values then performed Kolmogorov-Smirnov and Anderson-Darling adhesion tests to find the actual historical distribution more correctly. The results of these VaR estimates are more effective within a given confidence interval after back testing other than one sample. The result of the study shows that -1.45% is average daily VaR against USD and 65% risk is higher than the other 12 studied countries average value. There were 5% chances that the loss will be increase than 1.45% in a day.

The currencies of emerging market are less risky with average -0.78% VaR as compared to other studied currency markets in relation to the USD. Argentine Peso showed lowest VaR estimation with 0.16% risk so this currency is less risky. However, the exchange rates of developed market are riskier with average -1.15% VaR.

Argentine Peso exhibit resistance of external shocks because this currency was not connected to international market during the period. Results indicate that economies at same stage and near to maturity also show the similar behavior of exchange rate. The results provide that least risky currencies are Argentine Peso (ARG), Indian Rupee (INR), New Peruvian Sol (PEN) and Chinese Yuan (CNY).

Another empirical study conducted by Swami et al. (2016), apply different VaR estimation methods on foreign exchange currencies portfolio. To estimate exchange rate risk, VaR estimation used non-parametric like historical simulation and variance-covariance methods. To estimate the VaR by using different methods, that study has followed the regulatory framework by RBI on Prudential Guidelines on Capital AdequacyImplementation of Internal Models Approach for Market Risk in India (RBI, 2007).

VaR estimation use simple mean and standard deviation of a normal distributed return series. Mostly, returns of any financial market do not follow the assumption of normal distribution. Non-normal return distributions are leptokurtic and use appropriate VaR estimation model to handle this non-normality issue. Historical simulation and t-distribution methods are used to estimate VaR.

Back testing results show that VaR estimates are underestimated on the bases of conventional method. However, the performance of historical simulation is better than other VaR estimation methods. Whereas, t-distribution provided more accurate VaR estimation.

According to Omari et al. (2017) study on the daily average currency exchange rates of US Dollar vs Kenya Shillings (USD/KES), UK Sterling Pound vs Kenya Shillings (UKP/KES), European Union Euro vs Kenya Shillings (EUR/KES) and South Africa Rand vs Kenya Shillings (SAR/KES), the threshold value required to fit the GPD model is obtained using the graphical approach, which uses the Mean Excess Function (MEF) plot of the return series. Maximum likelihood estimation technique is used on the exceedances over the threshold.

The study reports the estimated parameters of the generalized Pareto distribution (GPD) as well as their estimated asymptotic standard errors resulting from applying the POT approach to the filtered standardized innovations. For all the returns series, the shape parameter is found to be positive and significantly different from zero, indicating heavy-tailed distributions of the innovation process characterized by the Frechet distribution.

This study extended the GARCH model to GED based GARCH-type models by taking into account major stylized facts into the price return volatilities of precious metal markets. The ndings reveal that precious metals are characterized by fat tail, volatility clustering and leverage eect behavior. After illustrating the GED based GARCH-type models combined with EVT methodology, the study is extended to present one-day ahead VaRs for precious metal markets and compared it with VaRs from GARCH-type model directly. It further compared VaRs from GARCH-EVT approach with that from GARCH based VaR model. The comparative analyses with the well-known GARCH-based VaR models were included as well (Zhang and Zhang, 2016).

One of the major challenges in modelling VaR is the distributional assumption made for the return data series of the asset or portfolio, which is taken to be normal in most of the quantication approaches. The assumption of normality is not valid when the data series have heavy tails, which are characterized by extreme events left outside the bounds of a normal distribution when modelling VaR. The problem of the normality assumption of the return series, can be addressed by using the distribution free assumption of quantile modelling statistics, and tools such as quantile regression (Koenker and Bassett Jr, 1978) or by applying extreme distribution based methods such as Extreme Value Theory (EVT).

A study has tackled two key issues in risk management: computation of value at risk (VaR) and stock market dependence using the new approach of EVT. First, this study analyzed different ways to compute value at risk for stock markets across the United States, Latin America, Europe, and Asia and concluded that quantile estimates based on EVT are best. Secondly, tested the degree of extremal dependence across different financial markets in the United States. We concluded that bond markets do not exhibit extremal dependence of stock markets, and much of the extremal dependence across stock markets disappear when controlling for both serial correlation and heteroscedasticity (Fernandez, 2005).

McNeil (1997) illustrates, how extreme value theory can be used to model tail related risk measures such as Value-at-Risk, expected shortfall, applying it to daily log-returns on six market indices. The conclusion is that EVT can be useful for assessing the size of extreme events. From a practical point of view this problem can be approached in dierent ways, depending on data availability and frequency, the desired time horizon and the level of complexity one is willing to introduce in the model. One can choose to use a conditional or an unconditional approach, the BMM or the POT method, and nally rely on point or interval estimates. The findings of the study provide that the POT method appear superior as it better exploits the information in the data sample. Being interested in long term behavior rather than in short term forecasting, the study preferred an unconditional approach. Finally, it is worthwhile computing interval estimates as they provide additional information about the quality of the model t (Gilli et al., 2006).

According to McNeil (1999), whenever tails of probability distributions are of interest, it is natural to consider applying the theoretically supported methods of EVT. Methods based around assumptions of normal distributions are likely to underestimate tail risk. Methods based on historical simulation can only provide very imprecise estimates of tail risk. EVT is the most scientic approach to an inherently dicult problem - predicting the size of a rare event.

A study conducted by de Jesús et al. (2013), suggests that evidence is in favor of high potential from extreme value theory not just for explaining asymptotic behavior of tails regarding exchange rates returns, but at the same time helps to estimate potential loses of investor during extreme financial events. The results indicate that the fat tails which is caused by high kurtosis in return distribution of peso/dollar exchange rate is result of high movements which are not caught by normal distribution. The continuous financial crises and decrease in the value of peso experienced in Mexican currency market are the main reasons throughout the period. This point gets support from negative values calculated from GEVD tail index which consequently exhibit that asymptotic distribution is at supreme area of attraction from (Frchet) distribution results from exchange rate returns which is caused by fat tails and used to forecast real returns.

The study also describes that the GEVD percentile method is most suitable risk evaluation method for VaR analysis which produces more solid information than other methods e.g historical simulation and delta normal distribution, at 99 percent and 99.9 percent confidence interval in short position. The estimation based upon empirical distribution tend to create more conservative outcomes than EVT for VaR measures for the long position at 99 percent confidence interval which is triggered by high volatility resulting from returns discrete behavior outside the tails. The results of EVT for VaR calculation are more accurate at 99.9% than other conventional methods. The reason behind this fact is GEVD measure more precise and accurate behavior related to the size of extreme events calculated at the probability distribution tails. The research concludes that there is advantage for investor to gain more accurate information of actual risk for risk measurement in their portfolio returns during the period of financial crunch.

Chapter 3

Methodology

This chapter covers different risk forecasting approaches for estimation of risk. Conventional approaches include historical simulation, normal distribution, *t*-distribution, EWMA and GARCH are used to calculate VaR at 95% and 99% confidence level. Moreover, Extreme Value Theory (EVT) approach consists of Generalized Extreme Value (GEV follow block maxima) and Generalized Pareto Distribution GPD (static & dynamic) methods is used to estimate extreme tails behavior of Asian currency markets.

3.1 VaR Estimation Through HS

Historical simulation (HS) is a mostly used non-parametric method in investment practice introduced by Boudoukh. The basic assumption of this method is that the future expected returns pattern will be the same as past return behavior because it is a complete and correct representation of expected returns. This method considers actual returns of any financial series and sort it from best to worst and then estimate the loss a given confidence interval.

The univariate HS model is better for passive risk measurement (Christoffersen, 2009). The VaR at probability p is simply the negative $T * P^{th}$ value. The historical simulation model anticipates 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.This study emphasis 250-day window for estimation of loss.

3.2 VaR Estimation Through Nor. Distribution

Normal distribution is the method of VaR calculation under parametric approach for risk measurement. It estimates the daily risk and return of daily currency price distribution by following standard deviation approach. Its basic assumption of this method is that the returns of any financial asset are normally distributed.

For a given condence level , the VaR estimates for time t-1 is then:

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

Where μ represents the mean of a financial series and σ tells us the standard deviations of a moving window of T returns up to time t which is estimated through maximum-likelihood. However, z_1- alpha is the (1-α) quantile of the standard normal distribution. (Linsmeier and Pearson, 2000)

3.3 VaR Estimation Through *t*-Distribution

It is another parametric approach for forecasting the risk. The basic assumption of this method is that daily returns of any financial asset are not normally distributed. For VaR estimation, the study assume that student t-distribution is better to describe the returns with the estimate of fat tail. We can estimate VaR through student t-distribution estimated as under:

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

Whereas, μ is mean and σ is standard deviation of a financial series. In (1-α) is the quantile of the Student t-distribution with v degrees of freedom. (Alexander, 2008) However, v = 5 is usually used for empirical applications in fat tailed data modelling (Campbell et al., 2001) or through v an optimum value of maximum-likelihood ratio.(Lange et al., 1989)

3.4 VAR Estimation via Time Varying Volatility

This is another approach to calculate VaR if volatility is time varying. Currently, financial markets are highly volatile and this approach helps to better forecast the risk and returns. Two methods are used in this section:

- Exponentially Weighted Moving Average (EWMA)
- Generalized Autoregressive Conditional Heteroscedasticity (GARCH)

3.4.1 VaR Estimation through EWMA

The Exponentially Weighted Moving Average (EWMA) is a method to calculate time varying volatility in a financial data series. This method assigns high weights to current dat and lower weights to past data. The VaR of EWMA is calculated through:

$$\hat{\sigma}_{t,i,j} = \lambda \hat{\sigma}_{t-1,i,j} + (1-\lambda)_{yt-1,iyt-1,j} \tag{3.4}$$

Where λ is the decay factor having the value of 0.94. It is simple to implement the univariate model of EWMA model. The unconditional volatility on day 1 is σ_1. Whereas the burn time consider the error embedded into the model through fixing it is arbitrary.

3.4.2 VaR Estimation Through GARCH

Generalized ARCH or GARCH model is used to estimate time-vary volatility of any time series, which relies on modelling the conditional variance as a linear function of the squared past innovations. The conditional mean of the daily return series can be assumed to follow a first-order autoregressive process,

$$r_t = \varphi_0 + \varphi_1 r_{t-1} + \varepsilon_t \tag{3.5}$$

Where, $r_(t-1)$ means lagged return, ϕ_0 and ϕ_1 are constants to be determined and μ_t is the innovations term. The conditional variance of the standard GARCH(1,1) is defined as:

$$\sigma_t^2 = \alpha_o + \sum_{i=1}^{p} \alpha_t \varepsilon_{t-1}^2 + \sum_{j=1}^{q} \beta_j \sigma_{t-j}^2 \tag{3.6}$$

The GARCH models have been extensively used in modelling the conditional volatility in financial time series and it assumes that both shocks positive and negative have same 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, VaR is computed as:

$$VaR_{t+1/t}^{p} = \hat{\mu} + \hat{\varphi} r_t + \phi(p)\widehat{\sigma_{t+1}} \tag{3.7}$$

Where ϕ(p) explaining p_{th} quantile of the standardized normal distribution.

3.5 ES Estimation of Conventional Approach

Expected shortfall is defined as the expected potential losses incurred when VaR is being violated. Expected shortfall is the debate of expected losses incurred 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 left tail observations. As compared with Value at risk, the ES estimate 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 ϕ will be changed because of change in distribution.

3.6 VaR Estimation Through EVT Approach

EVT is a type of modelling used to measure the extreme tails and risk in a distribution by using parametric models. For the measurement of EVT, there are 2 methods: first method is Generalized Extreme Value Distribution (GEV) which followed Block Maxima/Minima (BMM) Approach and the second method is Generalized Pareto Distribution (GPD) which also known as the Peak Over Threshold (POT) approach. In GPD method, this study use static and dynamic approach. Three parameters are estimated in these methods.

The extreme value theory calculate three parameters like:

- **Location Parameter:** In normal distribution if value is positive then it will move right side and if it is negative then it will move left side of the distribution.

- **Scale Parameter:** It is measured through standard deviation and standard deviation can be high or low. It tells us about dispersion. Its value cannot be negative.
- **Shape Parameter:** If $\xi>0$ then it is the key indication of fat tail and if $\xi<0$ then it is the indication that fat tail does not exist.

3.6.1 VaR Estimation Through Generalized Extreme Value Distribution (GEVD)

The BMM approach is usually used to calculate EVT. The BMM approach selects the maximum or minimum values in a financial data series that contain, extreme events. (Gilli et al., 2006) A block of extreme event maxima/minima in an independent data series and identically distributed observations (iid) to GEV using a statistical and tradition method which is maximum likelihood estimation (MLE). Singh et al. (2013)

Theorem of *Fisher Tippett Gnedenko: If there are constants (an >0, bnϵ $\Re$) as well as some non-degenerate distribution function H such that*

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

However, H represents the one of the 3 standard extreme value distributions:

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

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

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

This theorem recommends that the asymptotic distribution of the maxima value is related to the above three distributions, irrespective of the actual distribution of observed data. Generally, limiting distribution type and norming constants cannot be identified at early stage. For the identification, this study use, one parametric distribution projected by von Mises (1954) and Jenkinson (1955) which includes extreme value distribution of all above three types as a special case. Generalized Extreme Value Distribution (GEVD) which can be formed:

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

For, 1+ ξ $\frac{x-y}{\delta}$ >0 where γ represents location parameter and ϵ denote scale parameter representing constants of the unknown (Embrechts et al., 1999). This is unnormalised maxima limiting distribution which is more useful when we calculate the maximum likelihood VaR can be estimated as:

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

Where, γ is the location parameter, δ is the scale parameter and ϵ represents shape parameter. These are the parameters which uses to estimate maximum likelihood ratio. In this equation represents the given level of significance (5% or 1%) for tails estimation.

3.6.2 Expected Shortfall of Block Maxima

There is inequality in the tail distribution which can produce the conditional VaR for a fat tailed distribution placed at the maximum domain of attraction of the GEV distribution (De Jesús and Ortiz, 2011). Expected shortfall of block maxima is calculated through:

$$ES^{BM}_{t+1} = \left(\frac{\alpha}{\alpha-1}\right) VaR_c(X) \tag{3.15}$$

Where $\alpha = \frac{1}{\xi}$ and ξ is the shape parameter.

3.6.3 Generalized Pareto Distribution (GPD) and Peak Over Threshold (POT)

GPD is one of the method to calculate VaR of EVT by using exceedance threshold also called Peak Over Threshold (POT). This EVT method takes all the values over a threshold or it models the collection of the maximum random variable. (Zargar and Kumar, 2018) The calculation of VaR estimates are more efficient in GPD than GEV because GPD (POT) takes values over a certain threshold while GEV (BMM) have only a maximum value from a financial series for distribution estimation. (Singh et al., 2013)

Consider X is a random variable, u is a xed threshold and focus on X u positive part. The $F(x)$ represents the distribution is:

$$F_u = Pr(X - u \leq y \mid X > u) = \frac{F(y+u) - F(u)}{1 - F(u)}, 0 \leq y \leq x_F - u \tag{3.16}$$

Many studies claim that any financial market returns show the innite fourth moment of distribution. The main issue is that the normal distribution cannot capture these phenomena while the GPD method can model this behavior. Generalized Pareto distribution (GPD) which is given by:

$$G_{\xi\sigma}(y) = \begin{cases} 1 - \left[\{1 + \frac{\xi}{\sigma}\}^{-\frac{1}{\xi}}\right] & \xi \neq 0 \\ 1 - exp\left(\frac{-y}{\sigma}\right) & \xi = 0 \end{cases} \tag{3.17}$$

GPD requires, both shape parameter ξ and scale parameter σ. If the shape ξ= 0 then distribution will be Gumbel, if ξ <0 then it will be Weibull and when ϵ >0 then distribution will be Frchet.

3.6.3.1 GPD Static

To examine the behavior of extreme tails, one of the GPD method is static in which using of a user-supplied uniform random number generator to creates a random sample. The parameters of distribution are same location, scale and shape. In the estimation of GPD static VaR, we use location parameter as a threshold. The probability function of GPD-Static is:

$$VaR^S_{t+1} = u + \frac{\hat{\sigma}}{\hat{\xi}}\left[[\frac{n}{N_u}(1-p)]^{-\xi} \right] \tag{3.18}$$

The location parameter μ of the Pareto distribution indicates to the minimum possible value of that variable, scale parameter σ and shape parameter ξ which must be greater than 0.

- Expected shortfall is actually the expected potential loss that exceeds VaR at given confidence interval. Expected shortfall of GPD-Static related to its VaR is calculated through:

$$ES^S_q = VaR_q \frac{\sigma + \xi(VaR_q - u)}{1-\xi} = \frac{VaR_q}{1-\xi} + \frac{\sigma - \xi u}{1-\xi} \tag{3.19}$$

3.6.3.2 GPD Dynamic

Another probability distribution method to calculate GPD VaR at given confidence interval is GPD dynamic. It is used to forecast the estimates of conditional volatility the model provides dynamic 1 day ahead forecasts for VaR and ES for the financial time series.

$$VaR^d_{t+1} = \mu_{t+1} + \sigma_{t+1} * VaR^S_{t+1} \tag{3.20}$$

- Expected Shortfall of GPD Dynamic Expected shortfall is the average of the negative values in any financial series beyond a given level of significance e. g 95% or 99%. It is another tool of risk measurements the expected shortfall (ES) or conditional expectation of the tails which measure the potential loss exceeding VaR. The distribution function of the expected shortfall is:

$$ES^d_{t+1} = \mu_{t+1} + \sigma_{t+1} * VaR^D_{t+1} \tag{3.21}$$

3.7 Backtesting

It is an important component of the VaR evaluation. Back testing is a statistical procedure designed to assess the accuracy of all risk forecasting models by comparing the realized trading losses with the VaR predicted losses (Omari et al., 2017). The VaR violations is usually measured through rule-of-thumb and graphical methods, but it should be able to apply a formal statistical tests. Along with the analysis of violation ratio, there is another statistical violation ratio test at a given level of signicance will be useful to check the violations cluster. This study tests only two issues, violation ratio tested through unconditional coverage and clustering will be tested through the independence test.

Violation ratio used to select better method of forecasting losses by comparing expected with observed values. In VR (violation ratio), for better model selection, value should be equal to 1 or closer. According to literature, generally values between 0.80 1.20 are acceptable. If value >1 then it means observed violations are high so returns are forecasting at lower end so model is weaker. If value <1 then it is under estimated and model is not forecasting correct values.

3.7.1 Kupiec Back Testing

Kupiec back testing (1995) is a proportion of failures (POF) test. The POF test works with the binomial distribution approach. Measurement of this test is through likelihood ratio to check that the probability of exceptions between observed and expected violations are synchronized or not at given confidence level. If results show that the observed and expected violations are different then this model is rejected. The POF test measured through:

$$LR_{POF} = -2\log\left(\frac{(1-p)^{N-x}p^{x}}{(1-\frac{x}{N})^{N-x}(\frac{x}{N})^{x}}\right) \tag{3.22}$$

Where x represents the number of failures, N represents the number of observations and p = 1-VaR level. Null hypothesis of Kupiec back testing is that the observed violations should be equal to expected violation then null hypothesis will be accepted. Measurement of this method is through likelihood ratio, if LR $<x^2$ then null hypothesis will be accepted for 95% and 99% significance level. If LR $<x^2$ for 95% & 99% then it means observed values are different from expected values so null hypothesis is rejected.

3.7.2 Christoffersens Interval Forecast Tests

Christoffersen back testing method is introduced in 1998 to check whether the probability of observing an exception on a particular day depends on whether an exception occurred. Instead of unconditional probability of observing an exception, Christoffersen's test helps us to check the consecutive days dependency in risk and return forecasting. The statistic independence test in Christoffersens interval forecast (IF) estimated through:

$$LR_{CCI} = -2\log\left(\frac{(1-\pi)^{n00+n10}\pi^{n01+n11}}{(1-\pi_0)^{n00}\pi_0^{n01}(1-\pi_1)^{n10}\pi_1^{n11}}\right) \tag{3.23}$$

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 that there is no clustering in the financial time series, means the probability of todays loss does not follow past pattern. The null hypothesis is rejected if LR $<x^2$ (1) clustering between violations is identified.

3.8 Data

The samples forming the basis for analysis of this study is the daily exchange rate of 25 selected Asian currencies with US dollar. The sample period is 2005-2018. The extreme tail behavior is also examined for the following sample: China, Japan, India, Korea, Indonesia, Turkey, Saudi Arabia, Taiwan, Thailand, Iran, United Arab Emirates (UAE), Israel, Hong Kong, Singapore, Malaysia, Philippines, Pakistan, Bangladesh, Vietnam, Iraq, Qatar, Kazakhstan, Kuwait, Sri Lanka, Oman. The data is collected from investing.com

Chapter 4

Data Analysis and Results

This chapter represents the result of the study to achieve the basic motive. The chapter starts by showing the descriptive statistics of 25 Asian Currency markets. After that the VAR results are discussed and verified with the help of back testing. Then, expected shortfall is reported. In the last, results from extreme value theory is reported for the extreme distribution or extreme conditions.

4.1 Descriptive Analysis

Table 4.1 shows descriptive analysis of daily returns of Asian currency markets over the period of Jan 2005- Dec 2018. Mean values are the average daily return of that market. China, Singapore and Thailand report higher mean so their average daily returns are higher than other countries. Kazakhstan, Turkey and Iran are the countries which report lowest returns. These values are negative it means these are losses. Moreover, some countries like Oman, Qatar, Saudi Arabia and UAE report very low return.

Median tells about the middle value of any financial series that negative and positive values are equal or not. It should be zero ideally. In these Asian currency markets, Turkey, Singapore, Israel and Korea have positive median. Whereas, Japan has negative median. It happens when some countrys financial data is non-normal.

Table 4.1: Descriptive Analysis for the period of 2005-2018

	Mean	**Median**	**Max**	**Min**	**Std. Dev.**	**Skewness**	**Kurtosis**
Bangladesh	-0.000086	0	0.0459	-0.0506	0.0037	-0.8189	45.740
China	0.00005	0	0.0203	-0.0184	0.0015	0.2166	26.580
Hong Kong	-0.000002	0	0.0043	-0.0028	0.0003	1.0919	24.300
India	-0.000128	0	0.0355	-0.0369	0.0046	-0.1383	9.7160
Indonesia	-0.000122	0	0.0647	-0.0762	0.0046	-0.7645	42.340
Iran	-0.000397	0	0.7069	-0.7069	0.0342	-2.1813	413.10
Iraq	0.000046	0	0.0366	-0.0829	0.0050	-1.1751	37.670
Israel	0.00004	0.00003	0.0276	-0.0414	0.0049	-0.1889	7.7590
Japan	-0.000019	-0.00008	0.0377	-0.0522	0.0065	0.1083	7.4020
Kazakhstan	-0.000292	0	0.0714	-0.2464	0.0073	-19.321	579.00
Korea	-0.000021	0.00002	0.1095	-0.1022	0.0071	0.0639	37.830
Kuwait	-0.000007	0	0.0239	-0.0232	0.0016	-0.6519	52.480
Malaysia	-0.000024	0	0.036	-0.0203	0.0040	0.3780	8.4860
Oman	0	0	0.0039	-0.0063	0.0003	-1.5980	93.570
Pakistan	-0.000211	0	0.0541	-0.0796	0.0034	-3.5568	114.80
Philippines	0.000018	0	0.0225	-0.0177	0.0037	0.0259	5.4240
Qatar	0	0	0.0593	-0.0593	0.0027	1.0593	283.80
Saudi Arabia	0	0	0.0159	-0.0129	0.0005	3.9885	501.70
Singapore	0.00005	0.00008	0.0218	-0.0212	0.0035	0.0380	6.5770
Sri Lanka	-0.000155	0	0.0251	-0.0401	0.0025	-1.6962	50.370
Taiwan	0.000011	0	0.0175	-0.0182	0.0030	0.1909	6.7870
Thailand	0.000049	0	0.1103	-0.1095	0.0047	-0.2302	173.20
Turkey	-0.000371	0.00009	0.08	-0.1476	0.0097	-1.3955	24.400
UAE	0	0	0.0035	-0.0043	0.0002	0.2589	297.10
Vietnam	-0.000105	0	0.0436	-0.0651	0.0023	-8.4808	286.70

Iran, Thailand and Korean currency markets report maximum average return of a day. Whereas, Hong Kong, UAE and Oman report minimum average return of a day.

Standard deviation explains the risk of currency markets. Iran, Turkey and Kazakhstan currency markets are riskier as compared to other 22 Asian currencies markets. Hong Kong, Oman and UAEs currency markets are less risky. Currency market returns of Saudi Arabia, Hong Kong and Qatar are positively skewed. Whereas Pakistan, Vietnam and Kazakhstan are more negativity skewed.

Kurtosis of all Asian currency markets is more than 3 which report leptokurtic and fat tail non-normal distribution in currencies returns. Kazakhstan, Saudi Arabia and Iran have more fat tails while Taiwan, Singapore and Philippines have less fat tails. It explains that data is non-normal emphasis on fat tails is desired.

According to this descriptive analysis, risk and return relationships in these 25 Asian currency markets are inefficient. Ideally if risk is high then return should also high which is not true for these currency markets.

4.2 VaR Estimation via Parametric and Non-Parametric Approach

Value-at-Risk (VaR) describe about threshold that extreme losses will not exceed of that threshold. Table 4.2 explains the results of VaR calculations under non-parametric like historical simulation and parametric assumption includes normal distribution and t-distribution. This study uses 95% and 99% confidence interval to calculate VaR of 25 Asian currency markets.

According to Historical Simulation in 1st column of table 4.2, there is 95% chance that Turkish Lira will not suffer loss more than 1.49% in a day followed by Japanese Yen 0.99% and Korean Won 0.96%.

Table 4.2: VaR Estimation through Parametric and Non-Parametric Approach

	Historical Simulation		**Normal Distribution**		**t-Distribution**	
	95%	99%	95%	99%	95%	99%
Bangladesh	-0.0044	-0.0125	-0.0061	-0.0086	0	0
China	-0.0021	-0.0046	-0.0024	-0.0035	-0.0020	-0.0061
Hong Kong	-0.0005	-0.0009	-0.0006	-0.0008	-0.0004	-0.0012
India	-0.0075	-0.0133	-0.0076	-0.0107	-0.0068	-0.0134
Indonesia	-0.0063	-0.0125	-0.0076	-0.0107	-0.0060	-0.0160
Iran	-0.0020	-0.0101	-0.0563	-0.0796	-0.0019	-0.0155
Iraq	-0.0029	-0.0222	-0.0083	-0.0117	0	0
Israel	-0.0077	-0.0141	-0.0080	-0.0113	-0.0074	-0.0135
Japan	-0.0099	-0.0179	-0.0107	-0.0151	-0.0099	-0.0178
Kazakhstan	-0.0044	-0.0142	-0.0120	-0.0170	-0.0041	-0.0187
Korea	-0.0096	-0.0222	-0.0117	-0.0165	-0.0093	-0.0193
Kuwait	-0.0021	-0.0045	-0.0027	-0.0038	-0.0021	-0.0112
Malaysia	-0.0066	-0.0113	-0.0066	-0.0094	-0.0060	-0.0134
Oman	-0.0003	-0.0008	-0.0005	-0.0007	0	0
Pakistan	-0.0038	-0.0112	-0.0056	-0.0079	-0.0035	-0.0173
Philippines	-0.0058	-0.0099	-0.0060	-0.0086	-0.0058	-0.0099
Qatar	-0.0003	-0.0021	-0.0044	-0.0062	0	0
Saudi Arabia	-0.0002	-0.0009	-0.0008	-0.0011	0	0
Singapore	-0.0055	-0.0095	-0.0057	-0.0081	-0.0054	-0.0094
Sri Lanka	-0.0030	-0.0077	-0.0040	-0.0057	-0.0026	-0.0125
Taiwan	-0.0048	-0.0078	-0.0049	-0.0069	-0.0046	-0.0087
Thailand	-0.0054	-0.0102	-0.0078	-0.0110	-0.0054	-0.0113
Turkey	-0.0149	-0.0305	-0.0159	-0.0225	-0.0137	-0.0266
UAE	-0.0001	-0.0004	-0.0003	-0.0004	0	-0.7914
Vietnam	-0.0016	-0.0055	-0.0037	-0.0053	-0.0015	-0.0066

Least risky currencies are UAE Dirham with 0.01%, Saudi Dirham with 0.02% and Omani Rial with 0.03% of loss in a day. In Normal Distribution in 3rd column, results show that there is 95% chance that Irani Rial will not suffer more than 5.63% loss in a day during 2005-2018 period followed by Turkish Lira with 1.56% risk and Kazakhstani Tenge with 1.20% loss. Lower risk reported currencies are UAE Dirham 0.03%, Omani Rial, 0.05% and Hong Kong Doller 0.06% during this period. At 95% confidence interval t-distribution in 5th column indicate that Turkish Lira will not suffered more than 1.37% followed by Japanese Yen 0.99% and Korean Won with 0.93% loss. Lowest loss reported currencies are Iraqi Dinar, Omani Rial, Saudi Dirham, Qatari Riyal, Bangladeshi Taka and UAE Dirham that are almost 0.

The VaR is also estimated at 99% confidence level. In Historical Simulation in 2nd column, there is 99% chance that maximum loss by Turkish Lira in a day will not exceed 3.05% followed by Korean Won and Iraqi Dina with 2.22% risk. Least risky currencies are UAE Dirham 0.04%, Omani Rial 0.08% and Saudi Riyal 0.09%. normal distribution reported in 4th column explains that there is 99% chance that higher risk suffered by Irani Rial with 7.96% loss then Turkish Lira with 2.25% and Kazakhstani Tenge with 1.70% loss. Less risky currencies are UAE Dirham 0.04%, Omani Rial, 0.07% and Hong Kong Doller 0.08% during this period. t-distribution in 6th column, UAE Dirham will suffer maximum loss by 79.14% but there is a huge gap in next highly loss reported currencies like Turkish Lira reported 2.66% loss and Korean Won reported 1.93% loss. Lower loss suffering currencies are Omani Rial, Iraqi Dinar, Saudi Riyal, Qatari Riyal, and Bangladeshi Taka that is almost 0.

The results indicate that currencies of middle eastern Arab countries have lower VaR. It may be due to the stable supply and demand, inflation and interest rate in this region. These currencies have large share in oil and gas exports and manage exchange rate.

The political issue of Iran and Korea are also reflecting in the VaR estimates making these currencies riskier. Turkish Lira has also found problem in recent past and lost more than its 50% of its value.

4.3 VaR Estimation if Volatility is Time Varying

Table 4.3 reports the results of VaR estimates under the assumption of time varying volatility by using EWMA and GARCH at 95% and 99% confidence intervals.

TABLE 4.3: VaR Estimation if Volatility is Time Varying

	EWMA		**GARCH**	
	95%	99%	95%	99%
Bangladesh	-0.0054	-0.0076	-0.0038	-0.0054
China	-0.0043	-0.0060	-0.0035	-0.0050
Hong Kong	-0.0008	-0.0012	-0.0032	0
India	-0.0087	-0.0122	-0.0087	-0.0123
Indonesia	-0.0068	-0.0096	-0.0058	-0.0083
Iran	-0.0032	-0.0045	-0.0300	-0.0424
Iraq	-0.0018	-0.0026	-0.0037	-0.0052
Israel	-0.0039	-0.0055	-0.0044	-0.0062
Japan	-0.0073	-0.0103	-0.0084	-0.0119
Kazakhstan	-0.0075	-0.0106	-0.0104	-0.0146
Korea	-0.0061	-0.0087	-0.0064	-0.0091
Kuwait	-0.0008	-0.0012	-0.0013	-0.0018
Malaysia	-0.0025	-0.0035	-0.0034	-0.0048
Oman	-0.0001	-0.0002	-0.0004	-0.0005
Pakistan	-0.0081	-0.0115	-0.0037	-0.0052
Philippines	-0.0044	-0.0063	-0.0047	-0.0067
Qatar	-0.0002	-0.0003	-0.0003	-0.0004
Saudi Arabia	-0.0002	-0.0002	-0.0004	-0.0006
Singapore	-0.0028	-0.0040	-0.0035	-0.0049
Sri Lanka	-0.0057	-0.0080	-0.0053	-0.0075
Taiwan	-0.0033	-0.0047	-0.0045	-0.0063
Thailand	-0.0037	-0.0052	-0.0040	-0.0057
Turkey	-0.0129	-0.0182	-0.0106	-0.0149
UAE	-0.0001	-0.0001	-0.0001	-0.0002
Vietnam	-0.0025	-0.0036	-0.0203	-0.0057

According to 95% confidence interval in 1st column of EWMA, there are 95% chances that Turkish Lira will face loss not more than 1.29% in a day and followed by Indian Rupee with 0.87% and Pakistani Rupee with 0.81% loss. Lower losses are faced by UAE Dirham with 0.01%, Omani Rial with 0.01% and Saudi Riyal with 0.02%. GARCH based estimation in 3rd column, shows that Irani Rial will not bear loss more than 3% during 2005-2018 period then Vietnams Dong with 2.03% and Turkish Lira with 1.06% loss. Lower risk reported currencies are UAE

Dirham with 0.01%, Qatari Riyal with 0.03% and Omani Rial with 0.04% during this period.

At 99% confidence interval in 2nd column EWMA estimates provide that, there is 99% chance that loss of Turkish Lira will not exceed by 1.82% followed by Indian Rupee with 1.22% and Pakistani Rupee with 1.15% loss. Least risky currencies are UAE Dirham with 0.01%, Omani Rial and Saudi Riyal with 0.02% risk. However, in GARCH based estimation there is 99% chance that loss of Irani Rial will not exceed 4.24% in a day followed by Turkish Lira with 1.49% risk and Kazakhstani Tenge with 1.46% loss. Lower loss reported currencies are Hong Kong Dollar with 0%, UAE Dirham with 0.02% and Qatari Riyal with 0.04% during this period.

4.4 Back Testing

Back testing is the method which used to check the accuracy of the model that actual risk is equal to estimated risk. Comparison will be on the basis of violation ratio that how much observed values different from expected and on the basis on VaR volatility.

4.4.1 Violation Ratio

Table 4.4 shows the violation ratios of non-parametric approach like historical simulation, parametric approaches like normal and t-distribution and time varying volatility based model like EWMA and GARCH model at 95% and 99% confidence intervals.

According to 95% confidence interval, in parametric and non-parametric, 88% of normal distribution results are more closes to 1 (between 0.80-1.20) which are higher than historical simulation with 80% and t-distribution with 60%. However, in time varying volatility approach, EWMA is a better method with 96% results than GARCH with 40%.

A horizontal view of table provides that which method is better for forecasting risk. According to 95%, normal distribution will be the better method than other

TABLE 4.4: Violation Ratio of Conventional Approach

	Historical Simulation		**Normal Distribution**		***t*-Distribution**		**EWMA**		**GARCH**	
	95%	99%	95%	99%	95%	99%	95%	99%	95%	99%
Bangladesh	1.0376	1.1075	0.9968	3.1478	1.0259	1.9236	1.1717	2.9729	6.2198	31.041
China	1.2773	1.2540	0.8866	2.1581	1.0265	0.8166	0.8574	1.8956	7.6874	38.437
Hong Kong	1.1604	1.1662	0.9796	2.1866	0.9799	1.1957	1.0496	2.2157	9.7579	48.790
India	1.3041	2.2216	1.1945	2.1062	1.3503	1.1252	1.0675	1.0098	1.1656	2.1062
Indonesia	1.0324	2.1289	1.0440	2.4205	1.0440	1.1374	1.0499	0.9041	0.9041	2.0414
Iran	1.0575	1.0575	0.9924	3.0098	0.8134	1.4642	1.1063	3.1725	2.6410	9.3004
Iraq	0.9767	2.6482	1.0739	1.4334	0.9767	1.2391	1.1322	2.2595	2.9835	14.699
Israel	1.0855	1.8092	1.0622	2.0718	1.3131	0.9338	1.0446	0.7587	1.0388	1.7508
Japan	0.9802	1.4877	0.9627	1.4002	1.3003	0.6999	0.9977	0.9335	0.9043	1.2252
Kazakhstan	1.0259	1.1075	0.8802	2.0111	0.9502	0.8744	1.0143	2.3025	8.1317	40.717
Korea	1.0732	2.2164	1.1024	2.5372	1.1082	1.0499	1.0324	1.1957	1.0032	2.0706
Kuwait	1.0563	1.0118	0.8687	1.7275	0.8786	0.691	1.0661	2.1964	6.5449	32.725
Malaysia	0.8977	1.6613	1.0201	1.8362	1.3007	0.9915	1.1658	0.9910	0.9094	1.4282
Oman	0.6738	0.8725	0.7029	2.1328	0.6980	1.2118	0.6350	1.7935	2.0553	10.276
Pakistan	1.1251	2.5762	1.0883	2.8654	1.1199	1.4721	1.0410	1.1830	0.9621	2.3659
Philippines	1.0962	2.0408	1.0729	1.7784	1.2715	0.1750	0.9796	1.1662	1.0671	1.7784
Qatar	0.9831	0.8717	0.9782	2.3487	1.1671	1.2349	1.1041	1.9855	6.6295	33.099
Saudi Arabia	0.8682	0.9794	0.8894	2.4087	0.8894	1.2970	1.0111	2.5146	6.0296	30.148
Singapore	1.0612	1.5743	1.0787	2.0991	1.5223	1.3707	1.0496	1.1953	0.9971	1.4869
Sri Lanka	1.2187	1.4869	1.0496	2.9738	1.0965	1.9539	1.0671	2.6531	9.0055	45.028
Taiwan	1.0201	0.9327	1.0026	1.9528	1.3057	1.0201	0.8569	1.6905	9.8047	9.7697
Thailand	0.9563	2.0117	0.9504	2.3324	0.9974	0.7582	1.0729	1.1662	0.9271	1.8659
Turkey	1.3120	2.5364	1.3236	2.8280	1.2948	1.2540	1.1429	1.1370	1.2828	2.5656
UAE	0.8415	0.8997	0.8415	2.0905	0.8362	1.2702	1.1167	2.0640	5.1389	25.695
Vietnam	1.1020	0.9621	0.7638	2.2741	0.7582	1.3127	1.0962	3.0321	6.1534	30.825

conventional methods for Bangladeshi currency market with 0.9968 value, Irani currency market with 0.9968 value, Sri Lankan currency market with 1.0496 and Taiwani currency market with 1.0026 are closer to 1.

For Chinese currency market with 1.0265 value, Malaysian currency reported closer value 1.0201 and Thailand currency with 0.9974, t-distribution is better as compared to other methods.

Historical simulation is viable method for Hong Kong currency market with 0.9799 value, Indonesian currency market with 1.0324 value, Kuwaiti currency market with 1.0563 value, Qatar currency market with 0.9831 value.

EWMA method of forecasting is better for Indian currency market with 1.0675 value, Japanese Yen market with 0.9977 value, Kazakhstani Tenge market with 1.0143 value, Philippines Peso market with 0.9796 value, Saudi Riyal market with 1.0111 value, Turkish currency market with 1.1429 value, UAE currency market with 1.1167 value and Vietnami currency market with 1.0962 value because there is very minimum difference between observed and expected violations.

At 95% confidence interval, GARCH model is better for Israeli currency market with 1.0388, Korean Won market with 1.0032, Pakistani currency market with 0.9621 and Singapore currency market with 0.9971 because there is expected and observed variations are almost equal to 1. For Hong Kong Dollar market, t-distribution with 0.9796 value and historical simulation with 0.9799 value are recommended because both are closer to 1.

For Iraqi Dinar market, results of VR showing that historical simulation and t-distribution with VR ratio 0.9767 are better than other methods.

For Omani currency market, there is no consistent results in Omani currency market so no method has been identified for better forecasting. According to 95% significance level, if we recommend 1 better model for 25 Asian currency markets out of 5 conventional methods then it is EWMA because its risk and returns forecasting is 96% which is higher than all other methods.

At 99% confidence interval, in parametric and non-parametric, Historical simulation is better method with 44% higher than normal distribution with 0% and

t-distribution with 36%. However, in time varying volatility approach, EWMA is a better method with 40% results than GARCH with 0%.

If we recommend any better method for each county then historical simulation is the better method of forecasting risk and returns for Bangladeshi currency market with 1.1075 value, Hong Kong currency market with 1.1662, Irani currency market with 1.0575 value, Kazakhstani Tenge market with 1.1075 value, Kuwaiti currency market with 1.0118 value, Omani currency market with 0.8725 value, Qatari currency market with 0.8717 value, Saudi currency market with 0.9794 value, UAE currency market with 0.8997 value and Vietnami currency market with 0.9621 value than other conventional methods which is closer to 1.

t-distribution report values closer to 1 as compared to other methods in Chinese currency market with 0.8166 value, Korean Won market with 1.0499 value, Malaysian currency market with 0.9915 value and Taiwani currency market with 1.0201 value.

EWMA method of forecasting is better for Indian currency market with 1.0098 value, Indonesian currency market with 0.9041 value, Japanese Yen market with 0.9335 value, Pakistani currency market with 1.1830 value, Philippines Peso currency, with 1.1662 value, Singapore currency market with 1.1953 value, Thai Baht market with 1.1662 value and Turkish currency market with 1.1370 value.

GARCH model at 99% confidence level is better for Israeli currency market with 1.0388 because there is expected and observed variations are almost equal to 1.

For Iraqi and Sri Lankan currency markets, no good forecasting method is identified because in all models observed violations are at high end. However, forecasting at 99% and 95% of Omani currency is not consistent, generally 95% forecasting is better than 99%. Hence for Omani currency performance at 99% is better than 95%.

At 99% level of significance, a recommended model for Asian currency market is historical simulation because its risk forecasting is good in 44% cases which is higher than all other methods.

4.4.2 VaR Volatility

VaR Volatility helps to select a better model, if there are two or more methods reflecting same results in violation ratio then comparison to VaR volatility of these methods and which provides that better for estimation.

Table 4.5 illustrate the volatility ratio of all conventional method including non-parametric method (historical simulation), parametric method (normal and t-distribution) and time varying volatility methods (EWMA and GARCH) at 95% and 99% confidence intervals.

At 95% confidence interval, lowest volatility reported by historical simulation method for 25 Asian currency markets by 0.30% but it is not forecasting correctly in VR (violation ratio). Whereas, normal distribution reported 0.49% volatility during 2005-2018 period. So there is a minimum difference between historical simulation and normal distributions volatility ratio but normal distribution method forecast more accurate than historical simulation in VR ratio.

However, study recommend best method in time varying volatility approach is EWMA with 0.52% volatility in entire Asian currency market because its forecasting of risk and returns is 96% accurate. Only Irani currency market is highly volatile with 5.55%.

In Hong Kong currency market, t-distribution and historical simulation both method report same volatility 0.02%. For Iraqi currency market, results of VR exhibit same volatility of historical simulation and t-distribution with 0.59% so we could not decide better method for Iraqi currency market on the basis of volatility ratio.

In Oman (Rial) currency market, GARCH model show less volatility but its forecast is not correct according to violation ratio which has been underestimated. There are no consistent results in Omani currency market so no method has been identified for better forecasting.

TABLE 4.5: VaR Volatility of Conventional Approach

	Historical Simulation		**Normal Distribution**		**t-Distribution**		**EWMA**		**GARCH**	
	95%	99%	95%	99%	95%	99%	95%	99%	95%	99%
Bangladesh	0.0028	0.0081	0.0031	0.0043	0.0031	0.0059	0.0041	0.0057	0.00005	0.00008
China	0.0011	0.0025	0.0010	0.0014	0.0010	0.0020	0.0013	0.0018	0.000002	0.000003
Hong Kong	0.0002	0.0006	0.0002	0.0003	0.0002	0.0004	0.0003	0.0004	0.000001	0.000001
India	0.0033	0.0047	0.0027	0.0038	0.0028	0.0051	0.0027	0.0064	0.0035	0.0050
Indonesia	0.0040	0.0057	0.0031	0.0043	0.0031	0.0060	0.0026	0.0077	0.0057	0.0081
Iran	0.0024	0.1906	0.0531	0.0751	0.0536	0.1029	0.0555	0.0785	0.0068	0.0096
Iraq	0.0059	0.0083	0.0077	0.0096	0.0059	0.0114	0.0066	0.0094	0.00005	0.00007
Israel	0.0032	0.0045	0.0027	0.0038	0.0025	0.0048	0.0029	0.0047	0.0032	0.0045
Japan	0.0041	0.0058	0.0030	0.0042	0.0026	0.0051	0.0030	0.0054	0.0042	0.0060
Kazakhstan	0.0073	0.0142	0.0091	0.0129	0.0099	0.0184	0.0108	0.0152	0.0024	0.0034
Korea	0.0070	0.0099	0.0061	0.0086	0.0063	0.0120	0.0063	0.0107	0.0079	0.0112
Kuwait	0.0014	0.0048	0.0015	0.0021	0.0015	0.0029	0.0018	0.0025	0.00001	0.00002
Malaysia	0.0030	0.0042	0.0024	0.0034	0.0024	0.0044	0.0025	0.0042	0.0030	0.0043
Oman	0.0003	0.0007	0.0003	0.0004	0.0003	0.0005	0.0004	0.0005	0.000001	0.000002
Pakistan	0.0040	0.0056	0.0029	0.0041	0.0032	0.0059	0.0031	0.0081	0.0048	0.0068
Philippines	0.0020	0.0028	0.0016	0.0023	0.0015	0.0036	0.0018	0.0031	0.0020	0.0028
Qatar	0.0036	0.0133	0.0042	0.0060	0.0042	0.0080	0.0043	0.0061	0.00011	0.00015
Saudi Arabia	0.0003	0.0017	0.0006	0.0009	0.0006	0.0012	0.0007	0.001	0.00001	0.00001
Singapore	0.0022	0.0031	0.0016	0.0023	0.0015	0.0028	0.0018	0.0037	0.0021	0.0030
Sri Lanka	0.0021	0.0068	0.0020	0.0028	0.0022	0.0040	0.0027	0.0038	0.00004	0.0001
Taiwan	0.0013	0.0026	0.0013	0.0018	0.0011	0.0022	0.0018	0.0025	0.00001	0.00002
Thailand	0.0052	0.0074	0.0045	0.0064	0.0046	0.0088	0.0028	0.011	0.0081	0.0114
Turkey	0.0081	0.0115	0.0053	0.0076	0.0056	0.0105	0.0062	0.0155	0.0090	0.0128
UAE	0.0001	0.0005	0.0002	0.0003	0.0002	0.0004	0.0002	0.0003	0.0000004	0.000001
Vietnam	0.0013	0.0090	0.0025	0.0035	0.0026	0.0049	0.0030	0.0043	0.00073	0.00105
	0.30%	**1.32%**	**0.49%**	**0.69%**	**0.49%**	**0.94%**	**0.52%**	**0.85%**	**0.26%**	**0.36%**

At 99% confidence interval, in parametric and non-parametric, normal distribution results show lower volatility (0.69%) during 2005-2018 period in Asian currency market but forecasting of this method in violation ratio is not correct. However, Historical simulation report 1.32% volatility because of Irani Rial which has 19.06% volatility in its currency. Otherwise the average volatility of all other countries is 0.58%. On the other hand, in time varying volatility method GARCH showing less volatility 0.36% than EWMA method with 0.85% because of more fluctuation observed in Irani currency market (7.85%) during this period. The recommended method is EWMA because its forecasting is 44% correct which is higher than GARCH in VR.

At 99% confidence interval for Iraqi currency market, GARCH methods estimation report low volatility by 0.01% than other conventional methods but this method underestimate its returns and risk forecast so no method is forecasted better because in all models observed violations are high so returns are forecasting at lower end.

According to volatility ratio, GARCH method reported lower volatility of Sri Lankan currency market (0.01%) but this forecast is also not correct because in VR risk and returns are underestimated. So we cannot select best method on the basis of VaR volatility of this currency market.

4.4.3 Kupiec Back Testing under Conventional Approach

Kupiec back testing is actually explaining that if the data suggests that the probability of exceptions is different than p, the VaR model is rejected. In 95% confidence interval, if value <3.84 then null hypothesis will be accepted. According to 99% level of significance, if value <6.63 then null hypothesis will be accepted. If values >3.84 or 6.63 for 95% & 99% level of significance. The values are taken from x^2 table at 1 degree of freedom. It means observed values are different from expected values so null hypothesis will be rejected.

Table 4.6: Kupiec Back Testing of Conventional Approach

	Historical Simulation		**Normal Distribution**		***t*-Distribution**		**EWMA**		**GARCH**	
	95%	99%	95%	99%	95%	99%	95%	99%	95%	99%
Bangladesh	0.3360	0.3874	0.0019	101.92	0.1205	23.273	5.0558	88.243	2381.7	5606.1
China	12.811	21.998	2.4109	34.890	0.1261	1.2433	3.8485	21.998	3544.8	7613.1
Hong Kong	4.4239	0.9083	0.0757	36.441	0.0757	1.2442	0.4367	38.044	5456.8	10700
India	15.459	38.770	6.5117	32.501	20.265	0.5276	0.8143	0.0034	4.7613	32.500
Indonesia	0.1872	33.342	0.3452	50.024	0.3452	0.6258	0.4419	0.3295	1.7143	28.870
Iran	0.6301	111.69	0.0112	97.888	7.1951	7.0224	2.123	111.69	367.63	115.84
Iraq	3.3782	9.2255	0.1187	77.762	0.1187	2.2084	3.6359	48.597	570.09	2206.4
Israel	1.2843	18.282	0.6835	30.373	16.165	0.1553	0.3546	2.1991	0.2684	15.945
Japan	0.0714	7.1634	0.2546	4.9329	14.997	3.4787	0.001	0.1567	1.7042	1.6390
Kazakhstan	0.1205	0.3874	2.6956	27.392	0.4558	0.5711	0.0367	42.984	3931.0	8270.3
Korea	0.9454	38.068	1.8328	57.406	2.0441	0.0848	0.1872	1.2482	0.0019	30.330
Kuwait	0.0268	0.0057	3.8395	17.795	3.2727	4.3819	0.9141	43.686	3100.9	7144.3
Malaysia	1.9543	12.640	0.0726	19.433	14.901	0.0028	4.7261	0.0028	1.5282	5.6092
Oman	23.574	0.0133	21.300	40.367	22.0438	1.7517	33.054	21.241	187.82	1247.3
Pakistan	3.0182	66.520	1.5203	88.916	2.7742	7.4777	0.3324	1.2151	0.2904	51.811
Philippines	1.6226	28.846	0.9377	17.049	12.268	35.915	0.0757	0.9083	0.7951	17.049
Qatar	0.0115	0.4686	0.1039	55.009	5.7716	2.1413	2.2827	31.487	3238.6	7402.0
Saudi Arabia	0.2684	61.638	2.5242	54.313	2.5242	3.0777	0.0245	0.0164	2469.9	5918.5
Singapore	0.6640	9.7291	1.0919	31.799	42.688	4.2578	0.4367	1.2442	0.0015	7.1437
Sri Lanka	8.0931	7.1437	0.4367	88.284	1.8221	24.635	0.7951	65.132	4729.0	9546.6
Taiwan	0.0726	0.1607	0.0012	24.616	15.462	0.0139	3.8784	13.686	5513.6	10717
Thailand	0.3501	27.412	0.4506	44.719	0.0015	2.2137	0.9377	0.9083	0.9819	20.699
Turkey	16.066	57.375	17.237	77.441	14.381	2.0630	3.5290	0.623	13.305	59.280
UAE	1.7628	0.1281	5.2693	34.545	5.6376	2.5669	2.6143	33.061	1798.9	4692.8
Vietnam	1.8221	0.0504	10.922	41.329	11.494	3.0703	1.6226	92.764	2331.0	5546.1

Table 4.6 report the results of unconditional coverage kupiec back testing of all conventional methods including non-parametric (historical simulation), parametric (normal & t-distribution) and time varying volatility (EWMA & GARCH) with 95% and 99% confidence interval.

According to 95% level of significance in kupiec back testing table, results showing that 80% null hypothesis are accepted by normal distribution which is higher than historical simulation with 76% and t-distribution with 48% acceptance rate. Whereas, 80% null hypothesis have been accepted by EWMA in time varying approach which is higher than GARCH with 36% acceptance rate out.

In Hong Kong currency market, there was the issue of suitable method selection that historical simulation is better or t-distribution because both are closer to 1 in violation ratio table. After results of Kupiec test, t-distribution is better than historical simulation because in historical simulation value is 4.42 >3.84 so null hypothesis rejected while t-distribution value 0.08 <3.84 so null hypothesis is accepted.

For Iraqi currency market, results of VR shows that historical simulation and t-distribution has same acceptance rate between expected and observed variation. According to kupiec testing comparison both historical simulation and t-distribution null hypothesis are accepted.

This study further tested, the results at 99% confidence interval, highest 80% null hypothesis accepted by t-distribution but due to its forecasting is not correct so the result of accepted hypothesis is also not correct. So historical simulation is better model for this significance level with 36% accepted rate for null hypothesis.

4.4.4 Christoffersen Tests under Conventional Approach

Christoffersen test is conditional coverage method of back testing which helps to identify the clustering between risk forecasting events over a period of time. Whether violations are happening independently for one time or there is a specific pattern. Null hypothesis is accepted if value <3.84 in 95% confidence interval and

TABLE 4.7: Christoffersen back testing of Conventional Approach

	Historical Simulation		**Normal Distribution**		***t*-Distribution**		**EWMA**		**GARCH**	
	95%	99%	95%	99%	95%	99%	95%	99%	95%	99%
Bangladesh	1.5048	0.5298	1.8703	0.7159	2.3480	0.0642	5.4093	1.9722	17.904	17.777
China	14.59	0.0486	10.379	10.716	17.515	5.3631	11.812	0.0486	0.5472	0.5472
Hong Kong	29.095	21.217	31.317	39.783	34.256	32.649	14.030	13.414	0.3575	0.3575
India	8.2547	0.0485	19.376	7.9868	13.781	0.5411	19.141	0.811	4.3029	0.1327
Indonesia	24.245	11.036	36.959	25.51	28.509	11.160	33.504	9.2815	6.0781	3.2883
Iran	9.7882	1.2798	35.231	7.1314	10.333	1.3485	3.8625	1.2798	31.665	28.500
Iraq	5.2748	0.0047	13.890	1.7215	13.890	0.1871	15.995	0.0052	20.025	25.094
Israel	3.3359	4.6924	6.5526	3.1316	11.104	4.3879	5.7418	5.9180	0.8406	0.7070
Japan	0.7347	0.0719	2.0041	1.7811	0.0159	1.9618	2.3263	0.9576	3.1488	0.3235
Kazakhstan	65.925	6.9889	38.074	20.224	43.925	9.6665	12.106	9.2214	3.3950	3.2306
Korea	10.929	0.8785	19.266	19.657	14.735	12.395	19.406	10.402	5.7076	1.2875
Kuwait	1.6393	0.6061	0.0613	4.2188	0.0044	1.7191	3.5128	0.5907	15.052	15.052
Malaysia	1.3399	0.9240	8.1335	2.1422	11.703	0.8757	15.324	0.8757	2.0486	0.1171
Oman	0.8999	0.5160	2.5906	0.5130	2.5005	0.1891	3.7288	0.1104	0.9200	0.9200
Pakistan	1.3388	5.7557	10.836	5.7557	7.8436	0.1308	9.7771	5.7186	0.4369	0.8295
Philippines	1.3234	0.2123	0.0886	0.6443	0.0619	6.8181	0.3959	0.4195	0.9607	0.0071
Qatar	3.1921	4.0064	2.5659	9.3643	0.2884	0.1896	14.876	0.2916	105.52	105.22
Saudi Arabia	4.1064	1.0788	0.3227	4.801	0.3227	4.8179	2.9769	0.7770	65.317	65.317
Singapore	0.1993	1.1721	10.660	5.3397	17.592	1.9006	6.9949	0.4192	1.4070	0.0721
Sri Lanka	34.201	7.2491	18.267	20.008	15.243	17.005	7.8515	6.2185	3.0310	3.0310
Taiwan	6.5704	1.0462	5.7171	13.119	3.7554	7.8997	1.1268	8.8355	1.4017	1.1154
Thailand	9.1089	0.2479	6.0190	6.1961	7.4346	1.5693	18.980	0.4723	1.7270	2.0201
Turkey	5.7018	2.7796	17.320	15.546	13.642	19.469	16.248	6.7049	1.1354	0.2336
UAE	2.0779	0.5536	1.3270	0.3280	1.2557	0.1834	17.705	0.3107	50.875	50.875
Vietnam	6.5340	4.1729	2.8338	6.6518	2.9696	9.0260	0.7335	2.1892	0.7236	0.7540

for 99% level significance value <6.63. Null hypothesis acceptance shows that there the violation behavior is random in nature or not.

Table 4.7 report the results of Christoffersen back testing for all conventional methods including non-parametric (historical simulation), parametric (normal & t-distribution) and time varying volatility (EWMA & GARCH) model at 95% and 99% confidence interval.

In non-parametric/parametric approach, the results of christoffersen test at 95% confidence interval indicate that null hypothesis is accepted by normal distribution for 36%. This means Vietnami Dong, Omani Rial, Qatar, Riyal, Bangladeshi Taka, UAE Dirham, Saudi Riyal, Philippines Peso, Kuwaiti Dinar and Japanese Yen are the currency markets which behavior is independent in nature. However, 64% of Asian currency market have clustering in their risk forecasting.

In time varying volatility approach, EWMA perform better than GARCH model. According to results, null hypothesis of no clustering is accepted for 28% markets by EWMA. Which indicate that Omani, Kuwaiti, Saudi, Taiwani, Vietnam, Philippines and Japanese currency markets behave randomly and no clustering exist. In remaining 72% currency markets clusters exist. In case of GARCH model 60% of market behave randomly with very low forecasting by 40% violation ratio.

The results of non-parametric/parametric approach at 99% confidence interval indicate that historical simulation accepted null hypothesis for 84% Asian currency market behave randomly and the currencies are Pakistani Rupee, Israeli Shekel, Vietnami Dong, Qatari Riyal, Turkish Lira, Irani Rial, Singapore Dollar, Saudi Riyal, Taiwani Dollar, Malaysian Ringgit, Korean Won, Kuwaiti Dinar, UAE Dirham, Bangladeshi Taka, Omani Rial, Thai Baht, Philippines Peso, Japanese Yen, Chinese Yuan Renminbi, Indian Rupee and Iraqi Dinar. However, normal distribution acceptance ratio of null hypothesis is 56% and t-distribution acceptance ratio of null hypothesis is 60% but according to violation ratio its initial forecasting is not correct so these two methods are not viable.

EWMA model perform better in time varying volatility approach, 78% null hypothesis are accepted. It means Sri Lankan, Israeli, Pakistani, Vietnami, Bangladeshi, Irani, Japanese, Malaysian, Indian, Saudi, Kuwaiti, Thai, Philippines, Singapore, UAE, Qatari, Omani, Chinese and Iraqi currency markets do not exist clusters in risk forecasting. These currency markets have random behavior in nature. Whereas, GARCH reported that 72% null hypothesis are accepted so performance of this model is weaker.

4.5 Expected Shortfall (C-VaR) of Conventional Approach

Expected Shortfall covers all losses which are equal or greater than VaR, i.e. the average loss in the cases of worst (1-p)%, where p is level of significance. In other words, it provides the expected value of any investment in the case of worst q%.

4.5.1 Parametric and Non-Parametric Approach

Table 4.8 indicate the results of expected shortfall under parametric/nor-parametric approach by using historical simulation, normal distribution and t-distribution methods.

At 95% significance level, Historical simulation report highest expected shortfall of 2.7% for Irani Rial followed by Turkish Lira (2.44%) and Korean Won (1.68%). Least loss incurred currencies are UAE Dirham (0.03%), Omani Rial (0.06%) and Saudi Dirham (0.07%). According to normal distribution assumption, Irani Rial reports 7.05% loss during 2005-2018 period then Turkish Lira with 1.99% loss and Kazakhstani Tenge with 1.51% loss. Lower loss is reported by UAE Dirham (0.03%), Omani Rial (0.06%) and Hong Kong Doller (0.07%) during this period.

Under the assumption of t-distribution, highest loss of 76.91% reported by Pakistani Rupee but there is a huge gap in next highly loss report currencies like Sri Lankan Rupee reported 7.93% loss and Kazakhstani Tenge reported 5.68% loss. Lowest losses reported currencies are UAE Dirham, Iraqi Dinar, Omani Rial, Saudi Riyal, Qatari Riyal, and Bangladeshi Taka that is almost 0.

TABLE 4.8: Expected Shortfall of Conventional Approach

	Historical Simulation		**Normal Distribution**		***t*-Distribution**	
	95%	99%	95%	99%	95%	99%
Bangladesh	-0.0094	-0.0198	-0.0076	-0.0098	0.0000	0.0000
China	-0.0036	-0.0065	-0.0031	-0.0040	-0.0055	-0.0188
Hong Kong	-0.0008	-0.0014	-0.0007	-0.0009	0.0010	-0.0032
India	-0.0112	-0.0183	-0.0095	-0.0123	-0.0088	-0.0194
Indonesia	-0.0108	-0.0206	-0.0095	-0.0122	-0.0126	-0.0373
Iran	-0.0270	-0.1181	-0.0705	-0.0912	-0.0058	-0.0490
Iraq	-0.0130	-0.0281	-0.0104	-0.0134	0.0000	0.0000
Israel	-0.0115	-0.0185	-0.0101	-0.0130	-0.0089	-0.0175
Japan	-0.0145	-0.0229	-0.0134	-0.0173	-0.0117	-0.0229
Kazakhstan	-0.0138	-0.0421	-0.0151	-0.0195	-0.0568	-0.2697
Korea	-0.0168	-0.0326	-0.0146	-0.0189	-0.0130	-0.0304
Kuwait	-0.0038	-0.0079	-0.0033	-0.0043	-0.0470	-0.2626
Malaysia	-0.0094	-0.0142	-0.0083	-0.0107	-0.0092	-0.0232
Oman	-0.0006	-0.0015	-0.0006	-0.0008	0.0000	0.0000
Pakistan	-0.0086	-0.0197	-0.0070	-0.0090	-0.7691	-4.0103
Philippines	-0.0084	-0.0124	-0.0076	-0.0098	-0.0066	-0.0120
Qatar	-0.0030	-0.0128	-0.0055	-0.0071	0.0000	0.0000
Saudi Arabia	-0.0007	-0.0023	-0.0010	-0.0012	0.0000	0.0000
Singapore	-0.0079	-0.0121	-0.0072	-0.0093	-0.0062	-0.0117
Sri Lanka	-0.0065	-0.0133	-0.0051	-0.0066	-0.0793	-0.3978
Taiwan	-0.0067	-0.0104	-0.0062	-0.0080	-0.0057	-0.0121
Thailand	-0.0097	-0.0202	-0.0098	-0.0126	-0.0076	-0.0177
Turkey	-0.0244	-0.0442	-0.0199	-0.0257	-0.0174	-0.0380
UAE	-0.0003	-0.0007	-0.0003	-0.0004	0.0000	-0.0605
Vietnam	-0.0051	-0.0137	-0.0047	-0.0061	-0.0178	-0.0835

Finally, at 99% confidence interval, historical simulation method reports highest expected shortfall by Irani Rial with 11.81% expectation of loss, followed by Turkish Lira 4.42% and Kazakhstani Tenge (4.21%). Least loss is reported by UAE Dirham (0.07%) followed by Hong Kong Doller (0.14%) and Omani Rial (0.15%). According to normal distribution assumption, maximum loss incurred by Irani Rial with 9.12% expected shortfall followed by Turkish Lira with 2.57% and Kazakhstani Tenge with 1.95%. Lower loss reported currencies are UAE Dirham 0.04%, Omani Rial, 0.08% and Hong Kong Doller 0.09% during this period.

However, t-distribution reports highest loss by Pakistani Rupee with 401.03% expected shortfall which is a hug risk followed by Sri Lankan Rupee reported 39.78% and Kazakhstani Tenge reported 26.97% expected shortfall. Lowest losses bearing currencies are Omani Rial, Iraqi Dinar, Saudi Riyal, Qatari Riyal, and Bangladeshi Taka that is almost 0.

4.5.2 Time Varying Volatility

Time-varying volatility refers to the fluctuations in volatility over different time periods. Investors may choose to study or consider volatility of an underlying security during various time periods. The use of time-varying volatility measures can influence the expectations of investments.

Table 4.9 explaining the results of expected shortfall if volatility is time varying by using EWMA and GARCH methods.

According to EWMA results of expected shortfall, the highest loss of 1.61% is reported by Turkish Lira followed by Indian Rupee 1.09% and Pakistani Rupee 1.02%. Least expected losses bearing currencies are UAE Dirham with 0.01%, Omani Rial and Saudi Riyal with 0.02% expected shortfall. Remaining currencies like Qatari Riyal, Hong Kong Dollar, Kuwaiti Dinar, Iraqi Dinar, Malaysian Ringgit, Vietnami Dong, Singapore Dollar, Irani Rial, Taiwani Dollar, Thai Baht, Israeli Shekel, Chinese Yuan Renminbi, Philippines Peso, Bangladeshi Taka, Sri Lankan Rupee, Korean Won, Indonesian Rupiah, Japanese Yen and Kazakhstani Tenge markets have suffered losses between 0.03% to 0.94%.

Table 4.9: Expected Shortfall of Time Varying Volatility Approach

	EWMA		**GARCH**	
	95%	99%	95%	99%
Bangladesh	-0.0068	-0.0087	-0.0048	-0.0062
China	-0.0054	-0.0069	-0.0044	-0.0057
Hong Kong	-0.0010	-0.0013	-0.0041	-
India	-0.0109	-0.0140	-0.0109	-0.0141
Indonesia	-0.0085	-0.0110	-0.0073	-0.0095
Iran	-0.0040	-0.0052	-0.0376	-0.0486
Iraq	-0.0023	-0.0030	-0.0046	-0.0059
Israel	-0.0049	-0.0063	-0.0055	-0.0071
Japan	-0.0091	-0.0118	-0.0106	-0.0136
Kazakhstan	-0.0094	-0.0121	-0.0130	-0.0168
Korea	-0.0077	-0.0099	-0.0080	-0.0104
Kuwait	-0.0011	-0.0014	-0.0016	-0.0020
Malaysia	-0.0031	-0.0040	-0.0042	-0.0055
Oman	-0.0002	-0.0002	-	-
Pakistan	-0.0102	-0.0132	-0.0046	-0.006
Philippines	-0.0056	-0.0072	-0.0059	-0.0076
Qatar	-0.0003	-0.0003	-0.0004	-0.0005
Saudi Arabia	-0.0002	-0.0003	-	-
Singapore	-0.0035	-0.0046	-0.0043	-0.0056
Sri Lanka	-0.0071	-0.0092	-0.0066	-0.0086
Taiwan	-0.0042	-0.0054	-0.0056	-0.0073
Thailand	-0.0046	-0.0060	-0.0051	-0.0066
Turkey	-0.0161	-0.0208	-0.0132	-0.0171
UAE	-0.0001	-0.0002	-0.0002	-0.0002
Vietnam	-0.0031	-0.0041	-0.0255	-0.0065

Results of GARCH based estimation of expected shortfall, highest loss bearing currencies are Irani Rial with 3.76%, Vietnam Dong with 2.55% and Turkish Lira with 1.32%. Lower loss reported currencies are UAE Dirham with 0.02% Saudi Riyal and Omani Rial with 0% expected shortfall during this period. Other Asian currencies have suffered losses between 0.04% to 1.30%.

The results of EWMA method at 99% confidence interval, the higher loss incurred 2.08% reported by Turkish Lira followed by Indian Rupee 1.40% and Pakistani Rupee 1.15%. Least losable currencies are UAE Dirham and Omani Rial with 0.02%, Saudi Riyal and Qatari Riyal with 0.03%. Remaining Asian currencies bear 0.13% to 1.21% losses.

According to GARCH expected shortfalls calculation, maximum loss incurred by Irani Rial with 4.86%, Turkish Lira with 1.71% and Kazakhstani Tenge with 1.68. Lower loss reported currencies are Saudi Riyal, Hong Kong Dollar and Omani Rial with 0, UAE Dirham with 0.02% during this period.

4.6 VaR Estimation Through EVT Approach

In financial markets, the movements in currency price are in extreme nature so individual investors/institutions concern is not with whole distribution but also on extreme tails which can cause the great losses. So instead of study the whole distribution, the concern is with tails only. For tail shape forecasting, there are 2 types of distributions:

- GEV (Block Maxima Approach)
- GPD (Static and Dynamic Approaches)

Table 4.10 shows the results of VaR under EVT (Extreme Value Theory) Approach.

At 95% confidence interval in 1st column GEV (Block Maxima) Approach, there are 95% chances that loss of Irani Rial will not be exceeded 8.11% in a day followed by Iraqi Dinar (6.1%) and Turkish Lira (4.53%). Least risky currencies are UAE Dirham (0.06%), Saudi Riyal (0.14%) and Hong Kong Dollar (0.16%).

GPD Static calculation in 3rd column, there are 95% chances that Turkish Lira will not suffer more than 1.49% loss in a day followed by Japanese Yen with 0.98% and Korean Won with 0.95% loss. Lower risk reported currencies are Omani Rial with 0%, UAE Dirham with 0.01%, and Saudi Riyal with 0.02% during this period.

According to GPD Dynamic analysis in 5th column, results show that there are 95% chances that loss of Irani Rial will not exceed by 0.03% followed by Pakistani Rupee, Korean Won and Vietnams Dong that report 0.02% loss. Lowest loss reported currencies are Hong Kong Dollar, UAE Dirham, Saudi Riyal, Indonesian

Table 4.10: VaR Estimation through EVT Approach

	Block Maxima		GPD (Static)		GPD (Dynamic)	
	95%	99%	95%	99%	95%	99%
	VaR	VaR	VaR	VaR	VaR	VaR
Bangladesh	-0.0232841	-0.0546006	-0.0043546	-0.0118519	-0.0000080	-0.0000145
China	-0.0077069	-0.0145840	-0.0020552	-0.0045700	-0.0000855	-0.0000881
Hong Kong	-0.0015840	-0.0028093	-0.0004745	-0.0009111	-0.0000015	-0.0000020
India	-0.0197131	-0.0304406	-0.0074387	-0.0131760	-0.0000081	-0.0000141
Indonesia	-0.0238210	-0.0448701	-0.0062877	-0.0123866	-0.0000018	-0.0000370
Iran	-0.0810785	-0.6392229	-0.0020104	-0.0100937	-0.0003226	-0.0000544
Iraq	-0.0610006	-0.4467558	-0.0029014	-0.0217232	-0.0000707	-0.0001604
Israel	-0.0217178	-0.0352658	-0.0075875	-0.0140850	-0.0000865	-0.0001078
Japan	-0.0265097	-0.0405208	-0.0098363	-0.0175617	-0.0000699	-0.0000346
Kazakhstan	-0.0321235	-0.1333019	-0.0044084	-0.0136175	-0.0001431	-0.0000475
Korea	-0.0301490	-0.0540435	-0.0095002	-0.0209356	-0.0001963	-0.0002501
Kuwait	-0.0077513	-0.0148541	-0.0020768	-0.0043978	-0.0000040	-0.0000008
Malaysia	-0.0153369	-0.0207374	-0.0065813	-0.0111917	-0.0000682	-0.0000849
Oman	-0.0053787	-0.0268494	-0.0000351	-0.0007685	-0.0000041	-0.0000042
Pakistan	-0.0212579	-0.0588988	-0.0037185	-0.0110689	-0.0002493	-0.0002300
Philippines	-0.0135106	-0.0194716	-0.0058301	-0.0099077	-0.0000485	-0.0000615
Qatar	-0.0030329	-0.0139600	-0.0003022	-0.0021057	-0.0000130	-0.0000202
Saudi Arabia	-0.0014154	-0.0051230	-0.0001606	-0.0008381	-0.0000003	-0.0000009
Singapore	-0.0131401	-0.0188694	-0.0054697	-0.0092283	-0.0001034	-0.0001147
Sri Lanka	-0.0168498	-0.0462982	-0.0030017	-0.0076060	-0.0000207	-0.0000071
Taiwan	-0.0123837	-0.0176505	-0.0048144	-0.0077352	-0.0000368	-0.0000460
Thailand	-0.0202103	-0.0396765	-0.0053612	-0.0100854	-0.0000840	-0.0001102
Turkey	-0.0452667	-0.0767911	-0.0149199	-0.0294038	-0.0000075	-0.0001378
UAE	-0.0005836	-0.0016744	-0.0001084	-0.0003491	-0.0000001	-0.0000001
Vietnam	-0.0184145	-0.0750634	-0.0016326	-0.0053703	-0.0001837	-0.0001307

Rupiah, Kuwaiti Dinar, Omani Rial, Turkish Lira, Bangladeshi Taka, Indian Rupee Qatari Riyal, Sri Lankan Rupee, Taiwans Dollar and Philip Peso that are almost 0.

At 99% confidence interval in 2nd column GEV (Block Maxima), there are 99% chances that loss of Irani Rial will not increase 63.92% followed by Iraqi Dinar with 44.68% and Kazakhstani Tenge with 13.33% loss in a day. However, loss trend in Irani Rial and Iraqi Dinar currency is abnormally high at 99% confidence level. Less loss bearing losses currencies are UAE Dirham with 0.17% loss, Hong Kong Dollar with 0.28% loss and Saudi Riyal with 0.51% loss.

According to GPD Static calculation in 4th column, there are 99% chances that the loss of Turkish Lira will not be higher than 2.94% in a day followed by Iraqi Dinar with 2.17% risk and Korean Won with 2.09% loss. Lower loss reported currencies are UAE Dirham with 0.03%, Omani Rial and Saudi Riyal with 0.08% during this period.

According to GPD Dynamic analysis in 6th column, there are 99% chances that Irani Rial loss will not suffer more than 0.03% followed by Irani Rial, Pakistani Rupee, Korean Won and Vietnams Dong report 0.02% loss. However, lower risky currencies are Hong Kong Dollar, UAE Dirham, Kuwaiti Dinar, Saudi Riyal, Omani Rial, Sri Lankan Rupee, Indian Rupee, Bangladeshi Taka, Qatari Riyal, Japanese Yen, Indonesian Rupiah, Taiwans Dollar and Kazakhstani Tenge that are almost 0.

4.7 Back Testing

4.7.1 Violation Ratio

Table 4.11 shows the violation ratio of 25 Asian countries during 2005-2018 period with EVT approach which includes Block Maxima, GPD static and GPD dynamic methods with 95% and 99% level of significance.

At 95% and 99% confidence intervals in EVT VaR estimation, the VR reported that 96% of the estimated results are closer to 1, as its not violated by GPD static. Whereas, the other forecasting models like Block Maxima and GPD dynamic showed weak VaR estimates as 0%. So, the best forecasting method of risk and returns is GPD static.

Table 4.11: Violation Ratio of EVT Approach

	Block Maxima		**GPD (Static)**		**GPD (Dynamic)**	
	95%	99%	95%	99%	95%	99%
Bangladesh	0.0408	0	0.9735	0.9618	6.2256	31.0114
China	0.0408	0.0292	1.0732	1.0790	7.6874	38.4369
Hong Kong	0.0466	0.0292	1.0087	1.0496	9.7609	48.8047
India	0.0577	0.0577	1.0560	1.0675	9.5961	48.0958
Indonesia	0.0408	0.0292	0.9740	0.9915	9.5480	47.7399
Iran	0.0542	0.1356	1.0521	1.0304	4.0727	25.7863
Iraq	0.0049	0	1.0398	1.0690	3.0904	14.5044
Israel	0.0292	0.0292	1.0680	1.0213	9.5769	47.7969
Japan	0.0350	0.0292	1.0443	1.0210	9.8483	49.2707
Kazakhstan	0.0816	0.0874	1.0434	1.0784	8.0618	40.6587
Korea	0.0817	0.0292	1.0499	1.0790	9.2972	45.9609
Kuwait	0.0494	0.0740	1.0612	1.0612	6.5449	32.7246
Malaysia	0.0466	0	1.0726	1.0493	9.3967	46.9251
Oman	0.0048	0	2.0553	1.3815	2.0553	10.2763
Pakistan	0.0526	0.0263	1.0673	1.0515	7.1030	35.5152
Philippines	0.0583	0	1.0612	1.0787	9.8309	49.0671
Qatar	0.1743	0.3390	0.9249	1.0412	6.6392	33.0993
Saudi Arabia	0.1218	0.0794	0.9846	1.0588	6.0296	30.1482
Singapore	0.0466	0.0583	1.0379	1.0787	9.3644	46.8222
Sri Lanka	0.0583	0	1.0496	1.0787	9.0087	45.0146
Taiwan	0.0408	0.0291	0.9793	1.0784	9.8164	48.7904
Thailand	0.0525	0.0583	1.0204	1.0496	9.2362	46.0641
Turkey	0.0583	0.0292	1.0379	1.0787	9.7784	48.8338
UAE	0.0635	0.0794	1.1220	0.9526	5.1389	25.6946
Vietnam	0.0466	0	1.0729	1.0787	6.1399	30.8163

Only Omani currency market, where both in 95% and 99% confidence interval, Block maxima overestimate the risk because returns are forecasting at higher end. However, GPD static and dynamic underestimate the risk as values are greater than 1 because returns are forecasting at lower end.

EVT violation ratio trend analysis is same in 95% and 99% level of significance. However, literature says that performance of 95% significance level models will be better 99% significance level.

4.7.2 Kupiec Back Testing Under EVT Approach

Table 4.12 explains the results of kupiec back testing of EVT based approach including Block Maxima, GPD static and GPD dynamic at 95% and 99% level of significance.

TABLE 4.12: Kupiec Back Testing of EVT Approach

	Block Maxima		**GPD (Static)**		**GPD (Dynamic)**	
	95%	99%	95%	99%	95%	99%
Bangladesh	292.49	59.875	0.1281	0.0512	2386.0	5598.5
China	292.29	59.836	0.9454	0.2109	3544.8	7613.1
Hong Kong	286.03	59.855	0.0138	0.0837	5456.8	10700.4
India	277.52	54.220	0.5617	0.1561	5349.5	10589.9
Indonesia	292.29	59.836	0.1226	0.0025	5245.3	10366.8
Iran	299.05	44.055	0.5177	0.034	1073.1	4603.8
Iraq	409.49	73.280	0.3397	0.1936	623.96	2161.1
Israel	305.72	59.797	0.8165	0.0156	5270.5	10378.3
Japan	298.83	59.816	0.3499	0.0152	5540.7	10839.7
Kazakhstan	252.43	48.287	0.3360	0.2077	3869.6	8253.4
Korea	252.24	59.836	0.4419	0.2109	5002.0	9821.5
Kuwait	334.51	59.771	0.7839	0.1503	3100.9	7144.3
Malaysia	286.13	59.875	0.9301	0.0828	5101.0	10121.9
Oman	410.51	73.476	187.82	5.4207	187.82	1247.3
Pakistan	310.33	67.166	0.8881	0.1003	3396.5	7542.9
Philippines	274.04	59.855	0.6640	0.2093	5526.5	10782.3
Qatar	222.54	24.491	1.2548	0.0697	3247.6	7402.0
Saudi Arabia	242.49	54.683	0.0471	0.1293	2469.9	5918.5
Singapore	286.03	53.538	0.2563	0.2093	5068.3	10087.3
Sri Lanka	274.04	59.855	0.4367	0.2093	4729.0	9537.8
Taiwan	292.49	59.875	0.0778	0.2077	5513.6	10699.1
Thailand	279.92	53.538	0.0747	0.0837	4944.9	9855.8
Turkey	274.04	59.855	0.2563	0.2093	5474.2	10709.5
UAE	296.32	54.702	2.8523	0.0870	1798.9	4692.8
Vietnam	286.03	59.855	0.9377	0.2093	2322.5	5546.1

At 95% level of significance in kupiec back test, results show that null hypothesis is accepted in 96% cases by GPD static EVT approach which is higher than Block Maxima and GPD dynamic with 0% acceptance level. However, only Omani Rial results report insignificant likelihood ratio 186.82 >3.84 out of 25 Asian currencies.

For the results at 99% confidence interval, null hypothesis is accepted for 100% currencies when VaR is estimated by using GPD static because all values are less than 6.63. So after kupiec back testing the results shows that GPD Static is the best method for forecasting in extreme tails distribution in Asian currencies.

4.7.3 Christoffersen Back Testing Under EVT Approach

Table 4.13 explains the results of Christoffersen back testing of EVT based approach including Block Maxima, GPD static and GPD dynamic at 95% and 99% level of significance.

Table 4.13: Christoffersen Back Testing of EVT Approach

	Block Maxima		**GPD (Static)**		**GPD (Dynamic)**	
	95%	99%	95%	99%	95%	99%
Bangladesh	6.2529	12.737	1.7983	0.9584	17.625	17.373
China	6.8170	12.735	21.254	7.2784	0.5472	0.5472
Hong Kong	5.7598	12.737	23.493	7.5834	0.3575	0.3575
India	5.3442	12.756	19.721	7.3355	3.2945	2.5595
Indonesia	6.2518	12.735	23.558	23.558	0.4943	0.8253
Iran	5.0758	5.0758	1.4229	0.6780	21.014	6.9858
Iraq	13.100	13.101	12.225	0.4143	19.504	28.282
Israel	7.4797	12.734	13.060	0.7961	6.0708	6.0292
Japan	6.8170	12.735	2.2678	3.7616	6.0377	5.3794
Kazakhstan	10.905	9.2888	91.420	50.793	3.6033	3.3950
Korea	19.219	12.735	22.932	11.969	0.6493	1.2254
Kuwait	5.2592	9.6208	1.8528	6.5225	15.052	15.052
Malaysia	5.7604	12.737	6.1631	0.6555	8.0572	8.0123
Oman	13.105	13.106	0.9200	0.0402	0.9200	0.9200
Pakistan	14.218	12.943	26.835	22.393	20.486	19.842
Philippines	4.9348	12.736	3.9525	0.6548	0.0943	0.0588
Qatar	8.5886	4.0513	11.780	21.561	104.33	105.22
Saudi Arabia	2.2772	9.4810	14.833	16.638	65.317	65.317
Singapore	5.7598	10.645	7.4363	3.3867	0.7099	0.7099
Sri Lanka	5.3238	12.737	52.525	17.289	3.0310	2.8191
Taiwan	6.2529	12.736	6.5244	7.2815	1.2387	1.4307
Thailand	5.3244	10.645	8.1276	7.5834	10.763	11.084
Turkey	23.840	12.736	19.028	7.2800	0.1593	0.2157
UAE	4.7698	0.8504	6.6260	0.8504	50.875	50.875
Vietnam	5.7598	12.736	15.417	3.3867	0.5663	0.7540

Results of Christoffersen back testing at 95% level of significance shows that null hypothesis of independence is accepted for 20% currencies when VaR is estimated by using GPD static. Results indicate that there is no clustering in 20% Asian currencies but 80% currencies have clustering in their markets like Chinese Yuan Renminbi, Kazakhstani Tenge, Sri Lankan Rupee, Pakistani Rupee, Indonesian Rupiah, Hong Kong Dollar, Korean Won, Indian Rupee, Turkish Lira, Vietnami Dong, Saudi Riyal, Israeli Shekel, Iraqi Dinar, Qatari Riyal, Thai Baht, Singapore Dollar, UAE Dirham, Taiwani Dollar, Malaysian Ringgit and Philippines Peso because their likelihood ratio 3.952 - 21.25 >3.84 and null hypothesis is rejected.

At 99% confidence interval Christoffersens test provide the null hypothesis have been accepted for 48% currencies when VaR is estimated by using GPD static. However, there was 0% correct forecasting at 1st level of block maxima and GPD dynamic so their null hypothesis acceptance is not relevant. Remaining 52% currency markets i-e Kazakhstani Tenge, Indonesian Rupiah, Pakistan Rupee, Qatari Riyal, Sri Lankan Rupee, Saudi Riyal, Korean Won, Thai Baht, Hong Kong Dollar, Indian Rupee, Taiwani Dollar, Turkish Lira and Chinese Yuan Renminbi have the likelihood ratio between 7.28 - 50.79 which is more than tabulated value so null hypothesis is rejected indicating violations are not independent.

4.8 Expected Shortfall of EVT Approach

Expected shortfalls debate is beyond VAR means expected losses incurred when VaR is being violated. It is average of all losses which are greater or equal than VaR. The expected shortfall measures more uncertainty than VaR. It is used to obtain the expectation of tails. It is said to be the sub additive risk measure. Table 4.14 shows the results of expected shortfall under all methods like block maxima, GPD static and GPD dynamic of EVT Approach with 95% and 99% significance level.

According GEV Block Maxima Approach at 95% confidence interval, maximum loss incurred in a day reported by Irani Rial with 30.60% followed by Iraqi Dinar

Table 4.14: Expected Shortfall of EVT Approach

	Block Maxima		**GPD (Static)**		**GPD (Dynamic)**	
	95%	99%	95%	99%	95%	99%
Bangladesh	-0.0456900	-0.1071420	-0.0094461	-0.0196844	-0.00002867	-0.00002858
China	-0.0111984	-0.0211911	-0.0036129	-0.0064703	-0.00008283	-0.00008283
Hong Kong	-0.0021842	-0.0038738	-0.0007729	-0.0013563	-0.00408592	-0.02042461
India	-0.0243128	-0.0375433	-0.0111814	-0.0182500	-0.00004604	-0.00004594
Indonesia	-0.0359728	-0.0677596	-0.0107429	-0.0215457	-0.00004256	-0.00004236
Iran	-0.3061895	-2.4139980	-0.0395436	-0.0017255	-0.00038811	-0.00038022
Iraq	-0.2797656	-2.0489450	-0.0130074	-0.0278519	-0.00004685	-0.00004743
Israel	-0.0285549	-0.0463680	-0.0115106	-0.0184367	-0.00004753	-0.00004763
Japan	-0.0328213	-0.0501683	-0.0144897	-0.0228665	-0.00013561	-0.00013538
Kazakhstan	-0.2506489	-1.0401118	-0.0172093	-0.0460126	-0.00020984	-0.00020896
Korea	-0.0437408	-0.0784073	-0.0169147	-0.0323379	-0.00011647	-0.00011685
Kuwait	-0.0115534	-0.0221403	-0.0038949	-0.0079507	-0.00000816	-0.00000815
Malaysia	-0.0149979	-0.0202791	-0.0094176	-0.0141356	-0.00004028	-0.00004036
Oman	-0.2240939	-1.1186399	-0.0005646	-0.0015006	-0.00000400	-0.00000400
Pakistan	-0.0543140	-0.1504869	-0.0088338	-0.0196637	-0.00026989	-0.00026981
Philippines	-0.0158553	-0.0228509	-0.0084269	-0.0123824	-0.00002616	-0.00002621
Qatar	-0.0500317	-0.2302882	-0.0008630	-0.0146346	-0.00000203	-0.00000205
Saudi Arabia	-0.0064106	-0.0232030	-0.0009384	-0.0023098	-0.00000024	-0.00000024
Singapore	-0.0148641	-0.0213451	-0.0079123	-0.0120590	-0.00008398	-0.00008402
Sri Lanka	-0.0420859	-0.1156395	-0.0064661	-0.0134869	-0.00003215	-0.00003211
Taiwan	-0.0135157	-0.0192639	-0.0067348	-0.0103491	-0.00002283	-0.00002286
Thailand	-0.0328100	-0.0644121	-0.0095308	-0.0203721	-0.00004381	-0.00004395
Turkey	-0.0621916	-0.1055026	-0.0244607	-0.0437657	-0.00015464	-0.00015336
UAE	-0.0015440	-0.0044298	-0.0003622	-0.0007563	-0.00000002	-0.00000002
Vietnam	-0.1303075	-0.5311744	-0.0051439	-0.0138723	-0.00020273	-0.00020243

with 27.98% and Kazakhstani Tenge with 25.06% loss. Other 19 Asian currencies loss reported between 1.12% 22.41% in above mentioned tables column 1. However, minimum loss reported by UAE Dirham with 0.15% ES in a day followed by Hong Kong Dollar with 0.22% and Saudi Riyal with 0.64% expected shortfall.

GPD Static method estimation of expected shortfall reported during 2005-2018 period in 3rd column, maximum loss is suffered by Irani Rial with 3.95% expected shortfall followed by Turkish Lira with 2.45% and Kazakhstani Tenge with 1.72%. The maximum loss expected in a day is for UAE Dirham with 0.04% followed by Omani Rial with 0.06% and Hong Kong Dollar with 0.08%. Remaining currencies generally bear expected potential losses in a day between 0.09% - 1.69%.

In 5th column GPD Dynamic calculation, worst expected loss is forecast for Hong Kong Dollar with 0.41% expected shortfall in a day followed by Irani Rial 0.04% and Pakistani Rupee with 0.03%. Least losses are estimated by UAE Dirham, Saudi Riyal, Qatari Riyal, Omani Rial, Kuwaiti Dinar, Taiwani Dollar, Philippines Peso, Bangladeshi Taka, Sri Lankan Rupee, Malaysian Ringgit, Indonesian Rupiah, Thai Baht, Indian Rupee, Iraqi Dinar, Israel Shekel with almost 0% expected shortfall. However, Chinese Yuan Renminbi, Singapore Dollar, Korean Won, Japanese Yen with 0.01% and last 3 currencies of Asian Market Turkish Lira, Vietnami Dong and Kazakhstani Tenge with 0.02 expected shortfall also not at extreme stage.

Finally expected shortfall is estimated at 99% significance level, in 2nd column Block Maxima methods results illustrate that maximum loss reported in a day by Irani Rial is 241.40% followed by Iraqi Dinar with 204.89%, Omani Rial with 111.86%, and Kazakhstani Tenge with 104.01% expected shortfall. However, Hong Kong Dollar with 0.39%, UAE Dirham with 0.44% and Taiwani Dollar 1.93% are the countries which suffered least losses in a day during this period. Other 18 countries suffered losses between 2.12% - 53.12%.

Results of GPD Static during this period in 4th column shows that maximum loss incurred by Kazakhstan Tenge with 4.60% followed by Turkish Lira with 4.38% and Korean Won with 3.23% expected shortfall. However, minimum loss suffered by UAE Dirham with 0.08%, Hong Kong Dollar with 0.14% and Omani Rial with 0.15%. leftover Asian countries have loss incurred between 0.17% - 2.79%.

Results of GPD Dynamic are in 6th column, highest loss is faced by Hong Kong Dollar with 2.04% followed by Irani Rial with 0.04% and Pakistani Rupee with 0.03%. Lowest loss reported currencies are UAE Dirham, Saudi Riyal, Qatari Riyal, Omani Rial, Kuwaiti Dinar, Taiwani Dollar, Philippines Peso, Bangladeshi Taka, Sri Lankan Rupee, Malaysian Ringgit, Indonesian Rupiah, Thai Baht, Indian Rupee, Iraqi Dinar and Israeli Shekel that are almost 0.

4.9 Appropriate Method for Each Market

Table 4.15 shows the method selection of each country in conventional and EVT approach at 95% and 99% level of significance. These results are compiled after VaR estimation, back testing with Kupiec and Christoffersen test of 25 Asian currencies.

At 95% confidence interval of conventional approach in 1st column, normal distribution method is suitable for forecasting of risk and returns of Bangladeshi, Irani, Malaysian, Sri Lankan and Taiwani currency market. Results show that the t-distribution is the correct method of forecasting for Chinese, Hong Kong and Thai currency markets. EWMA method is better for Indian, Japanese, Kazakhstani, Philippines, Saudi, Turkish, UAE and Vietnam currency market. However, historical simulation is the better method for Indonesian, Kuwaiti and Qatari currency market. However, GARCH is the reasonable method of risk and returns forecasting for Israeli, Korean, Pakistani and Singapore currency market. Only for Iraqi currency market recommended 2 methods t-distribution and historical simulation of forecasting risk and return. Whereas, no method of forecasting risk and return for Omani inefficient currency market.

At 99% confidence interval results in 2nd column shows that best forecasting method for Bangladeshi, Hong Kong, Indonesian, Kazakhstani, Kuwaiti, Omani,

TABLE 4.15: Appropriate Method for Each Asian Currency Market

	Conventional Approach		**EVT Approach**	
	95%	**99%**	**95%**	**99%**
Bangladesh	Nor Distribution	Historical Simulation	GPD Static	GPD Static
China	t-Distribution	t-Distribution	GPD Static	GPD Static
Hong Kong	t-Distribution	Historical Simulation	GPD Static	GPD Static
India	EWMA	EWMA	GPD Static	GPD Static
Indonesia	Historical Simulation	EWMA	GPD Static	GPD Static
Iran	Nor Distribution	Historical Simulation	GPD Static	GPD Static
Iraq	t-Distribution, Historical Simulation	Nil	GPD Static	GPD Static
Israel	GARCH	t-Distribution	GPD Static	GPD Static
Japan	EWMA	EWMA	GPD Static	GPD Static
Kazakhstan	EWMA	Historical Simulation	GPD Static	GPD Static
Korea	GARCH	t-Distribution	GPD Static	GPD Static
Kuwait	Historical Simulation	Historical Simulation	GPD Static	GPD Static
Malaysia	Nor Distribution	t-Distribution	GPD Static	GPD Static
Oman	Nil	Historical Simulation	Nil	Nil
Pakistan	GARCH	EWMA	GPD Static	GPD Static
Philippines	EWMA	EWMA	GPD Static	GPD Static
Qatar	Historical Simulation	Historical Simulation	GPD Static	GPD Static
Saudi Arabia	EWMA	Historical Simulation	GPD Static	GPD Static
Singapore	GARCH	EWMA	GPD Static	GPD Static
Sri Lanka	Nor Distribution	Nil	GPD Static	GPD Static
Taiwan	Nor Distribution	t-Distribution	GPD Static	GPD Static
Thailand	t-Distribution	EWMA	GPD Static	GPD Static
Turkey	EWMA	EWMA	GPD Static	GPD Static
UAE	EWMA	Historical Simulation	GPD Static	GPD Static
Vietnam	EWMA	Historical Simulation	GPD Static	GPD Static

Qatari, Saudi, UAE and Vietnami currency market is historical simulation. t-distribution is correct method of forecasting for Chinese, Israeli, Korean, Malaysian and Taiwani currency market. For Indian, Indonesian, Japanese, Pakistani, Philippines, Singapore, Thai and Turkish currency markets most favorable method is EWMA. Iraqi currency market is so inefficient at 99% confidence interval so no method is recommended for this market.

The selection of 1 method from EVT approach in 3rd and 4th column of above table provides that GPD static for both 95% and 99% confidence intervals is best, except of Omani currency.

Omani currency market remained stable artificially during this period which results in no fat tail, So, we cannot predict the better model for this specific market by using EVT. If there is free floating in the currency market, then we can capture more variation and it help us to forecasting its risk and returns.

Table 4.16 shows the generalized overview of recommended method for each Asian currency market at 95% and 99% confidence interval.

TABLE 4.16: Generalized Overview of Recommended Method for Asian Currency Market

Conventional Approach		
	95%	**99%**
Historical Simulation	16%	40%
Normal Distribution	20%	0%
t-Distribution	16%	20%
EWMA	32%	32%
GARCH	16%	0%
No Method	4%	8%
EVT Approach		
Block Maxima	0%	0%
GPD Static	96%	96%
GPD Dynamic	0%	0%
No Method	4%	4%

Under conventional approach in above mentioned table at 95% significance level, historical simulation, t-distribution and GARCH models are recommended to 16% Asian currencies. Normal distribution method is recommended to 20%

and EWMA model is suitable for 32% Asian currencies. Only for 4% Asian currency market, no suitable method is recommended for risk forecasting due to low variation in this specific currency market.

At 99% interval, historical simulation is better method for risk measurement in 40% Asian currency markets. While, normal distribution and GARCH models failed to correct forecast losses at this interval. t-distribution method is recommended to 20% and EWMA method is recommended to 32% Asian currency markets. 8% Asian currency market is inefficient and every method is failed to predict potential losses.

At 99% interval, historical simulation is better method for risk measurement in 40% Asian currency markets. While, normal distribution and GARCH models failed to correct forecast losses at this interval. t-distribution method is recommended to 20% and EWMA method is recommended to 32% Asian currency markets. 8% Asian currency market is inefficient and every method is failed to predict potential losses.

According to EVT based approach, GPD static is best estimation model at both 95% and 99% confidence intervals because other two methods block maxima and GPD dynamic are failed to correctly forecast the losses.

4.10 Appropriate Method for Each Approach

Table 4.17 tells us the criteria of method selection from each approach like non-parametric/parametric, time varying volatility and EVT at 95% and 99% level of significance for 25 Asian countries.

These methods selection have done after calculation of VaR, expected shortfall and back testing of VaR to check the accuracy of methods for 25 Asian currency market.

At 95% level of significance, VR ratio of historical simulation correctly estimates in 80% cases. When Kupiec POF test is applied, 76% observed and expected

Table 4.17: Method Selection Criteria for Each Approach in Asian Currency Market

Approaches	**Method**	**VR**		**Kupiec**		**Christoffersen**	
		95%	**99%**	**95%**	**99%**	**95%**	**99%**
Non-Parametric /Parametric	HS	80%	44%	76%	36%	44%	84%
	Nor-Dist	88%	0%	80%	4%	36%	56%
	t-Dist	60%	36%	48%	80%	40%	60%
Time Varying Volatility	EWMA	96%	40%	80%	48%	28%	76%
	GARCH	40%	0%	36%	8%	60%	72%
EVT	BMM	0%	0%	0%	0%	4%	12%
	GPD (S)	96%	96%	96%	100%	20%	48%
	GPD (D)	0%	0%	0%	0%	52%	60%

violations are same. Only 44% cases are qualified independence test in Christoffersen. At 99% confidence interval, VR ratio correctly estimates exceptions in 44% cases. After running Kupiec test, 36% observed and expected violations are same. Whereas, 84% cases are qualified independence test and very few cases are found exception clustering.

Under the assumption of normal distribution at 95% confidence interval, VR ratio correctly estimates exceptions in 88% cases. The observed and expected violation are found in same in 80% cases when Kupiec POF test is applied. However, the Christoffersen test identified exception clustering in many cases and only 36% of the above qualified independence test.

At 99% confidence level, VR ratio failed to predict losses. It either over estimate or under estimate the risk. Kupiec test also supports the weak performance of normal distribution at 99% confidence interval.

In the case of t-distribution at 95% confidence interval, VR ratio is correctly estimated only in 60% cases. In 48% cases, observed and expected violations are same when Kupiec test is applied. The results of Christoffersen test shows that 40% cases qualify independence test. However, other 60% cases are found exception clustering. At 99% confidence interval, VR ratio is correctly estimated only in 36% cases which is lower than historical simulation and normal distribution. When Kupiec test is applied, 80% observed and expected violations are same.

However, Christoffersen test shows that 60% cases qualify independence test and remaining cases report exception clustering.

In EWMA based estimation at 95% confidence level, VR ratio is correctly estimated in 96% cases which is higher than other time varying volatility method i-e GARCH with just 40% correct estimation. Kupiec test also supports the strength of this model that in 80% cases the observed and expected are same which is also greater than GARCH based estimation with 36%. After running Christoffersen test to check independence of Asian currency market returns, only 28% cases qualify independence test and remaining 72% cases report exception clustering.

At 99% significance level, again EWMA based model estimated correctly VR ratio by 40% which is better than GARCH estimation with 0%. Other two tests are also support the strength of EWMA model estimation. In 48% cases, observed and expected violations are same which is greater than GARCH with 8%. The results of Christoffersen tests show that 76% cases are independent and only very few cases indicate exception clustering. While at this interval, GARCH estimation shows that 72% cases are free from clustering and that ratio is lower than EWMA.

The analysis of EVT based approach shows that GPD static perform better than block maxima and GPD dynamic at both 95% and 99% confidence interval. In 96% cases VR ratio estimation is correct. While other two models block maxima and GPD dynamic are failed to estimate the correct losses. Results of Kupiec test also support the strength of GPD static estimation. At 95% level of significance, the observed and expected violations are same in 96% cases. At 99% confidence level, 100% observed and expected violations are same but other two methods again failed to predict the losses at both 95% and 99% confidence intervals. Christoffersen test at 95% confidence level identify exception clustering in many cases and only 20% of the above qualify independence test and at 99% confidence interval only 48% cases qualify independence test.

Table 4.18 shows the recommended model from each approach at 95% and 99% level of significance.

At 95% confidence interval, normal distribution is a recommended method from parametric and non-parametric approach. According to table 4.18, analysis show

TABLE 4.18: Method for Each Approach in Asian Currency Market

Approaches	**95% Confidence Interval**	**99% Confidence Interval**
Non-Parametric/ Parametric	Normal Distribution	Historical Simulation
Time Varying Volatility	EWMA	EWMA
EVT	GPD Static	GPD Static

that normal distribution estimate losses more correctly than other parametric and non-parametric methods. Whereas, at 99% confidence interval historical simulation predict more correct losses than other parametric and non-parametric methods. Under the assumption of time varying volatility, EWMA performed better at both 95% and 99% confidence intervals according to the analysis in table 4.18. EVT talks about extreme tails, EVT based estimation shows that GPD static is better model for forecasting the risk on extreme tails at both 95% and 99% confidence intervals.

4.11 Method for 25 Asian Currency Markets

Table 4.19 shows the best method selected from conventional and EVT Approach at 95% and 99% level of significance for Asian currency markets.

TABLE 4.19: Method for 25 Asian Currency Market

Conventional Approach		**EVT Approach**	
95%	99%	95%	99%
EWMA	Historical Simulation	GPD Static	GPD Static

According to conventional approach at 95% interval, EWMA performed better so it is a recommended model to forecast correct losses. At 99% significance level, historical simulation predicts correct losses than other conventional method. However, for extreme tails analysis, better model for forecasting extreme losses is GPD static at 95% and 99% both confidence intervals with appropriate VR ratio.

Chapter 5

Conclusion and Recommendation

5.1 Discussion

VaR has been estimated for all Asian currency markets by using conventional approach including non-parametric i-e historical simulation, parametric i-e normal distribution, t-distribution and time varying volatility models i-e EWMA, GARCH at 95% and 99% confidence intervals. The forecasted risk estimated by each model is compared with each other, to find the best suited model for risk estimation in both parametric/non-parametric and time varying volatility models. The descriptive analysis reported non normality of data, which indicates that returns follow fat tails distribution.

For the estimation of parametric/non-parametric VaR, higher forecasted risk is reported by Iran in normal distribution at 95% confidence interval and UAE in t-distribution at 99% confidence interval. Whereas, lowest forecasted risk is reported by Iraq, Oman, Saudi Arabia, Qatar, Bangladesh in t-distribution at 95% and 99% both confidence intervals. Under the estimation of time varying volatility, maximum forecasted risk reported by Iran in GARCH at 95% and 99% confidence intervals. However, minimum risk reported under this assumption reported by Hong Kong in EWMA at 95% and UAE in GARCH and EWMA at 99% significance level.

To examine the validity that VaR models are providing true forecasting or not, different back testing approaches like VR ratio, VaR volatility, Kupiec test and Christoffersens test are applied. According to VR ratio, the normal distribution model reported minimum number of violations under 95% and historical simulation at 99% significance level in parametric/non-parametric approach. However, EWMA predict correct estimation under time varying volatility approach of VR ratio in 96% cases at 95% level and 40% cases at 99% level of significance.

VaR volatility under parametric/non-parametric approach at 95% confidence interval, normal distribution estimated average 0.49% volatility of entire Asian currency market during this period. Irani Rial reported highest volatility by 5.31% due the period. Under the time varying volatility assumption, EWMA reported 0.52% volatility and again Irani currency market is highly volatile by 5.55%. At 99% level of significance, historical simulation reported 1.32% volatility and Irani Rial reported maximum volatility by 19.06% under parametric/non-parametric approach. The results of time varying volatility shows that EWMA reported 0.85% volatility of Asian currency market and Irani Rial reported highest volatility by 7.85%.

When Kupiec POF test is applied to examine the accuracy of the models, the results of normal distribution estimation at 95% confidence interval show that the observed and expected violations are same in 80% cases higher than other parametric/non-parametric methods. Under the time varying volatility assumption, 80% null hypothesis are accepted. At 99% interval, historical simulation shows that 36% observed and expected violations are same in parametric/non-parametric assumption. Whereas, the results of time varying volatility shows that in 48% cases null hypothesis are accepted by EWMA.

Christoffersens test used to check the return behavior of violation of previous day is independent or not. Volatility clustering effect in parametric/non-parametric approach at 95% confidence level, normal distribution reported 36% of entire Asian currency markets return behavior is independent and under time varying volatility approach, only 28% of Asian currency market is qualified independence test by EWMA method. At 99% confidence interval, historical simulation reported only

16% clustering effect under parametric and non-parametric approach and 76% of Asian currency market is free from clustering effect reported by EWMA under time volatility assumption.

VaR estimation covers maximum interval of any distribution but it ignores the tails. To resolve this problem, expected shortfall is estimated. Under parametric/non-parametric approach, t-distribution is reported highest expected shortfall by Pakistani Rupee with 76.91% at 95% level and 401.03% at 99% level of significance. However, lowest expected losses in a day reported by Iraqi Dinar, Omani Rial, Saudi Riyal, Qatari Riyal and Bangladeshi Taka at both intervals. According to time varying volatility approach GARCH reported highest expected shortfall in a day by Irani Rial with 3.76% at 95% level and 4.86% at 99% confidence level. Whereas, minimum expected losses currencies are Saudi Riyal and Omani Rial at both confidence intervals.

To estimate the risk behavior of extreme left tail of Asian currency market, Extreme Value Theory (EVT) is used. Investors concern is more on extreme losses than average. EVT helps to cover all events which are extreme in nature. The outcome of EVT application is different from common outcome of traditional methods for risk forecast like VaR. Risk measurement through EVT approach is based on two methods, GEV follows block maxima approach and GPD follows static and dynamic approaches.

For the application of block maxima, the study picked top value of each period but in financial markets these violations and extreme events are not evenly spread. When bubbles are created in financial markets the market goes up or down for number of days. At the same time, there are crisis in the financial markets the extreme events concentrated at one point in time. If tails are not fat and longer because of low kurtosis, then EVT models do not work. Whereas, on high kurtosis EVT based models will be more effective.

Results of VaR estimation under EVT approach show that block maxima report maximum losses of 8.11% for Irani Rial at 95% confidence interval and 63.92% at 99% level. However, lowest losses are reported by GPD dynamic in various countries at 95% and 99% significance level. Back testing applied to check these models accuracy which shows that GPD static estimation is more correct in 96% of Asian currency market only the losses of Omani currency is over estimated at both 95% and 99% intervals. However, this study cannot compare VaR volatility under this approach because block maxima and GPD static assume constant volatility.

Kupiec POF test at 95% confidence interval under EVT approach shows that in 96% cases observed and expected violations are same in GPD static. Only Omani Rial is under estimated at higher end. However, at 99% significance level, 100% null hypothesis are accepted by GPD static. The Christoffersens test is used to examine clustering effect at 95%, the results indicate that 80% of Asian currency market have clustering effect and at 99%, only 48% of Asian currency market is free from clustering effect.

Finally, expected shortfall of EVT approach shows that in block maxima, maximum loss is suffered by Irani Rial with 30.62% at 95% level and 241.40% at 99% confidence interval. Whereas, GPD dynamic reports lowest expected shortfall in a day by UAE Dirham, Saudi Riyal, Qatari Riyal, Omani Rial, Kuwaiti Dinar, Taiwani Dollar, Philippines Peso, Bangladeshi Taka, Sri Lankan Rupee, Malaysian Ringgit, Indonesian Rupiah, Thai Baht, Indian Rupee, Iraqi Dinar and Israeli Shekel at both 95% and 99% confidence interval.

5.2 Conclusion

Risk management is integral part of decision making process. VaR is a common method for risk measurement. For the estimation of VaR, various methods are used. One model may not be suitable for all currency portfolios in the world because behavior of each currency market is different. Sometime variation in currencies are higher, somewhere currencies rates are constant or big shocks exist in some currencies. So appropriate model is required for each currency market according to its currency behavior. Confidence interval does matter for the selection of the model because level of significance effects the quality of results. On higher confidence interval, performance of the model become weaker.

EWMA based estimation is more correctly estimation in both confidence intervals in conventional approach. The basic assumption of EWMA model is volatility is time varying. There is highest acceptance ratio of null hypothesis of Kupiec POF and Christoffersen independence lest, which shows that the market is highly volatile and need a Time Varying Volatility based model which estimate risk more accurate in normal market conditions. The analysis of EVT based approach in extreme market conditions shows that GPD static perform better and estimate more correctly at both confidence intervals.

Currency markets behavior is different from other financial asset markets. There is no free floatation because there are many regulatory interventions in buying and selling of currency. Central bank of a country manages floatation of currency. The information is in chunks that some periods are stable and some are not. All methods designed on this assumption that currency prices correctly reflect relevant information in the market. But due to interventions, prices of currencies become over/under valued. So these models should be used vigilantly in currency markets because nature of currency market is different from stock and other financial markets. If any country manages currency and it is stables its currency artificially at 1 year then VaR will be 0. On the other hand, in Pakistan, in 2004-2006 currency data, it was stable at Rs. 60/USD and VaR value will be very low. Then in 2007-2008 data, currency value falls almost 37

5.3 Recommendation

The finding of this study shows the results are mixed with the highest success rate at 95% and 99%. For conventional approach, EWMA is more suitable method at 95% and historical simulation is forecasting more accurate estimation of VaR at 99% level of significance. For EVT approach, GPD static method performs better for both intervals because this model provides more true estimation of extreme loss forecasting in left tail of distribution. Most risky currencies are Turkish Lira and Irani Rial and less risky currencies are UAE Dirham, Omani Rial and Saudi Riyal.

However, the estimation of VaR of the Gulf currencies (Omani Rial, UAE Dirham, Irani Rial and Iraqi Dinar) is an issue due to very low volatility in currency price. The results of these currencies unable to capture market dynamics. There is no free float in these currency markets. Most of transaction are done in only one commodity which is oil. Currency price has constant with US dollar through manage float. When governments preferred manage float or artificially stabilize their currencies then VaR model does not work on forecasting the financial risk because VaR model give better results on free floating currency markets.

Investor can form its investment portfolio according to risk tolerance. The investors who have high risk tolerance can invest in more risky currencies like Irani Rial and Turkish Lira and the investors who have low risk tolerance, can invest in Gulf currencies due to their stable currencies. Risk estimation models are failed in Omani Rial and Sri Lankan Rupee to identify the appropriate model because these countries manage their currencies through manage floating. Regulators can use EWMA model at 95% confidence interval for normal market conditions and GPD Static at 95% and 99% confidence intervals for extreme market conditions. Other stakeholders and institutions should not ignore country specific dynamics.

5.4 Directions for Future Research

The risk and return forecasting approaches may fail to estimate accurate losses of any financial series (Omari et al., 2017) specially in currency market where governments stabilized their currency rate artificially through manage float. Basic assumption of risk forecasting is data is normally distributed because currencies are fairly priced. Moreover, each method uses different assumptions and techniques in order to come up with the probability distribution of possible outcomes.

Secondly, there are some observations that VAR is not the good estimator of risk because it ignores to measure the maximum loss which may lie in 1% uncovered area (may be 2-3 days in a year) (Uylangco and Li, 2016). For the good and correct estimation of risk, need to conduct a comprehensive study on conditional VaR (ES) and its detailed back testing for better risk estimator method.

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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