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Value at Risk in Islamic Banks – An Evaluation of Extreme Behaviour and Capital Requirements

by

Zeeshan Arif

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I wish to take this opportunity to dedicate this humble effort to The Holy Prophet Hazrat Muhammad (P.B.U.H), the greatest social worker, whose every tear was for the cause of humanity. And I would also like to dedicate this to the unfathomable love, unflinching support, prayers and steadfastness of my beloved parents who have been a beacon house for us for the whole of our lives, who have always guided us to the right path, the path of struggle, hard work, truthfulness and honesty.

CERTIFICATE OF APPROVAL

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Abstract

The main idea behind this research is to estimate Value at Risk (VaR) using various risk forecasting models for one day for top 20 Islamic Banks of the Gulf Cooperation Council (GCC) and the listed Islamic Banks of Pakistan. Initially five conventional models are applied to estimate VaR for whole distribution and three Extreme Value Theory models to estimate the risk of the tail distribution only to capture non-normality of financial data. Back-testing is done to identify the models capturing fair picture of risk estimation. This study uses data for Islamic Banks from 2000 to 2018. By comparing all the conventional risk estimation models, Exponential Weighted Moving Average (EWMA) better forecasts the risk for Islamic Banks in the GCC and Pakistan. For estimation of the tail risk, Generalized Pareto Distribution (GPD) with static VaR outperforms the other models. Considering the adequacy of capital requirements, it is recommended that the regulators should take into account the individual risks of the financial institutions and accordingly make necessary amendments to the capital requirements.

Key words: Extreme value theory (EVT), Generalized Pareto distribution (GPD), Exponential Weighted Moving Average (EWMA), Back Testing, Value-at-risk (VaR).

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Abbreviations

BMM	Block Maxima Model
CVaR	Conditional Value at Risk
ES	Expected Shortfall
EVT	Extreme Value Theory
EWMA	Exponential Weighted Moving Average
GARCH	Generalized Autoregressive Conditional Heteroscedasticity
GEV	Generalized Extreme Value
GPD	Generalized Pareto Distribution
HS	Historical Simulation
N-Distribution	Normal Distribution
POF	Point of Failure
VaR	Value at Risk

Chapter 1

Introduction

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

1.1 Theoretical Background

Since the inception of times, people have been interested in investments that give good returns. Along with the interest in the returns, the investors are also interested in the magnitude of risk they have to assume while making any investment. Financial institutions offering such investments are prone to risks due to economic, social, political or socio-political changes in the environment, hence fluctuating the risks and returns on the investments.

With the global financial crisis of 1990 and 2007-2008, the entire world has become more cautious with respect to the risk in the investments, so are the financial institutions who offer such investments. The basic experience gained after the occurrence of every crisis and loss of millions of dollars is to devise a way to manage risk before time. This can only be possible by strong supervision by the regulatory bodies. In this regard the concept of Value at Risk (VaR) emerges as a result of the financial crises in the 1990s and gains much attention with respect to risk management. VaR actually tells the maximum potential loss, at a specific time period at a certain level of confidence. It gains popularity with time as it is summarizes the quantity that depicts the entire market risk of any entity. Financial markets have become sensitive ever since and hence highly volatile. Therefore the researchers have spent a good amount of time identifying various methods of risk assessment, devising ways of risk management and verifying it via some tests. At the same time the regulatory bodies have put immense pressure and focus on the financial institutions for maintenance of capital up to a certain level to bear the consequences of the risks in case of crisis.

After the VaR concepts are introduced in the market and efforts are made to estimate and manage risk timely, again the crisis of 2007-2008 happened, leaving all the financial institutions to bankruptcy. It is again a time when the models for risk estimation fail and the concept of Extreme Value Theory (EVT) gains more importance, as it estimates the risk in the extreme and crisis situations. Since VaR assesses the risk of the entire distribution, whereas EVT assesses the risk in the extreme crisis situations, so as to say that EVT focuses only on the tail distribution.

In recent years, the financial markets have experienced exponential growth coupled with significant extreme price movements such as recent global financial crisis, currency crisis and extreme default losses. Value-at-risk is widely used as a risk forecasting tool all around the globe, specially in the financial institutions industry. It is the worst estimated loss, may be the change in asset valuation or a portfolio at a given confidence level. Different VaR models are adopted for risk forecasting with different distributional assumptions. After risk estimation, different back testing techniques are used to check accuracy of VaR models and eventually risk mitigation and management strategies are devised by the regulatory bodies in order to overcome the assessed risk.

Numerous perspectives render risk management a vast concept. Involving the mathematical perspective, risk management can be termed as a procedure for carving shape to a loss distribution. VaR is a distribution independent method to identify risk statistically and also the most commonly used method now, especially in the financial market. Although it also has some of the limitations, yet it is the first choice to estimate risk in the financial industry (Berkowitz et al., 2011). Keeping in view the theoretical properties and considering the issues in applying these models and easy methods for back-testing, the reason becomes quite evident. VaR gives the best equilibrium among the other methods of risk estimation that are available and hence constructs most practical risk models (Gençay and Selçuk, 2004). With the advancement in information technology and ease of availability of financial data, now various other methods of VaR estimation have also been derived.

With the same confidence level, there is a good relationship between VaR and Conditional Value-at-Risk (CVaR). VaR is related as lower bound for CVaR, whereas CVaR is coined as popular risk management tool. CVaR is also a risk estimation tool like VaR, which is a potential measure of a worst case loss scenario (Rockafellar et al., 2000).

The techniques of value-at-risk and stress testing for risk measurement are by now well developed. Until its appearance in the Group of Thirty report published in July 1994 (of Thirty, 1994), and the release of the first version of Risk Metrics in October 1994 (Morgan, 1997) value-at-risk is almost unknown except for being used by the large derivatives dealers whereas now it is difficult to find financial professionals who are not acquainted with VaR. Presently, VaR is in use by banks of all types and sizes, pension plans, fund managers, brokerage firms, and other institutional investors, insurance companies, other financial institutions and non-financial corporations.

Stress testing is used in conjunction with value-at-risk and is almost equally well accepted as the complementary risk measurement methodology. Three approaches to computing value-at-risk are proposed initially at the outset i.e. Monte Carlo simulation, historical simulation and variance-covariance method, for which repricing entire portfolio for each factor realization is required (Raei and Cakir, 2007). While these three techniques remain the basis of value-at-risk computations, the years since their outset, release of Risk Metrics have witnessed significant refinements of and elaborations upon these approaches.

EVT based approaches have in the recent past been considered in finance to address the shortcomings of the conventional techniques as well as improve the estimation of VaR. The EVT theory focuses on modeling the tail behaviour of the distribution instead of the entire distribution of observations. Modeling extreme values has become popular in financial risk management since it targets the extreme events that happen rarely but have catastrophic effects such as market crashes, currency crisis, and extreme default losses. EVT provides a robust framework for modeling the tail distributions and it does for the maxima of independently and identically distributed (i.i.d.) random variables what the central limit theorem (CLT) does for modeling the summation of random variables and both theories give the asymptotically limiting distributions as the sample increases (Omari et al., 2017).

Islamic Banks operate on the basic principles of Shariah and have all their policies and procedures that are Shariah complaint. As per the Shariah laws, the receipt and payment of Riba (interest) is prohibited, which means these banks are not allowed to receive or pay interest on all the financial transactions that they make. As a result to this, these banks use instruments that are Shariah compliant and that are not used by other conventional banks around them (Harzi, 2011). The market risk for Islamic banks is more or less similar to that of the conventional banks, but it has two different dimensions. The first one constitutes the processes and procedures that are similar to conventional banks but do not oppose the Shariah laws, and the other ones are the processes and procedures specifically tailored as per the Shariah laws and regulations (Akhtar et al., 2011).

Although Islamic banks are different in nature from the conventional banks when it comes to their structure of financial statements, financial instruments and even financial intermediaries, yet they are prone to the same financial risk as conventional banks and the same methodologies for the estimation and management of financial exposures.

The analysis of conventional banks traditionally is done by running some mathematical procedures and using certain tools to assess whether the performance of the banks is up to the mark or not. This is usually done with the help of certain ratios. These ratios include capital adequacy ratios, liquidity ratios, investors related ratios, capital structure related ratios, open foreign exchange positions, leverage and quality of portfolio related ratios, etc. Although these ratios tell a lot about the entities and their financial position, but less do they tell about the entity's risk and exposure. The main technique for assessing the risk is however the detailed analysis of banks' balance sheets. For this detailed analysis the ratios are used in combination with other risk assessment techniques, which are later used for management of the same risk exposure as well (Van Greuning and Iqbal, 2007).

For a bank's profile, the risk assessment includes the calculation and maintenance of a certain Capital Adequacy Ratio. This ratio constitutes the first point of the Basel II Accord. According to this principle, the capital at a bank should be related to its risk profile. There are three components of the capital adequacy requirement, i.e. operational risk, market risk and credit risk (Van Greuning and Iqbal, 2007).

After the occurrence of the previous financial crunch, the Basel Committee on Banking Supervision, (BCBS), an entity operating internationally with the objective of finding ways to identify appropriate risks and recommend appropriate reforms against those risks to be able to avoid future crises from happening, issued certain postulates, which they named as the Basel III new framework. It contains some of the major reforms that if applied, may save economies from big financial crises. USA and European Union have appreciated this effort and tried to incorporate these reforms in their legislative frameworks. With the implementation of Basel III reforms, the financial institutions have to, now, do a lot of amendments in the way they used to do things, like the calculations of certain ratios previously, and addition of new calculations, in addition to some set standards that these financial institutions need to maintain to be able to comply with the Basel III regulations (Harzi, 2011).

As per requirements of the State Bank of Pakistan (SBP), the Bank is required to comply with the capital adequacy framework which comprises of the Minimum

Capital Requirements (MCR) and Capital Adequacy Ratio (CAR). MCR defines the minimum paid-up capital that the bank is required to hold at all times and CAR assesses the capital requirement based on the risks faced by the bank. The banks are required to comply with the CAR requirements on a standalone as well as consolidated basis. The SBP issued these instructions based on BASEL III Capital Reform as published by the Basel Committee on Banking Supervision. These instructions are effective from December 31, 2013 will full implementation intended by December 31, 2019.

As per the BASEL Committee, all the banks have to maintain up to a certain level of capital to absorb prospective losses and continue to run as going concerns. This is because in the recent crisis situations, the banks have incurred losses much more than the value of the capital maintained by them for this purpose (Varotto, 2011).

1.2 Gap Analysis

Various Value-at-risk methods including non-parametric method (Historical Simulation), parametric methods (student t-distribution and normal distribution), through time-dependent volatility models (GARCH, EGARCH, TARCH) individually tested by (Berkowitz and O'Brien, 2002), (Webwe and Diehl, 2016), (Ball and Fang, 2006), (Yildirim, 2015) and (Vlaar, 2000), etc. and also using Extreme Value Theory (GEV & GPD methods) applied by (Bekiros and Georgoutsos, 2005), (Huang et al., 2017), (Kuester et al., 2006), etc. are not jointly evaluated in any study and specifically on Islamic Banks. This study tries to bridge this gap. It does so by giving more understanding of the Islamic banks characteristics and depict the need of considering the more appropriate model in risk management based on our outcomes in order to suggest the appropriate method for risk estimation in banking industry and Islamic Banks specifically. This would be better for the purpose of calculating and hence maintaining the appropriate capital adequacy level by the banks in compliance with the instructions from their respective regulatory bodies .

1.3 Problem Statement

The problem of the choice between different approaches to calculate VaR, especially in financial risk management, has been quite highlighted in academic literature. Reasons affecting the choice between these models are based on the differences in mathematical properties, statistical estimation stability, simplicity of optimization procedures, and acceptance by regulators, etc. Conclusions drawn from these properties may be quite contradictory.

While identifying which method performs better in estimating VaR, as compared to others, not a single method clearly outperforms other method, and is rejected by at least one test. As a consequence, the uncertainty of VaR forecasts and their validation are important domains that still deserve more research in order to get more conclusive results on the performances of alternative procedures.

1.4 Research Questions

Following are the research questions formulated for this study:

- How do non-parametric and parametric models of Value-at-Risk perform in determining the loss in Islamic Banks?
- How does Extreme Value Theory based models perform in determining the Value-at-Risk in Islamic Banks?
- Which model is the most appropriate in capturing the value at risk for Islamic Banks in general?
- Is performance of models consistent across banks?
- Are existing capital requirements adequate?
- Are Pakistani Islamic banks riskier than major GCC Islamic banks?

1.5 Objectives of the Study

The objectives of the current study are listed as under:

- To estimate value at risk by applying conventional measures of VaR estimation.
- To study the tail behavior of the fat tailed distributions using EVT.
- To propose risk estimation models for Value-at-Risk on the basis of back testing.
- To evaluate the existing capital requirements proposed by Basel accord.
- To compare the risk profile of Pakistani Islamic banks with major Islamic banks from GCC.

1.6 Significance of the Study

Risk management is very crucial when it comes to investors. Over the period of time there have been different methods introduced, to calculate risks. But the process of risk identification and calculation is so sensitive that the methods keep on getting out dated, as they are applicable for a certain period of time generally or, to a specific domain. To be able to apply appropriate risk management techniques, it is first important to measure risk appropriately for which this study helps in the identification of the appropriate approach and appropriate method to do so.

This study is a significant contribution in the sphere of risk measurement techniques evaluation on the basis of validation of models through back-testing. The empirical analysis is to be performed on stock prices of the Islamic banks in order to compare the performance of all the approaches in the study gives more comprehensive insight. This study helps us in identifying which confidence interval should be used while the calculation of VaR. The precise prediction of VaR measures has important implications towards financial institutions, fund managers, portfolio managers, regulators, business practitioners and investors. It helps the investors in beter decision-making to identify avenues for future investments, and also to calculate the risks of their current investments. For fund managers, portfolio managers and such other financial institutions this study helps in assessing risks for the assets in their portfolios, so they can manage their portfolios better and hence get the investors the magnitude of returns, they expect. As for the regulatory bodies, this study helps in the identification of the optimum level of capital maintenance requirements.

In addition to above, this study results in assessing whether the Pakistani Islamic banks are riskier than the major Islamic banks of GCC or not and accordingly whether the existing capital requirements adequate in the scenario tested. As per the BASEL Committee of Banking Supervision the level of capital maintained by each bank is based on the risk associated with that bank and the risk is calculated by calculating VaR. Hence, better and accurate the estimation of VaR, better and accurate shall be the approximation of capital to be maintained, as suggested by the regulatory bodies.

1.7 Plan of Study

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

Chapter 1: It focus on the fundamental idea of the study. This section introduces topic by providing basic information, problem statement, gap analysis, research questions and objectives and significance of this research 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: This chapter 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 summarizes research outcomes and recommend different risk forecasting models according to market conditions.

Chapter 2

Literature Review

This chapter exhibits past research carried out on the estimation of VaR using the parametric, non-parametric, time dependent volatility methods and also the methods using the EVT theory for the estimation of VaR.

2.1 VaR via Parametric, Non-Parametric & Time Dependent Volatility Models

VaR has emerged as one of the most vital tools to estimate risk in the recent past, especially in the financial services industry that includes banks and insurance companies. An overview of literature provides that a lot of research has been conducted already on risk estimation and management using different models and techniques. Especially through the European financial regulations, the use of VaR for risk estimation in the banking and insurance industry is no longer an option, but has been declared mandatory (Dos Reis et al., 2010).

Bohdalová (2007) states that VaR can be used for a variety of tasks such as setting targets for risks and then measurement later on, at different stages of an entity's operations and the risk should be estimated every time before entering into any deal by the entity. According to Bohdalova, VaR estimation can be used as a very vital tool but it should not be made mandatory by the regulatory bodies.

The research conducted by Bao et al. (2006) mentions that during the crises period, the risk estimation methods act differently. However, before and after the crises period, different models for risk estimation act in a similar fashion and report similar risk values. Ufer (1996) states that the concept of VaR is gaining strength with a good speed, especially in the financial institutions industry and is slowly becoming an industry benchmark. With the concept being widely used, it is becoming a worldwide best practice, whereby the entities are not reporting their risk assessments for merely their regulators, but also for their client reporting as well. Volatility is the uncertainty or change in returns. So, in order to measure the extent to which an asset or a portfolio of assets move with the general market, VaR should be used, which is a simple technical method to identify the worst possible loss that may occur at a certain level of probability (Mahjundar, 2008).

Berkowitz and O'Brien (2002) work extensively on a large sample from the banking industry to evaluate the performance of risk management using various VaR models to check the accuracy of these models. A lot of studies have already examined these models to identify the best fit for financial industry. In another study, VaR is used to identify possible losses in the risk management process for insurance companies and it is identified that VaR is a better model for risk estimation than other models – it is easy, simple to understand with ease of implementation (Webwe and Diehl, 2016).

In another study the VaR estimation and risk management for the banking industry is studied in detail by Ball and Fang (2006). From the conventional methods of estimation VaR, a study conducted by Yildirim (2015) estimates the foreign exchange risk in the financial institutions. The results obtained through Historical Simulation method are a little higher than the Monte Carlo Simulation method. Similarly the losses estimated for a 10 day holding period are exceeding the ones for a single day holding period. However the VaR estimates studied in this research do not affect the capital requirements adversely.

Another study is conducted to estimate VaR on Dutch interest rates and multiple methods are used in the study, including Historical Simulation, Variance-Covariance method and Monte Carlo Simulation, etc. The results reveal that the best results are obtained by combining variance-covariance method with Monte Carlo Simulation and using GARCH and normal distribution and worst results are obtained by using t-distribution method (Vlaar, 2000).

Abad et al. (2014) use several VaR models to estimate risk. These models included Historical Simulation method, variance-covariance method, Monte Carlo Simulation method and EVT methods with student t-distribution of returns on stock indices. As per their research variance-covariance method performs the best, out of all the methods studied, which is estimates by asymmetric GARCH model. Successful VaR estimated can be fetched through parametric models if estimates of conditional variance are accurate.

In another research various GARCH methods are studied to calculate VaR under the global financial crises period for various countries from the emerging and developed markets. Back testing is also conducted using Kupiec and Christofferson tests and the results reveal that ARCH method is the best one to calculate VaR, and GARCH (1,1) and student t-distribution methods followed it and the worst results are reported by normal distribution approach (Orhan and Köksal, 2012).

Lin and Shen (2006) conduct a research to estimate VaR using the student t-distribution approach and to investigate how the results are, on the basis of back testing. The results reveal that this method turns out well for VaR estimation, provided the confidence interval exceeds 98.5 % and the tail index technique is used to determine the degree of freedom.

Another study in which various VaR methods are applied to calculate VaR is conducted in 2013. In this study seven methods are applied collectively to estimate VaR from the GARCH family on the exchange rates and different market indices. It included parametric methods, semi-parametric methods and non-parametric methods. Back testing is conducted to check the reliability of the results shown by these methods. The results reveal by applying fat-tail distributions and asymmetric methods, the results of VaR calculations can be improved as Exponentially Weighted Moving Average shows the worst results and that the application of GARCH method is dependent on various assumptions of return distributions (Romero et al., 2013).

Krämer and Wied (2015) propose a new method of back-testing models for value at risk and suggest a simple improvement of recent VaR-back-testing procedures based on time intervals between VaR-violations and depicts through Monte Carlo that the test has more robustness than its competitors against numerous empirically relevant clustering substitute options. The large values of the Gini coefficient of durations between VaR-violations have been rejected by the test. Many deviations from independence of VaR-violations are countered by it.

So and Philip (2006) conduct a research using two long memory GARCH models and RiskMetrics to estimate VaR in the exchange rate market as stock market indices from various countries. The results reveal that RiskMetrics is better at estimating 1% VaR and also that no asymmetry is observed in exchange rate data but there is asymmetric behaviour found out in the data from the stock market indices.

M-estimators are used for generalized autoregressive conditional heteroskedastic (GARCH) type models for forecasting of value-at-risk (VaR) of Karachi Stock Exchange (KSE). Symmetric and asymmetric GARCH models are fitted to these pre, during and post crisis time periods and in-sample and out-of-sample estimates of VaR are obtained. The findings show that M-estimators provide accurate and reliable estimates of VaR in low and high volatile time and the asymmetric model provides better fit than the symmetric model for the KSE (Iqbal, 2017).

Another research is conducted to calculate VaR for three samples – a period before crises, the post crises period and the full sample. Various GARCH models are applied for this research at 1% and 5% probability levels. Back testing methods using Kupiec and Christofferson tests are also conducted to check the reliability of these models. The results show that it is very difficult to identify and recommend one model of VaR calculation for all these scenarios studied, however, RiskMetrics performed best for pre-crises sample, GARCH (1,1) performed best (Ragnarsson, 2011).

Another research is conducted on sensitivity of the VaR and Conditional VaR models with non-normal distribution, on three market indices, i.e. BSE Midcap, S&P 500 and BISE Small Cap. The period under the study is the recession and the post-recession period. GARCH method is used and back testing is also conducted. The results reveal that VaR volatility is inversely proportional to market capitalization. Moreover, the liquidity of the firms is inversely proportional to the VaR of those firms (Sinha and Agnihotri, 2014).

Wang and Zhao (2016) analyzes semi parametric CVaR computation and inference for parametric model with nonparametric noise distribution. A bootstrap approach is introduced to facilitate non-expert users to perform confidence interval construction for CVaR. This methodology is explained through Monte Carlo studies as well as an application to S&P 500 index.

Walther (2017) analyses the conditional volatility of the VN-Index and the HNX-Index with a special focus on their application to risk management tools like Expected Shortfall. The study perform test on both indices for long memory in their returns and squared returns and then applied some Generalized Autoregressive Conditional Heteroskedasticity (GARCH) models to account for asymmetry and long memory effects in conditional volatility. When back tested the GARCH models' forecasts for Value-at-Risk and Expected Shortfall, long memory in returns is not obtained yet it is found in the squared returns. Differences are found in both indices for the asymmetric impact of negative and positive news on volatility and the perseverance of shocks. Long memory models show best performance when estimating risk measures for both series.

Backtesting is an approach to validate the performance of a VaR estimation method. It has both conditional and unconditional approaches. The conditional approach (Christofferson Test) is used to identify whether there is clustering in the returns data and the unconditional approach (Kupiec Test) shows whether the actual violations fall within expected violations range or goes beyond that. And on the basis of this a method of VaR estimation is termed as a good method or not. Blanco and Oks (2004) conducted a research and gave an overview on the qualitative and quantitative approaches towards backtesting.

Campbell et al. (2005) conducts a research on the conditional and unconditional backtesting methods and concludes that the methods that can examine several quantiles are the best methods for VaR estimation.

Another study on a sample of Indian banks for the application of various backtesting methods is conducted by Patra and Padhi (2015). This study identifies the presence of ARCH effect and long-memory effects in daily BANKEX returns. Various methods for VaR estimation are used in this study too, that include APAGARCH, FIEGARCH, HYGARCH and RiskMetircs. Backtesting methods like Kupiec and Christofferson tests are conducted and the results show that the BANKEX returns have both asymmetry and long-memory effects.

A study by Nieppola et al. (2009) is conducted for VaR estimation and conducted on stocks of various companies. Conditional and Unconditional backtesting methods are also applied to identify the validity of the VaR estimation models to identify which backtesting methods works better in identification of a suitable VaR estimation method. Results revealed that conditional coverage test report better results as compared to unconditional coverage test, since the latter suggest an underestimation of risk for the stocks of those companies.

Virdi (2011) also conducts a research to critically evaluate the backtesting methods. In order to do that, the critical assumptions and features of various backtesting methods are studied to check their accuracy level. Ninety five securities are examined for the period of 2007-08. The results of this study revealed that none of the existing backtesting methods is good enough to be used for the identification of best VaR estimation model. However, the regulatory bodies still use these to different the good VaR estimation models from the bad ones.

Risk management has been one of the most important areas to look into both for individuals who seek guidance to invest in some stocks, shares or bonds or for financial and non-financial institutions. The concepts of VaR and Conditional VaR have gained much attention over the past few years as investors are interested in the risky side of the investment, more than the profit magnitude. In this respect researchers use both VaR and Conditional VaR (CVaR) methods for risk estimation as recommended by the Basel Committee on Banking Supervision (BCBS) (BIS, 2019).

VaR estimates the risk at a specific threshold level but if an investor is interested to know the risk magnitude beyond that threshold limit, CVaR is used. A study is conducted to estimate risk on the Malaysian industry using different non-parametric and parametric methods and calculated both VaR and CVaR. Backtesting methods are also applied on the VaR and CVaR models. The results reveal that the VaR models underestimated the risk, whereas the CVaR models overestimated the risk. Hence the choice for the best model, lies with the firm and their mind-set, whether they are risk takers or risk averse (Dargiri et al., 2013).

Banihashemi and Navidi (2017) conduct another study for risk assessment using both VaR and CVaR models. The study employs methods like Historical Simulation and Monte Carlo method to identify efficiency of companies with respect to risk assessment and risk management. Their study concludes that CVaR is a better measure of risk assessment as compared to VaR, semi-variance and variance because these methods project the downside risk measure. Another study conducted on the comparison of VaR and CVaR methods for risk estimation shows that CVaR is a better model to identify risk in firms (Kerkhof and Melenberg, 2004).

Rockafellar et al. (2000) conducts a research on the CVaR methods for risk estimation and used linear programming to reduce the risk using CVaR. According to this study CVaR is a better model to be used by brokerage firms, financial institutions, investment companies, mutual funds or such other businesses.

Another study conducted on the similar subject for banking sector, evaluated VaR and CVaR models simultaneously, using the linear programming approach. The results reveals that CVaR is very useful in the banking sector, also that the banks should have enough capital to respond to unexpected losses and they should have enough reserves to cater to the expected losses (Andersson et al., 2001).

2.2 VaR under EVT Models

Most statistical methods used in risk management deal with the estimation of VaR keeping in view the entire distribution of observations. While doing this, the major observations lie in the center of the distributions. Hence giving a fair idea of the center part, and not giving proper focus and attention to the tails region. In certain cases where extreme scenarios occur the estimation of VaR through normal statistical methods give inaccurate estimate of the distribution at tail regions (Danielsson, 2011).

Here the concept of Extreme Value Theory (EVT) is introduced. EVT focusses on the extreme tails, to estimate the risk of extreme instances and hence manage risk appropriately. An interesting fact about the EVT models is that these do not assume about the return distributions prior to the calculations.

The concept of EVT is first introduced by Jansen and De Vries (1991) and Koedijk et al. (1990). Later on more detailed working on EVT is conducted by Embrechts et al. (1999) and a summarized version is presented by McNeil (1999).

A comparative predictive performance evaluation of a selection of VaR models with special reference to the recent emerging market financial turmoil is conducted which covers the financial crisis in Asian economies. A systematic ranking among the models could not be revealed. For different countries, different periods, different tail probability levels, and for different evaluation criteria, different risk forecasting performances are obtained. Christofferen tests and reality check, both show that Monte Carlo methods and ARCH models generally produce more consistent and satisfactory risk forecasts than EVT models but none of the methods studied exhibits consistently superior predictive ability for all countries and periods (Bao et al., 2006).

Similarly, Bekiros and Georgoutsos (2005) have also conducted a comparative evaluation of the predictive performance of various models for Value-at- Risk (VaR). Special emphasis is paid on two methodologies related to the Extreme Value Theory (EVT) i.e. the Peaks over Threshold (POT) and the Blocks Maxima (BM). The results reinforce previously obtained ones, accordingly traditional methods might yield same outcomes at conventional confidence levels but at very high ones the EVT methodology produces the most accurate forecasts of extreme losses.

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

Acerbi et al. (2001) review some classical arguments which are revealed in the recent years in the debate on Value at Risk (VaR) as a tool for evaluating the financial risks of a portfolio and analyzes an alternative measure of risk, which is a version of the Expected Shortfall used in Extreme Value Theory and the comparison between the two risk measures is made on a more technical ground by analyzing some mathematical characteristics that have a significant part in the explaining a risk measure.

A comparison of the out of sample performance of current methods and few new models for univariate forecasting of value-at-risk (VaR) using more than 30 years of the daily return data on the NASDAQ Composite Index found inadequacy of most approaches. Moreover, a hybrid method which combines a heavy-tailed generalized autoregressive conditionally heteroskedastic (GARCH) filter with an extreme value theory-based approach shows best performance overall followed by a variant on a filtered historical simulation, and a new model based on heteroskedastic mixture distributions (Kuester et al., 2006).

Nawaz and Afzal (2011) find how the margin calculated on VaR impact the Volume of trade for Pakistani bourse. Pro method is considered to be more accurate one than other two models for five hundred days at 99% confidence interval. Based on the study it is found that in the case of Slab System, the initial margin charged by the clients fell between 5 and 25%. It has been observed that the cap of margins under VaR system is about 5%. The VaR based margin system has shown to be better than slab system based on the theoretical as well as empirical grounds.

Which is the best model for forecasting risk is a question that needs to be figured out still. As yet, nobody has answered this question. Different studies have proposed models to be accurate in different circumstances. Hence this study focuses on performance of various models in prediction of VAR and their validation is done through back-testing to suggest the most appropriate model for risk identification and measurement.

Chapter 3

Data Description and Methodology

The following chapter includes data description and methodology of this research.

3.1 Data Description

The sample comprises of the share prices of top 20 listed Islamic Banks in Gulf Co-operation Council (GCC) based on their credit ratings from Fitch valid up till July 31, 2017, conducted on the banks' financial statements dated December 31, 2016. Daily data is used in this research and is obtained for the period of 2000 to 2018 from www.investing.com. The banks include Kuwait Finance House, Qatar Islamic Bank, Abu Dhabi Islamic Bank, Barwa Bank, Ahli United Bank (Kuwait), Qatar International Islamic Bank, Boubyan Bank, Al Rajhi Bank, Dubai Islamic Bank, Warba Bank, Sharjah Islamic Bank, Bank Aljazira, Masraf Al Rayan, Kuwait International Bank, Alinma Bank, Bank AlBilad, Al Baraka Banking Group, Bank Nizwa, Bahrain Islamic Bank and Khaleeji Commercial Bank. The sample also includes listed Islamic banks from Pakistan that include Meezan Bank Limited and BankIslami Pakistan Limited. This list is obtained from the Islamic Banking Bulletin issued by the Islamic Banking Department at the State Bank of Pakistan in June 2018.

TABLE 3.1: Sample Description

Bank Name	St Ex Code	Country	Founded in	Period	No. of Obs.
ISLAMIC BANKS IN GCC					
Abu Dhabi Islamic Bank	ADIB	UAE	1997	2012-2018	1562
Ahli United Bank (Kuwait)	AUBK	Kuwait	1971	2006-2018	2799
Al Baraka Banking Group	BARKA	Bahrain	1978	2006-2018	1388
Al Rajhi Bank	1120	Saudi Arabia	1957	2000-2018	5000
Alinma Bank	1150	Saudi Arabia	2006	2008-2018	2620
Bahrain Islamic Bank	BISB	Bahrain	1979	2000-2018	1774
Bank AlBilad	1140	Saudi Arabia	2004	2005-2018	3447
Bank Aljazira	1020	Saudi Arabia	1975	2010-2018	1610
Bank Nizwa	BKNZ	Oman	2012	2012-2018	1589
Barwa Bank	BRES	Qatar	2008	2006-2018	3199
Boubyan Bank	BOUK	Kuwait	2004	2006-2018	3121
Dubai Islamic Bank	DISB	UAE	1975	2001-2018	4451
Khaleeji Commercial Bank	KHCB	Bahrain	2004	2008-2018	1594
Kuwait Finance House	KFH	Kuwait	1977	2000-2018	4462
Kuwait International Bank	KIBK	Kuwait	1973	2000-2018	4454
Masraf Al Rayan	MARK	Qatar	2006	2006-2018	3102
Qatar Intl Islamic Bank	QIIB	Qatar	1990	2000-2018	4440
Qatar Islamic Bank	QISB	Qatar	1982	2000-2018	4447
Sharjah Islamic Bank	SIB	UAE	1976	2012-2018	1425
Warba Bank	WARB	Kuwait	2010	2013-2018	1296
ISLAMIC BANKS IN PAKISTAN					
BankIslami Pakistan Ltd	BIPL	Pakistan	2004	2012-2018	1605
Meezan Bank Limited	AMZN	Pakistan	1997	2012-2018	1561

3.2 Methodology

The methods for Value at Risk (VaR) and Expected Shortfall (ES) can mainly be divided into the following categories. Estimation using the non-parametric method, parametric methods, time varying volatility methods and Extreme Value Theory (EVT) methods. Non-parametric method generally involves the use of Historical Simulation method, Parametric methods include the use of N-distribution and Student t-Distribution methods, Time Varying Volatility methods include Exponential Weighted Moving Average (EWMA) method and GARCH and EVT methods include Block Maxima Method (BMM) using the Generalized Extreme Value (GEV) distribution and the Peak-Over-Threshold (POT) method using the Generalized Pareto Distribution (GPD) distribution.

The non-parametric approach, i.e. Historical simulation (HS) is one in which no statistical model is applied. It is based on a simple proposition that history repeats itself. Therefore it is assumed that the pattern of returns in the past will continue to follow in the future too. On the other hand, the parametric methods have underlying assumptions that use the return distributions to estimate VaR and ES. These methods generally involve the calculation of covariance matrix where MA, GARCH or EWMA approaches are used to calculate this. Mostly they are used in connection with student t-distribution and only sometimes with normal distribution. Therefore, these methods are also known as variance-covariance approach. Lastly the EVT models tend to estimate the risk at the extreme ends of the tails of the distribution.

The above mentioned models are applied on the daily returns data of share prices for Islamic Banks. The data is obtained from online sources from a period of January 2000 to December 2018.

For all the models under consideration a rolling window of 250 days is used to estimate the new VaR and ES for the following day . After VaR estimation, violation ratios and VaR volatility ratios are calculated to check whether the models predicted correctly or not . Back-testing is done on these estimates by conducting Kupiec and Christofferson test to identify and compare the suitability of the models.

3.2.1 VAR Estimation through Non-Parametric Method

Non-parametric method is a method which does not fulfill certain parameters of assumptions, one of which could be to follow a normal distribution. Therefore this is a method which can be classified as distribution free. This method is generally used when the data has an unknown distribution. One famous method in this regard is Historical Simulation.

3.2.1.1 Historical Simulation (Univariate)

Historical Simulation (HS) is the most widely used method for estimating Value at Risk. Empirical distribution of financial returns is used in this method. Each item in the distribution carries equal weightage. This method is based on the assumption that history repeats itself. With this notion whatever is the trend in the past, is expected to occur in future too.

There are certain advantages of this method as well as disadvantages. The advantages include the simplicity and ease of implementation of this method. There is no assumption about the normal distribution of risk factors in this method. It does not involve the estimation of parameters. The disadvantages include that it requires a large volume of data to implement this, which sometimes is not possible. Also if the data period shows high volatility, this method often overestimates the risk.

The VaR at probability p is simply the negative TxP^{th} in the arranged return distribution multiplied by the fiscal value of the portfolio.

The historical simulation model anticipate the VaR at a confidence interval a and forecasts VaR in t + 1 through quantile (1-α), 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 is the return in time t.

3.2.2 VaR Estimation through Parametric Methods

Parametric models are the models in which data is normally distributed. There are certain methods who comply with such requirements that include Normal Distribution method, Student t-Distribution method, variance/covariance method, etc.

3.2.2.1 Normal Distribution Method

Normal distribution (N distribution) method, as the name suggests, is one in which the data is normally distributed. This method has the following assumptions. First is that the returns are normally distributed and mean return is zero. All the changes in the value of the portfolio are independent of the value of the assets constituting the portfolio. To estimate VaR at time t + 1 is the following formula shall be used.

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

Where μ stands for the mean of returns up to a time t and σ denotes the standard deviations for the same time bracket, and $z_{1-\alpha}$ is the quantile of the N distribution (Vasileiou, 2017).

This method too has certain advantages and disadvantages. The main advantage is that it is a simple method of VaR estimation and is widely used in the market. Understanding of this method and its application are also important advantages of this method. The disadvantages include that it is not suitable for portfolio of options because of the normal distribution assumption. Also that the standard deviations and correlations are calculated on the basis of historical data. Another criticism about this method is the existence of fat tails in the distribution, which may result in underestimation of VaR at higher confidence intervals.

3.2.2.2 Student-T Distribution Method

For leptokurtic time series, the forecasting of risk is generally done using the Student t-distribution. This method is used for fat tails. This is because due to high kurtosis, the assumption of normality results in underestimation of VaR. In this method the mean of the distribution equals zero and to create variance, the degree of freedom is used. The formula to calculate VaR under this method is given below.

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

Where μ denotes the mean of the distribution, σ denotes the standard deviation (Lin and Shen, 2006). The fat tailed data or returns are usually modelled by estimating an optimal value of p (Campbell et al., 2001).

There are several advantages of this method over the normal distribution method. The major advantages include that it is a simple method for the estimation of VaR, it caters to fat tails and there is no need to assume the symmetric spread of returns. Fat tails mean that there is a large positive or negative return in the tails which means there is volatility in the returns. If there is high fluctuation in returns, it means there is high volatility and vice versa. It is assumed that the mean of the returns is zero but in actual it is not. It changes with change in time. To explain volatility rate in VaR estimation, the time dependent volatility models are used.

3.2.3 VaR Estimation through Time-Dependent Volatility Methods

Then there are models in which volatility is time varying. Two models with this feature are used to estimate VaR in this research, named Exponential Weighted Moving Average (EWMA) and Generalized Auto-Regressive Conditional Heteroskedasticity (GARCH).

3.2.3.1 Exponential Weighted Moving Average (EWMA) Method

This is the simplest time dependent volatility method for estimating VaR. when we use the term moving average this means that the average keeps moving with time whereby more weights are assigned to recent observations. Volatility is calculated to solve this issue. If there is a big sample size, the estimation tends to be correct and results are better but in case of smaller samples chances of error increase. Also volatility shows that the more recent observations have more impact on the future volatility. For quick fluctuations in returns, volatility is high and vice versa. This is the main reason for volatility clusters (Danielson, 2011).

The formula used to estimate EWMA Value at risk:

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

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

3.2.3.2 GARCH Method

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

In this method more specifications are allowed for volatility. This method estimates better volatility forecasts as compared to EWMA and at the same time estimates the parameters of the model too.

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

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

Where r_{t-1} is the lagged return, φ_0 and φ_1 are constants to be determined and ε_t is the innovations term.

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

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

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

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

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

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

Where ϕ(p) used to represent p_{th} quantile of the normal distribution. Under this assumption, VaR can be computed as

$$VaR^{p}_{t+1/t} = \hat{\mu} + \hat{\varphi}r_t + t_{v,p}\sigma_{t+1} \tag{3.8}$$

Where $t_{v,p}$ is the p-th quantile of the Student-t distribution with v degrees of freedom.

3.2.4 Expected Shortfall Estimation through Conventional Methods

VaR considers a threshold and in case where extreme losses happen, they exceed the VaR threshold. Therefore, to study the losses beyond the VaR threshold, conditional VaR of Expected Shortfall (ES) is studied. 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. It is normally recommended to estimate ES whenever VaR is estimated to give a better picture to the investors. In order to estimate ES, first we have to estimate VaR and then both tails of the distribution are studied.

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

The function of Expected short fall is:

$$ES = -\int_{-\infty}^{-VaR(p)} x f_{VaR}(X) dx \tag{3.9}$$

Where, the expected short fall is:

$$ES = -\frac{\sigma^2 \phi(-VaR(P))}{P} \tag{3.10}$$

In the above equation, σ^2 represent the variance or standard deviation of the distribution, where ϕ represent the distribution like normal, t-distribution, EWMA, GARCH etc. The equation for expected short fall is same for all models, only the value of ϕ will be changed because of change in distribution (McNeil et al., 2005).

3.2.5 VAR Estimation through EVT

VaR estimation using EVT models include the estimation through two methods. In extreme value theory, there are two statistical approaches for analyzing extreme values: the Block Maxima Method (BMM) and Peaks-Over-Threshold (POT) method. In BMM approach, the extremes (maxima and minima) are studied in a distribution series of Independent and Identically Distributed (iid) observations. This approach consists of splitting the observation period into non-overlapping periods of equal size and only considers the maximum observation in each period. The set of extreme observations selected under extreme value conditions approximately follows the generalized extreme value (GEV) distribution. The peak-over-threshold (POT) approach selects extreme observations that exceed a certain high threshold. The probability distribution of the exceedances over a given high threshold follows approximately a generalized Pareto distribution (GPD). POT method is considered to be more data efficient since it makes better utilization of all the available information and is therefore mostly used for practical applications (Omari et al., 2017).

The extreme value theory calculate three parameters like:

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

- *Location parameter:* The μ is used to represent about location of the distribution, means if the value of location parameter is negative, than tail is on left side and vice versa.

- *Scale parameter:* The σ of the distribution is measured through standard deviation.

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

Since in this method the tails of the distribution are of utmost important, therefore, provided the distribution of return remains unchanged over time, the shape of the tails fall into three categories- named Frechet, Weibull and Gumbel. Let X1, X2, X3.........Xn represent the independent variable. The term M represent the maximum value from the sample size T. The Gnedenko (1943) and Fisher and Tippett (1928) theorems are used to explain the type of distribution, whether it is relevant from Gumbel, Frechet or the Weibull. This model estimates by selecting the maximum value from sample of normally distributed variables are the fundamental results in EVT.

Theorem 1 (Fisher-Tippett-Gnedenko Theorem) states that:

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

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

$$Ferchet : \phi_\vartheta(y) = \begin{cases} 0 & \text{if} \quad y \leq 0, \quad \vartheta{>}0 \\ exp(-y^{-\vartheta}) & \text{if} \quad y{>}0, \quad \vartheta{>}0 \end{cases} \tag{3.11}$$

$$Weibull : \psi_\vartheta(y) = \begin{cases} exp(-(-y^{-\vartheta})) & \text{if} \quad y \leq 0, \quad \vartheta{>}0 \\ 1 & \text{if} \quad y{>}0, \quad \vartheta{>}0 \end{cases} \tag{3.12}$$

$$Gumbel : \wedge(y) = exp(-exp(-y)) \text{ if } y \,\epsilon\, \Re \tag{3.13}$$

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

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

$$H_{\xi,\gamma,\partial}(x) = \begin{cases} exp\left(-(1+\xi\frac{x-y}{\sigma})\right)^{\frac{1}{\xi}} & \text{if} \quad \xi \neq 0 \\ exp\left(-exp(-\frac{x-y}{\sigma})\right) & \text{if} \quad \xi = 0 \end{cases} \tag{3.14}$$

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

$$VaR_{t+1,\alpha}^{BM} = \begin{cases} \gamma - \frac{\sigma}{\xi}(1-(-\ln(1-\alpha))^{-\xi}) & \text{if} \quad \xi \neq 0 \\ \gamma - \sigma\ln(-\ln(1-\alpha)) & \text{if} \quad \xi = 0 \end{cases} \tag{3.15}$$

There is inequality in the tail distribution which can produce the conditional VaR for a fat-tailed distribution. Expected shortfall of BMM will be calculated through the following equation.

$$ES_{t+1}^{BM} = \left(\frac{\alpha}{\alpha-1}\right) VaR_c(X) \tag{3.16}$$

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

3.2.5.2 Generalized Pareto Distribution (GPD) and POT Method

The second method that is based on threshold exceedances, known as Peak Over Threshold (POT) which fits the excess distribution to the Generalized Pareto Distribution (GPD). The POT method uses available data more efficiently which is an obvious advantage over BMM, in POT we use all the data which exceeds a particular threshold level while in BMM only the maximum from a block length is retained for distribution estimation.

The POT method considers the distribution of exceedances conditionally over a given high threshold u is defined by the following equation.

$$F_u = Pr(X - u \leq y \mid X > u) = \frac{F(y+u) - F(u)}{1 - F(u)}, 0 \leq y \leq x_F - u \tag{3.17}$$

Then GPD will be:

$$G_{\xi\sigma}(y) = \begin{cases} 1 - \left[\{1 + \frac{\xi}{\sigma}\}^{-\frac{1}{\xi}}\right] & \xi \neq 0 \\ 1 - exp\left(\frac{-y}{\sigma}\right) & \xi = 0 \end{cases} \tag{3.18}$$

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

So, VaR for extreme events is estimated using the below equation.

$$VaR^P_{t+1} = u + \frac{\hat{\sigma}}{\hat{\xi}}\left[[\frac{n}{N_u}(1-p)]^{-\xi}\right] \tag{3.19}$$

To check 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 given by the following equation.

$$VaR^S_{t+1} = u + \frac{\hat{\sigma}}{\hat{\xi}}\left[[\frac{n}{N_u}(1-p)]^{-\xi}\right] \tag{3.20}$$

The location parameter (γ) of the Pareto distribution which 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 is related to its VaR calculated through the following formula.

$$ES_q^S = VaR_q \frac{\sigma + \xi(VaR_q - u)}{1-\xi} = \frac{VaR_q}{1-\xi} + \frac{\sigma - \xi u}{1-\xi} \tag{3.21}$$

Another method to calculate GPD VaR at given confidence interval is GPD dynamic. McNeil et al. (2005), proposed a two step dynamic VaR forecasting method based using EVT in which they make use of GARCH modelling to model the current market volatility background in the first step. In the second step, the market volatility background is fed into VaR estimates obtained from the POT model fitted to residuals of a GARCH model. These two steps are elaborated as under:

- A GARCH(1,1) model is fitted to the historical data which gives the residuals for step-2 and also 1 day ahead predictions of μ_{t+1} and σ_{t+1}
- EVT (POT method) is applied to the residuals extracted from the above step for a constant choice of threshold to estimate VaR and ES as mentioned in the equations below.

$$VaR_{t+1}^D = \mu_{t+1} + \sigma_{t+1} * VaR_{t+1}^S \tag{3.22}$$

Expected shortfall is the average of the negative values in any financial series beyond a given level of significance e. g 0.95 or 0.99. 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 calculated as follows.

$$ES_{t+1}^D = \mu_{t+1} + \sigma_{t+1} * VaR_{t+1}^D \tag{3.23}$$

3.2.6 Backtesting

Back testing is a procedure to calculate the expected returns and compare them with the actual ones. Several methods are used to perform this task. Basically this compares the expected losses for a period of time, based on the previous data with actual losses of the time in future of time, where the expectation is calculated.

The more the expectations coincide with the actual losses, the better the method of estimation is considered to be. Similarly, the less the matching, the weaker the method is. Back testing is an approach that can be used to identify whether there has been an underestimation or overestimation of risk, by using a certain approach to estimate VaR and ES.

3.2.6.1 Violation Ratio

This is a ratio calculated to see how well a model performs in estimating VaR. Once VaR estimation is done, and compared with the returns of the subsequent periods, the violations are identified. The observed violations are then compared with the expected violations and hence we get this violation ratio (Danielsson, 2011). The ideal value of this ratio is 1. Since, in financial industry it is not possible to get an exact 1 every time, therefore as a rule of thumb a violation ratio between 0.8 to 1.2 is considered appropriate in this research. There are variations from the rule of thumb we can say that the model is either underestimating or overestimating the risk. As for understanding, it means that VR <0.5 or VR >1.5 explains that respective model is defective in forecasting of risk. Most of the times, the results of violation ratio are considered as a good forecasting technique, and decision be made on violation ratio (Danielson, 2011).

3.2.6.2 VaR Volatility

Another back testing technique is to estimate the volatility in estimation of any model. The parameter used to check volatility is standard deviation of VaR. If violation ratio for VaR estimation via two different models gives the same results, then VaR volatility helps to identify the better model out of those. This technique suggests that model with minimum volatility i.e. minimum standard deviation should be selected (Danielson, 2011).

3.2.6.3 Kupiec POF Tests

Kupiec Probability of Failure (POF) test which is also known as Unconditional Coverage Test is also a method used in back testing. Kupiec (1995) test uses the likelihood ratio in comparison to the violation rate. The null hypothesis in this method is that the actual observed number of violations is equal to the expected total number of violations. Through this test, the likelihood ratios are calculated for all the banks using different models at different confidence intervals, which are then compared with a benchmark, i.e. the chi-square value. This chi-square value is also different at different confidence intervals. If the calculated likelihood ratio value exceeds the benchmark chi-square value, this means the null hypothesis has been rejected and the observed number of violations are greater than the expected number of violations and hence the model is not suited for VaR estimation and vice versa.

The POF test statistic is

$$LR_{POF} = -2\log\left(\frac{(1-q)^{Z-x}q^{x}}{(1-\frac{x}{Z})^{Z-x}(\frac{x}{Z})^{x}}\right) \tag{3.24}$$

Where x represents the no of times a model failed, Z is the count of observations and q = 1 – VaR interval (confidence interval).

If the likelihood ratio calculated via the bove formula ranges within the critical value of chi-square of one degree of freedom, the null hypothesis is accepted that model did correct forecasting of risk.

3.2.6.4 Christoffersen's Interval Forecast Tests

Christoffersen (1998) test is another method used in back testing. This test is used to identify whether or not there is any volatility clustering. To check whether the violations observed during a specific period are distributed evenly over that period or they occurred one after another, forming a cluster. The null hypothesis in this case is the occurrence of violations and their independence. Here again we calculate the likelihood ratio and compare it with the benchmark chi-square value, which is different at different confidence intervals. If the likelihood ratio is within/below the range mentioned above it means the null hypothesis is accepted the violations occurring are independent of each other and hence there is no clustering. But if the likelihood ratio exceeds the chi-square value, this means that the null hypothesis is rejected and the violations occurred are not independent of each other and are connected, hence resulting in clustering.

The likelihood ratio here is calculated as follows.

$$LR_{CCI} = -2\log\left(\frac{(1-\pi)^{z00+z10}\pi^{z01+z11}}{(1-\pi_0)^{z00}\pi_0^{z01}(1-\pi_1)^{z10}\pi_1^{z11}}\right) \tag{3.25}$$

Where

- z00 = Count of instances without any failure followed by an instance without any failure.
- z10 = Count of instances with failures followed by an instance without any failure.
- z01 = Count of instances without any failure followed by an instance with failures.
- z11 = count of instances with failures followed by an instance with failures.
- π_0 = Probability of having a failed instance at time t, provided no failed instance occurred at time $(t-1)$ = z01/(z00+n01)
- π_1 = Probability of having a failed instance at time t, provided a failed instance occurred at time $(t-1)$ = z11/(z10+z11)
- π = Probability of having a failed instance at period t = (z01+z11/(z00+z01+z10+z11)

The null hypothesis assumes to have no clustering, which means that there is no dependency of a day with violation, on it's previous day's violation. Otherwise the null hypothesis is rejected and reported time period clustering between violations will be identified.

Chapter 4

Data Analysis, Results and Discussion

This chapter represents the result of the study to achieve the basic motive. The chapter starts by showing the descriptive statistics for all the islamic banks in the sample. After that the VaR results are discussed and verified with the help of back testing for the analysis of whole distribution. Then, expected shortfall beyond VaR is reported. Finally, results from EVT are reported for the analysis of extreme distribution or extreme conditions.

4.1 Descriptive Analysis

The sample comprises of the share prices of twenty listed Islamic Banks in Gulf Cooperation Council (GCC) and two listed Islamic banks from Pakistan. Table 4.1 shows the descriptive statistics of daily share prices for islamic banks in the sample.

The mean value explains the return earned by any islamic bank. The negative mean shows that these banks experience negative average returns. The lowest average returns are shown by Meezan Bank Limited, Qatar Islamic Bank and Qatar International Islamic Bank amounting to 0.00084, 0.00079 and 0.00078 respectively. In terms of a positive average return, Al Baraka Banking Group leads the sample with 0.0013 followed by Khaleeji Commercial Bank and Bank Aljazira with 0.0009 and 0.0005 average returns respectively.

The standard deviation shows the riskiness of investment in these stocks. The descriptive statistics show that riskiest of our sample is Al Rajhi Bank with a standard deviation of 0.0641 followed by Qatar International Islamic Bank and Bahrain Islamic Bank with standard deviations of 0.0544 and 0.0350 respectively. The 3 least risky banks in the sample are Warba Bank, Abu Dhabi Islamic Bank and Alinma Bank with standard deviations of 0.0152, 0.0168 and 0.0173 respectively.

Ideally where there is high risk, there should be high returns too. But the descriptive statistics show an inefficient relationship between the risks and average returns between the stocks of the banks in the sample.

An ideal median should be zero which means that the number of positive returns equate to the number of negative returns and in the sample studied here, the median is zero for all the banks. The maximum return 2.8934 is reported by Al Rajhi Bank and the minimum return -2.8884 is also reported by the same bank.

Bank Aljazira, Al Baraka Banking Group, Ahli United Bank (Kuwait), Barwa Bank, Al Rajhi Bank, Bank AlBilad, Qatar Islamic Bank and Bank Nizwa show positive skewness, which means the Mean here exceeds the mode, whereas Khaleeji Commercial Bank, Meezan Bank Limited, Abu Dhabi Islamic Bank, Boubyan Bank, Alinma Bank, Bahrain Islamic Bank, Masraf Al Ryan, Kuwait International Bank, Sharjah Islamic Bank, Warba Bank, Dubai Islamic Bank, BankIslami Pakistan Limited, Qatar International Islamic Bank and Kuwait Finance House show negative skewness, which means that the mean here is less than mode.

The value of kurtosis for all the banks are greater than 3, which shows fat tail distributions of stock returns and non-normality of the data. All of the banks in the sample show a leptokurtic nature with Al Rajhi Bank being the most leptokurtic with a kurtosis value of 1672 followed by Qatar International Islamic Bank with a value of 1665.

Table 4.1: Descriptive Statistics

Bank Name	Mean	Median	Std. Dev.	Minimum	Maximum	Skewness	Kurtosis
ISLAMIC BANKS IN GCC							
Abu Dhabi Islamic Bank	-0.0003	0	0.0168	-0.1269	0.1058	-0.1023	13.7434
Ahli United Bank (Kuwait)	0	0	0.0203	-0.1908	0.1947	0.1814	16.5095
Al Baraka Banking Group	0.0013	0	0.0286	-0.1562	0.1684	0.2422	8.184
Al Rajhi Bank	-0.0003	0	0.0641	-2.8884	2.8934	0.1129	1672.546
Alinma Bank	-0.0001	0	0.0173	-0.0953	0.1077	-0.1391	10.7425
Bahrain Islamic Bank	-0.0002	0	0.035	-0.539	0.5216	-0.1868	66.6346
Bank AlBilad	0.0003	0	0.0222	-0.0984	0.1089	0.0767	8.7539
Bank Aljazira	0.0005	0	0.0275	-0.4348	0.4317	1.3462	95.6163
Bank Nizwa	0.0001	0	0.0235	-0.1335	0.1335	0.0372	16.1137
Barwa Bank	-0.0001	0	0.0226	-0.1095	0.1309	0.1353	8.5484
Boubyan Bank	-0.0002	0	0.0222	-0.1283	0.1346	-0.1194	10.8752
Dubai Islamic Bank	-0.0005	0	0.0225	-0.1572	0.1485	-0.6243	12.7771
Khaleeji Commercial Bank	0.0009	0	0.0294	-0.1503	0.1513	-0.0059	7.1265
Kuwait Finance House	-0.0004	0	0.0183	-0.3557	0.2678	-0.8567	47.4718
Kuwait International Bank	-0.0003	0	0.0201	-0.0973	0.0965	-0.1921	5.9928
Masraf Al Rayan	-0.0003	0	0.0188	-0.1178	0.1129	-0.1918	11.0677
Qatar International Islamic Bank	-0.00078	0	0.0544	-2.3979	2.3671	-0.7169	1665.142
Qatar Islamic Bank	-0.00079	0	0.0202	-0.1555	0.1156	0.0382	8.8393
Sharjah Islamic Bank	-0.0002	0	0.0235	-0.1385	0.1009	-0.2864	6.5848
Warba Bank	0.0003	0	0.0152	-0.1072	0.069	-0.5563	8.2178
ISLAMIC BANKS IN PAKISTAN							
BankIslami Pakistan Limited	-0.0005	0	0.0286	-0.1442	0.1328	-0.6484	5.8921
Meezan Bank Limited	-0.00084	0	0.0189	-0.0635	0.1115	-0.0841	4.6113

4.2 Estimation through Conventional Models

Value at Risk (VaR) and Conditional Value at Risk (CVaR), also known as Expected Shortfall (ES) is determined using the conventional methods. These methods include both the non-parametric (Historical Simulation) methods, the parametric (N-Distribution and T-Distribution) methods and the time varying volatility (EWMA and GARCH) methods. All risk values for VaR and ES, being the negative values are to be read with a negative sign, wherever reported in this study.

4.2.1 VaR Estimation through Conventional Methods

The study first calculates VaR using the conventional methods of VaR estimation is calculated and reported.

4.2.1.1 VaR Estimation via Non-Parametric and Parametric Methods

Table 4.2 represents the results of VaR calculation under the Non-Parametric and Parametric Assumptions based models. In non-parametric assumption, Historical Simulation model is used, whereas in the parametric assumptions based models, N-Distribution and T-Distribution models are used.

- Historical Simulation Method

In the Historical simulation approach, at 95% confidence interval, the results report a maximum VaR of 5% for Khaleeji Commercial Bank with Bahrain Islamic Bank and Al Baraka Banking Group at second and third riskiest bank in the sample with a VaR estimation of 4.92% and 4.83% respectively. This means that at there are 95% chances that the losses will not exceed these percentages in any given day. Also, historical simulation methods, at the same confidence interval, reports that the least risky stock in the sample is Warba Bank with a VaR of 1.98%, which means that the potential loss to the investor for one day, is the least if invested in the stocks of this bank. The second and third least risky stocks are from Abu Dhabi Islamic Bank and Bank Nizwa with estimated VaR of 2.23% and 2.30% respectively.

At 99% confidence interval, using the historical simulation assumption, the maximum VaR of 10.1% is reported by Al Baraka Banking Group, followed by Bahrain Islamic Bank with a VaR of 10.01% and Bank Nizwa with a VaR of 9.53%. This means that there are 99% chances that the loss in a day will not exceed these percentages. The least risk is being reported by Meezan Bank Limited with a VaR of 4.65%, where Warba Bank is the second least riskiest bank in the sample and Kuwait Finance House is the third least riskiest with estimated VaR values of 4.70% and 5.21% respectively.

This means that at 95% confidence interval, the most risky stocks are of Khaleeji Commercial Bank and the least risky are of Warba Bank. As for 99%, the most risky stocks relate to Al Baraka Banking Group and the safest relate to Meezan Bank Limited.

- Normal Distribution Method

Using the N-distribution assumption of VaR estimation, at 95% confidence interval, Al Rajhi Bank reports the highest risk with an estimated VaR value of 10.54% followed by Qatar International Islamic Bank and Bahrain Islamic Bank with VaR values of 8.94% and 5.75% respectively. The least VaR are reported by Warba Bank with 2.50%, followed by Abu Dhabi Islamic Bank at 2.77% and Alinma Bank at 2.85%.

At 99% confidence interval, the n-distribution assumption showed the maximum and minimum VaR estimations by the same banks, i.e. Al Rajhi Bank with the highest VaR of 14.91%, followed by the same Qatar International Islamic Bank and Bahrain Islamic Bank with VaR values of 12.64% and 8.13% respectively. Similarly the safest investments being in Warba Bank (3.54%), Abu Dhabi Islamic Bank (3.91%) and Alinma Bank (4.03%).

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

Bank Name	H.S		N-DIST		T-DIST	
	95%	99%	95%	99%	95%	99%
ISLAMIC BANKS IN GCC						
Abu Dhabi Islamic Bank	0.0223	0.0613	0.0277	0.0391	0.0258	0.0524
Ahli United Bank (Kuwait)	0.0261	0.0633	0.0334	0.0472	0.0293	0.0646
Al Baraka Banking Group	0.0483	0.101	0.047	0.0665	0.0228	0.1768
Al Rajhi Bank	0.0251	0.0572	0.1054	0.1491	0.0318	0.0714
Alinma Bank	0.0248	0.0562	0.0285	0.0403	0.0272	0.0574
Bahrain Islamic Bank	0.0492	0.1001	0.0575	0.0813	0.0276	0.213
Bank AlBilad	0.0325	0.0806	0.0364	0.0515	0.0311	0.0809
Bank Aljazira	0.0317	0.0617	0.0452	0.064	0.0241	0.0734
Bank Nizwa	0.023	0.0953	0.0386	0.0547	0.0297	0
Barwa Bank	0.0341	0.0778	0.0371	0.0525	0.0227	0.0777
Boubyan Bank	0.0302	0.0657	0.0366	0.0518	0.0358	0.0816
Dubai Islamic Bank	0.0308	0.0685	0.037	0.0523	0.0317	0.0768
Khaleeji Commercial Bank	0.05	0.0935	0.0484	0.0685	0.0253	4.94E+48
Kuwait Finance House	0.0245	0.0521	0.0302	0.0427	0.0308	0.0516
Kuwait International Bank	0.0314	0.0541	0.0331	0.0469	0.0238	0.0613
Masraf Al Rayan	0.0248	0.0611	0.0308	0.0436	0.0308	0.0637
Qatar International Islamic Bank	0.028	0.0601	0.0894	0.1264	0.0056	0.0947
Qatar Islamic Bank	0.0299	0.059	0.0333	0.0471	0	0.0762
Sharjah Islamic Bank	0.0392	0.0648	0.0386	0.0546	0.0461	0.0743
Warba Bank	0.0198	0.047	0.025	0.0354	1.48E+20	0.0476
ISLAMIC BANKS IN PAKISTAN						
BankIslami Pakistan Limited	0.0426	0.0678	0.0471	0.0666	0.0302	0.0885
Meezan Bank Limited	0.0287	0.0465	0.0312	0.0441	0.0436	0.0513

- Student t-Distribution Method

Using the student t-distribution assumption the VaR estimation showed that for 95% confidence interval, the highest risk is reported by Warba Bank, followed by Sharjah Islamic Bank (4.61%) and Boubyan Bank (3.58%) and the least risky banks include Qatar Islamic Bank (0%), Qatar International Islamic Bank (0.56%) and Barwa Bank (2.27%). At 99% confidence interval the most risky banks reported under student t-distribution method are Khaleeji Commercial Bank, Bahrain Islamic Bank (21.30%) and Al Baraka Banking Group with a reported VaR of 17.68%. Also the least risky banks include Bank Nizwa (0%), Warba Bank (4.76%) and Kuwait Finance House (5.16%).

From the above it is evident that using the parametric and non-parametric methods of VaR estimation, which include Historical Simulation, N-distribution and student t-distribution approach, Khaleeji Commercial Bank, Bahrain Islamic Bank and al Baraka Banking Group rest among the top 3 with respect to risk and from the bottom there are stocks from Warba Bank, Bank Nizwa and Meezan Bank Limited that can be considered as safest from the lot.

4.2.1.2 VaR Estimation through Time Dependent Volatility Methods

Two methods of VaR estimation are applied on the sample data with the time varying volatility assumptions, i.e. EWMA (Exponentially Weighted Moving Average) and GARCH (Generalized Auto-Regressive Conditional Heteroskedasticity). Table 4.3 shows the results for 95% and 99% confidence intervals for VaR estimation using these two models.

- EWMA Method

In 95% confidence interval, with the EWMA assumption, the maximum loss that a bank may face, goes up to 6.76% as reported by Khaleeji Commercial Bank, and the second highest is Bahrain Islamic Bank (4.98%) and Abu Dhabi Islamic Bank on third riskiest bank in the sample with a VaR of 4.02%. The least risk is reported by Kuwait Finance House with 1.18% VaR following by Ahli United Bank (Kuwait) and Dubai Islamic Bank with estimated VaR values of 1.33% each.

In 99% confidence interval, the top 3 most risky and the 3 least risky banks remain the same as in 95% confidence interval with Khaleeji Commercial Bank at 9.56%, Bahrain Islamic Bank at 7.05% and Abu Dhabi Islamic Bank at 5.68% VaR estimation and Kuwait Finance House, Ahli United Bank (Kuwait) and Dubai Islamic Bank showed VaR values of 1.66%, 1.88% and 1.89% respectively.

Table 4.3: VaR Estimation through Time Dependent Volatility Methods

Bank Name	**EWMA**		**GARCH**	
	95%	**99%**	**95%**	**99%**
ISLAMIC BANKS IN GCC				
Abu Dhabi Islamic Bank	0.0402	0.0568	0.0390	0.0552
Ahli United Bank (Kuwait)	0.0133	0.0188	0.0162	0.0229
Al Baraka Banking Group	0.0235	0.0332	0.0348	0.0492
Al Rajhi Bank	0.0214	0.0303	0.0628	0.0891
Alinma Bank	0.0261	0.0369	0.0243	0.0344
Bahrain Islamic Bank	0.0498	0.0705	0.0537	0.0759
Bank AlBilad	0.0264	0.0373	0.0242	0.0342
Bank Aljazira	0.0244	0.0345	0.0359	0.0508
Bank Nizwa	0.0266	0.0377	0.0334	0.0472
Barwa Bank	0.0192	0.0272	0.0256	0.0362
Boubyan Bank	0.0193	0.0273	0.0254	0.0359
Dubai Islamic Bank	0.0133	0.0189	0.0191	0.0270
Khaleeji Commercial Bank	0.0676	0.0956	0.0423	0.0598
Kuwait Finance House	0.0118	0.0166	0.0196	0.0277
Kuwait International Bank	0.0152	0.0215	0.0194	0.0274
Masraf Al Rayan	0.0234	0.0330	0.0288	0.0407
Qatar International Islamic Bank	0.0156	0.0220	0.0569	0.0795
Qatar Islamic Bank	0.0219	0.0310	0.0221	0.0312
Sharjah Islamic Bank	0.0230	0.0326	0.0323	0.0457
Warba Bank	0.0308	0.0436	0.0509	0.0720
ISLAMIC BANKS IN PAKISTAN				
BankIslami Pakistan Limited	0.0332	0.0469	0.0395	0.0558
Meezan Bank Limited	0.0299	0.0423	0.0324	0.0458

- GARCH Method

As far as GARCH model is concerned, for the 95% confidence interval, Al Rajhi Bank tops the sample with the highest risk reported of 6.28%, whereas Qatar

International Islamic Bank and Bahrain Islamic Bank are on number two and three with reported VaR values of 5.69% and 5.37%. Also from the least risk reported angle, Ahli United Bank (Kuwait) is at 1.62%, followed by Dubai Islamic Bank and Kuwait International Bank with estimated VaR values of 1.91% and 1.94% respectively. The order remained the same for 99% too for the most risky and the least risky banks in the sample.

Using the EWMA and GARCH approaches, it can be sees that stocks from Qatar International Islamic Bank and Bahrain Islamic Bank rank among the riskiest investments and the ones from Dubai Islamic Bank and Ahli United Bank (Kuwait) are termed as the safest, in the sample.

4.2.2 Backtesting for Conventional Methods of VaR

Back testing is performed through the calculation of violation ratio and VaR volatility ratios for all the twenty-two islamic banks in the sample.

4.2.2.1 Violation Ratio

Violation ratio is a comparison between the expected violations in a model with the actual violations, based on back testing. Ideally the actual total number of violations should be equal to the expected total number of violations and this ratio turns out to be 1. Table 4.4 shows the violation ratios calculated for 95% and 99% confidence intervals, using the assumptions based on the conventional methods of VaR estimation.

At 95% confidence interval, with the Historical Simulation model, majority (17 out of 20) of the banks in the GCC show a violation ratio of 1 approximately (ranging from 0.8 to 1.2), hence historical simulation can be a good model to estimate VaR in GCC, with the exception of Qatar International Islamic Bank, Kuwait International Bank, and Al Baraka Banking Group. In Pakistan both the banks show an appropriate violation ratio, hence historical simulation can also be suggested to be a good model for VaR estimation in Pakistan. Using the N-distribution approach, only 9 out of 20 banks in the GCC depict an appropriate violation ratio, also 1 out of two banks, BankIslami Pakistan Limited also falls out of the appropriate range for this approach. As far as student t-distribution is concerned, 10 out of 20 banks in the GCC fulfil the criteria and their violation ratio falls within the acceptable region, whereas the other 10 banks' ratio falls beyond the acceptable range and same is the case with the banks in Pakistan. Calculations using the EWMA model reveal that 100% banks fall within the acceptable region and the violation ratios reported by all the banks in the GCC as well as in Pakistan report a violation ratio ranging from 0.8 to 1.2. The last conventional method GARCH, when used for the calculation of violation ratio shows that only 8 out of 20 banks in the GCC comply with the appropriate ratio and only 1 out of 2 banks in Pakistan complies with the appropriate violation ratio. Hence from the above discussion we may report that out of the conventional methods of VaR estimation, at 95% confidence interval, EWMA seems to be the best suited method so far.

At 99% confidence interval, calculating violation ratios using the conventional methods of VaR estimation reveal that with Historical Simulation method and N-distribution method are absolutely inappropriate for VaR estimation as not even a single bank complies to the appropriate range of violation ratio. With the student t-distribution method, 6 out of 20 banks from the GCC and 1 bank from Pakistan report a violation ratio within the acceptable range and GARCH method also reports that this method is not suitable for VaR estimation for the banks in the GCC. However the EWMA approach reveals the best results in 99% confidence interval as well. 18 out of 20 banks report an appropriate violation ratio along with the two banks in Pakistan too.

By comparing the violation ratio reported by 95% confidence interval with 99% confidence interval, the number of expected violations increased with the increase in confidence interval. However, by testing at both 95% confidence interval as well as 99%, it can be suggested that EWMA is best suited model for VaR estimation both for the Islamic banks in the GCC as well the ones in Pakistan.

TABLE 4.4: Violation Ratio for Conventional Methods of VaR Estimation

Bank Name	H.S		N-DIST		T-DIST		EWMA		GARCH	
	95%	**99%**	**95%**	**99%**	**95%**	**99%**	**95%**	**99%**	**95%**	**99%**
ISLAMIC BANKS IN GCC										
Abu Dhabi Islamic Bank	0.8085	2.3646	0.6407	1.9069	0.7170	1.2204	0.9306	0.9153	0.6407	1.5256
Ahli United Bank (Kuwait)	0.8634	1.5699	0.7300	1.7661	0.8791	0.8634	1.0283	0.7849	0.7692	1.3344
Al Baraka Banking Group	1.2313	3.6060	1.1434	3.5180	1.1609	1.4072	0.8795	0.7916	1.0202	3.2542
Al Rajhi Bank	0.8381	1.9373	0.6822	1.5582	0.6570	0.8212	1.0360	0.8633	0.7454	1.8320
Alinma Bank	0.8780	1.8995	0.6669	1.7307	0.7767	0.8864	1.0215	0.7176	0.7683	1.6041
Bahrain Islamic Bank	1.0768	2.7577	1.0112	2.8890	1.0112	1.2475	1.1294	0.9192	0.9849	2.4294
Bank AlBilad	0.8949	2.0025	0.8636	2.3780	0.9887	1.4080	1.0325	1.2203	0.8073	1.8461
Bank Aljazira	0.8536	1.9132	0.7064	1.7660	0.6917	0.5887	0.8977	0.5151	0.6475	1.5453
Bank Nizwa	0.8371	2.1674	0.8221	2.1674	0.8520	1.4200	0.9417	0.8221	0.7922	1.1211
Barwa Bank	0.9362	1.9335	0.8005	1.9335	0.9294	0.9498	0.9973	0.8480	0.8412	1.8318
Boubyan Bank	0.8223	1.3240	0.7247	2.0557	0.7875	0.8362	1.1289	1.2195	0.7108	1.2195
Dubai Islamic Bank	0.8000	1.8333	0.7286	1.6905	0.8238	0.7857	1.0048	1.0000	0.7333	1.2381
Khaleeji Commercial Bank	1.1765	2.4572	1.1169	2.6061	1.2360	1.3403	1.1318	0.8191	1.0276	2.5316
Kuwait Finance House	0.8312	1.6148	0.8122	1.7336	0.8312	0.5937	0.9974	0.9974	0.7884	1.4486
Kuwait International Bank	0.7994	1.4513	0.7756	1.6417	0.7138	0.1190	0.9089	0.8803	0.7423	1.4751
Masraf Al Rayan	0.8348	1.8590	0.7085	1.8941	0.7997	0.9120	0.9260	0.8769	0.7576	1.7888
Qatar International Islamic Bank	0.7018	1.5039	0.6923	1.5039	0.7305	0.7878	0.8785	0.8116	0.6445	1.5517
Qatar Islamic Bank	0.8770	2.0734	0.8627	1.9066	1.0391	1.2393	1.0343	0.9056	0.8484	1.7874
Sharjah Islamic Bank	1.1925	1.9591	1.0051	1.4480	1.2947	0.5963	1.0221	1.0221	1.0221	1.6184
Warba Bank	0.9187	1.8182	0.6507	1.7225	0.8038	0.7656	0.8612	0.8612	0.8612	1.4354
ISLAMIC BANKS IN PAKISTAN										
BankIslami Pakistan Limited	0.9158	1.3294	0.7238	1.4771	0.6942	0.0739	0.9010	0.8124	0.8419	0.9601
Meezan Bank Limited	0.8397	1.2977	0.8092	1.2214	3.7710	2.8244	1.0382	0.9924	0.7786	0.8397

4.2.2.2 VaR Volatility Ratio

Volatility refers to the instability in the market. The less the volatility calculated using a specific model, the better is that model considered. Table 4.5 below reports the VaR volatility ratios for the 22 banks calculated using the conventional methods, i.e. Historical Simulation, N-distribution, student t-distribution, EWMA and GARCH.

From the results reported in the table below, at 95% confidence interval first, for all the models used here, the volatility ratio gives the highest value for Al Rajhi Bank, Qatar International Islamic Bank and Bahrain Islamic Bank, which means these banks are the riskiest in the lot to invest in. Their volatility ranges from 3% to 16% using different VaR estimation methods. But using EWMA approach, the highest values of volatility ratios are reported by Bank Nizwa and Boubyan Bank, 3% and 2% respectively. Also the least volatility reported in all the models are by Warba Bank, BankIslami Pakistan Limited and Meezan Bank Limited, ranging from 0% to 1% only.

Considering the number of banks having the volatility ratio reported within a range of 0-3%, we can see that in Historical Simulation method, 82% banks report a volatility ratio within this range. Using GARCH approach 86% banks reports a volatility within this range. Using N-distribution approach and student t-distribution approach 91% banks reports a similar volatility and using the EWMA approach 95% banks in the sample report a volatility within a range of 0-3%.

With the increase in confidence interval, the VaR volatility also increases. Considering the 99% confidence interval, the results are similar to those of 95% confidence interval. The highest volatility ratios are reported by Al Rajhi Bank, Qatar International Islamic Bank and Bahrain Islamic Bank, which means these banks are the riskiest in the lot to invest in. Their volatility ranges from 3% to 23% using different VaR estimation methods here. And the least volatility is also reported by the same banks, i.e. Warba Bank, BankIslami Pakistan Limited and Meezan Bank Limited, ranging from 0% to 2% only.

Table 4.5: VaR Volatility for Conventional Methods of VaR Estimation

Bank Name	H.S		N-DIST		T-DIST		EWMA		GARCH	
	95%	**99%**	**95%**	**99%**	**95%**	**99%**	**95%**	**99%**	**95%**	**99%**
ISLAMIC BANKS IN GCC										
Abu Dhabi Islamic Bank	0.0127	0.0179	0.0078	0.011	0.0078	0.0148	0.0091	0.0253	0.0143	0.0202
Ahli United Bank (Kuwait)	0.0173	0.0244	0.0135	0.0191	0.0137	0.026	0.0193	0.0254	0.0184	0.026
Al Baraka Banking Group	0.0189	0.0267	0.0093	0.0132	0.0086	0.0165	0.0181	0.0112	0.0217	0.0307
Al Rajhi Bank	0.1007	0.1424	0.0944	0.1335	0.0953	0.1841	0.0172	0.1343	0.16	0.2262
Alinma Bank	0.0117	0.0165	0.0085	0.012	0.0085	0.016	0.0104	0.0201	0.0144	0.0204
Bahrain Islamic Bank	0.0324	0.0458	0.0189	0.0267	0.0187	0.0363	0.0168	0.0421	0.0525	0.0742
Bank AlBilad	0.0173	0.0245	0.0126	0.0178	0.0133	0.0242	0.0206	0.0253	0.0186	0.0264
Bank Aljazira	0.0273	0.0386	0.0138	0.0196	0.0135	0.0264	0.009	0.0167	0.017	0.024
Bank Nizwa	0.0199	0.0281	0.0141	0.0199	0.0142	0.027	0.034	0.0397	0.0201	0.0284
Barwa Bank	0.0179	0.0253	0.014	0.0198	0.0136	0.0257	0.0201	0.0251	0.0194	0.0274
Boubyan Bank	0.0205	0.0289	0.0158	0.0224	0.0152	0.0293	0.0238	0.0303	0.0201	0.0284
Dubai Islamic Bank	0.0199	0.0281	0.0156	0.0221	0.0157	0.0297	0.0197	0.0267	0.0221	0.0313
Khaleeji Commercial Bank	0.0168	0.0237	0.0066	0.0094	0.0046	0.01	0.0066	0.0175	0.0171	0.0241
Kuwait Finance House	0.0142	0.0201	0.0101	0.0143	0.0107	0.0201	0.0113	0.0168	0.0149	0.0211
Kuwait International Bank	0.0131	0.0185	0.0098	0.0138	0.0102	0.024	0.0107	0.0193	0.0134	0.0189
Masraf Al Rayan	0.0147	0.0209	0.011	0.0155	0.0112	0.0209	0.0167	0.0223	0.0183	0.0259
Qatar International Islamic Bank	0.0833	0.1179	0.0773	0.1093	0.0776	0.1502	0.0152	0.0265	0.1488	0.2105
Qatar Islamic Bank	0.0155	0.0219	0.0115	0.0163	0.0107	0.0206	0.0129	0.0224	0.0177	0.025
Sharjah Islamic Bank	0.0114	0.0161	0.006	0.0085	0.0052	0.0099	0.0082	0.0114	0.0123	0.0174
Warba Bank	0.0085	0.012	0.0037	0.0052	0.0034	0.0065	0.0047	0.0076	0.0096	0.0135
ISLAMIC BANKS IN PAKISTAN										
BankIslami Pakistan Limited	0.012	0.017	0.0046	0.0064	0.0049	0.0112	0.0054	0.0102	0.0119	0.0168
Meezan Bank Limited	0.0072	0.0102	0.0028	0.0039	0.0015	0.0032	0.0036	0.0094	0.0064	0.0091

Considering the number of banks having the volatility ratio reported as less than 3%, we can see that in GARCH method, only 50% banks report a volatility ratio of less than 3%. Using EWMA approach 55% banks reports a volatility within a range of 0-3%. In student t-distribution approach and Historical Simulation approach 59% banks report a similar volatility and using the N-distribution approach 86% banks in the sample report a volatility within a range of 0-3%.

Comparing the volatility ratios reported by different methods here, we can see that maximum values are reported using the GARCH method, in both 95% and 99% confidence intervals. Hence it is not a stable method for risk estimation. In cases of Historical Simulation, N-distribution and student t-distribution the maximum values go up to 10%, 9% and 10% respectively for 95% confidence interval and 14%, 13% and 18% respectively for 99% confidence interval. Only in EWMA approach the maximum volatility ratio goes up to 3% for Bank Nizwa and the ratio for the rest of the banks are even below this value.

Considering the above discussion, if VaR volatility is used as a measure of risk estimation, for 95% confidence interval, EWMA seems to be the best suited model for all the banks in the GCC as well the ones in Pakistan and for 99% confidence interval, N-distribution method seems to be the best suited model for risk estimation for the banks in Pakistan as well as for the ones in GCC, except Qatar International Islamic Bank and Al Rajhi Bank, where it is evident that for Qatar International Islamic Bank even at 99% confidence interval the best suited method is EWMA and no conventional model is suitable for Al Rajhi Bank at 99% confidence interval.

4.2.2.3 Kupiec POF (Unconditional Coverage) Test

Table 4.6 reports the Likelihood Ratios calculated for all the banks at 95% confidence interval, using Historical Simulation, N-distribution, Student t-Distribution, EWMA and GARCH methods. The below table reports that 77% banks fall under the benchmark of 3.84 hence making historical simulation a suitable method for true forecasting of risk. N-distribution method reports the worst results as null hypothesis is accepted for 32% banks. Using GARCH approach only 36% banks fell within the benchmark range, 41% with student t-distribution and once again the EWMA approach exhibits the best results with 86% banks complying with the chi-square criteria.

For the banks in the GCC, EWMA is the best suited model for risk forecasting, at 95% confidence interval, except for Al Rajhi Bank showing a likelihood ratio of 6.91, Dubai Islamic Bank (9.46) and Boubyan Bank (6.00). For Al Rajhi Bank and Dubai Islamic Bank the better approach is the Historical Simulation approach as their respective likelihood ratios under that approach are calculated to be 0.32 and 0.01. For the banks in Pakistan, both Historical Simulation and EWMA seem to be appropriate, but generalizing it all, for 95% confidence interval EWMA seems to be the most reliable model for risk forecasting.

Table 4.7 shows the results of Kupiec Unconditional Coverage test for these banks at 99% confidence interval. According to these results Historical Simulation approach presents the worst results with only 27% countries falling within critical value range of chi-square of one degree of freedom, for N-Distribution approach the results showed 23% and it was 45% for GARCH method that the likelihood ratios of these banks are complying with the chi-square criteria of 6.64. On the contrary student t-distribution method shows better results with the likelihood ratios of 82% banks falling within the range and by far EWMA shows the best results with the 91% banks complying with the chi-square criteria and accepting the null hypothesis. However, the hypothesis is rejected for Dubai Islamic Bank whose likelihood ratio turns out to be 23.64 and Al Rajhi Bank with a likelihood ration of 33.07, for which EWMA is not the best suited model and it shall be GARCH or Historical Simulation method for these two banks. For banks in Pakistan, Historical Simulation, N-distribution, EWMA and GARCH, all show favorable results.

Generalizing the above discussion, as similar to 95% confidence interval, in 99% confidence interval too, EWMA turns out to be the most reliable approach for risk forecasting.

Table 4.6: Kupiec POF Test at 95% Confidence Interval

Bank Name	Historical Simulation	Normal Distribution	Student t-Distribution	EWMA	GARCH
	ISLAMIC BANKS IN GCC				
Abu Dhabi Islamic Bank	2.6988	10.1505	6.1044	0.34	10.1505
Ahli United Bank (Kuwait)	2.6175	10.7464	2.0392	0.2556	7.7323
Al Baraka Banking Group	2.9918	1.1779	1.4772	0.904	0.0243
Al Rajhi Bank	0.3204	28.27	33.2902	6.9192	17.6986
Alinma Bank	1.9318	15.5907	6.7124	0.0574	7.2525
Bahrain Islamic Bank	0.462	0.01	0.01	1.2897	0.0184
Bank AlBilad	1.9244	3.2754	0.0214	0.1763	6.6708
Bank Aljazira	1.6103	6.8399	7.5874	0.7738	10.0983
Bank Nizwa	1.9743	2.3658	1.6201	0.0573	3.2633
Barwa Bank	0.6441	6.6057	0.7903	0.0011	4.1236
Boubyan Bank	5.0643	12.6051	7.3379	6.0073	13.9906
Dubai Islamic Bank	0.005	17.9095	7.2817	9.4643	17.2546
Khaleeji Commercial Bank	2.0884	0.9323	3.6751	1.1798	0.0532
Kuwait Finance House	6.687	8.3333	6.687	0.0105	10.6661
Kuwait International Bank	9.5272	12.0273	20.0457	0.1912	16.0658
Masraf Al Rayan	4.3287	14.1306	6.4432	0.8418	9.5856
Qatar Intl Islamic Bank	21.7835	23.2903	17.5986	3.3883	31.6974
Qatar Islamic Bank	3.4781	4.3555	0.3333	0.2573	5.3369
Sharjah Islamic Bank	2.1627	0.0016	4.9304	0.0937	0.0301
Warba Bank	0.3736	7.6153	2.2624	1.1089	1.1089
	ISLAMIC BANKS IN PAKISTAN				
BankIslami Pakistan Ltd	0.5192	5.9905	7.4271	0.7209	1.8768
Meezan Bank Limited	1.8695	2.6788	320.5651	0.1936	3.6454

Table 4.7: Kupiec POF Test at 99% Confidence Interval

Bank Name	Historical Simulation	Normal Distribution	Student t-Distribution	EWMA	GARCH
ISLAMIC BANKS IN GCC					
Abu Dhabi Islamic Bank	17.8257	8.6043	0.6013	0.0977	3.1509
Ahli United Bank (Kuwait)	7.1226	12.3006	0.5033	1.2854	2.6045
Al Baraka Banking Group	46.6996	44.1065	1.6906	0.5374	36.6436
Al Rajhi Bank	0.9393	12.7746	1.6326	33.0763	26.6506
Alinma Bank	15.3191	10.4866	0.3208	2.1165	7.38
Bahrain Islamic Bank	32.1479	36.3737	0.874	0.1031	22.462
Bank AlBilad	25.1285	44.2056	4.7698	1.4636	18.4919
Bank Aljazira	9.0305	6.5593	2.7249	3.9243	3.4988
Bank Nizwa	13.8099	13.8099	2.1096	0.4552	0.1907
Barwa Bank	20.385	20.385	0.0763	0.7251	16.536
Boubyan Bank	2.7628	24.7598	0.8233	2.2218	1.3055
Dubai Islamic Bank	-	16.7542	2.1028	23.6404	2.2358
Khaleeji Commercial Bank	20.4846	24.2618	1.4194	0.4733	22.343
Kuwait Finance House	13.5554	18.7749	8.2197	0.0003	7.5175
Kuwait International Bank	7.5904	14.6449	53.0991	0.6336	8.3611
Masraf Al Rayan	16.957	18.2336	0.23	0.4554	14.5199
Qatar Intl Islamic Bank	9.3067	9.3067	2.0554	1.6043	11.0232
Qatar Islamic Bank	37.2894	27.519	2.2551	0.3898	21.2992
Sharjah Islamic Bank	8.5241	2.091	2.26	0.132	3.8201
Warba Bank	5.6887	4.5309	0.6312	0.2132	1.7635
ISLAMIC BANKS IN PAKISTAN					
BankIslami Pakistan Ltd	1.3449	2.7145	19.9857	0.5142	0.022
Meezan Bank Limited	1.0722	0.6057	29.4778	0.0008	0.3596

4.2.2.4 Christofferson (Independence) Test

Table 4.8 shows the likelihood ratios for all the banks at 95% confidence interval. If we look into the results reported by this table, N-distribution method, student t-distribution and EWMA report almost similar results, i.e. in only 23% of the banks, the null hypothesis is accepted. The rest showing greater values than the benchmark chi-square value of 3.84. Looking into results from Historical Simulation, the results are even better as in 32% of the banks, null hypothesis is accepted. The better results out of all the models are shown by GARCH method, where 73% of the banks in the sample fall within the accepted range, hence they pass Christofferson test.

Considering the Islamic banks in Pakistan, all models are acceptable and they do not show any volatility clustering through any model. However for the Islamic banks in the GCC, the Christofferson test explicitly rejects all the models for Dubai Islamic Bank, Boubyan Bank, Bank AlBilad, Kuwait Finance House, Barwa Bank, and Ahli United Bank.

Summarizing the above discussion, it can be said that based on Christofferson independence test, GARCH model shows best results among all the VaR estimation models under discussion at 95% confidence interval.

Table 4.9 shows the likelihood ratios for all the banks at 99% confidence interval, at which the benchmark chi-square value turns out to be 6.64. Noticing the values of likelihood ratio reported in the below table, it is evident that 36% of the banks reject the null hypothesis in the N-distribution method. Student t-distribution showed even better results with 41% banks falling within range. Then comes EWMA with for which 64% banks have their null hypothesis accepted. Historical simulation ranks at second best method for VaR estimation based on Christofferson test at 99% confidence interval with 82% banks having their likelihood ratios falling within the range. GARCH method reports the best results in this case with 100% banks accepting the null hypothesis at 99% confidence interval. Also for the banks in Pakistan it can be seen that except student t-distribution method, all the other methods seem reasonable with no volatility clustering.

Table 4.8: Christofferson Independence Test at 95% Confidence Interval

Bank Name	Historical Simulation	N Distribution	Student t-Distribution	EWMA	GARCH
ISLAMIC BANKS IN GCC					
Abu Dhabi Islamic Bank	5.2484	13.4469	13.5631	12.7361	3.7629
Ahli United Bank (Kuwait)	6.7467	9.4095	12.1902	12.0191	3.9693
Al Baraka Banking Group	1.6354	6.3104	7.521	7.6211	1.8932
Al Rajhi Bank	26.7509	20.3207	24.9161	4.7696	0.8533
Alinma Bank	9.4827	27.6523	29.5657	35.4555	1.6196
Bahrain Islamic Bank	1.458	5.6132	7.2025	13.5497	1.0175
Bank AlBilad	11.534	36.0612	45.8032	59.3255	7.2228
Bank Aljazira	6.2716	10.5214	13.7587	10.3143	0.2212
Bank Nizwa	1.1579	0.9534	0.1419	2.172	0.7654
Barwa Bank	15.9386	24.9068	35.5974	33.8446	5.429
Boubyan Bank	12.922	62.0051	65.6824	31.995	8.3994
Dubai Islamic Bank	41.4295	61.2358	57.4267	30.6897	14.2749
Khaleeji Commercial Bank	0.1073	1.7953	2.4743	1.6285	0.5935
Kuwait Finance House	19.4348	59.6726	60.5987	40.7541	5.4722
Kuwait International Bank	21.9705	46.3916	39.0004	33.4321	2.7494
Masraf Al Rayan	4.3861	11.0397	19.1553	25.8087	0.204
Qatar International Islamic Bank	9.244	50.3016	47.9434	37.555	2.6544
Qatar Islamic Bank	10.1867	30.2106	31.3883	32.5275	0.0284
Sharjah Islamic Bank	0.4115	2.7262	2.8464	0.2238	0.4662
Warba Bank	5.0775	5.0226	6.8976	6.2385	3.8041
ISLAMIC BANKS IN PAKISTAN					
BankIslami Pakistan Limited	0.0096	0.4278	0.0414	1.5837	1.2293
Meezan Bank Limited	0.0476	0.3316	1.1067	0.1315	0.6411

Table 4.9: Christofferson Independence Test at 99% Confidence Interval

Bank Name	Historical Simulation	Normal Distribution	Student t-Distribution	EWMA	GARCH
ISLAMIC BANKS IN GCC					
Abu Dhabi Islamic Bank	1.5878	2.8819	5.2241	2.4764	0.8952
Ahli United Bank (Kuwait)	0.1571	6.9958	1.5465	1.921	0.4421
Al Baraka Banking Group	0.1786	9.3667	15.897	3.2118	0.066
Al Rajhi Bank	0.8055	4.483	3.8558	0.7217	0.2639
Alinma Bank	1.1693	11.8967	11.0149	2.5441	2.0762
Bahrain Islamic Bank	0.5357	4.0708	4.7841	2.2204	0.0029
Bank AlBilad	1.7611	28.0147	16.845	6.3373	4.8839
Bank Aljazira	0.4108	23.5392	10.6256	4.9968	0.8161
Bank Nizwa	0.1458	0.1458	0.9938	2.8115	1.7748
Barwa Bank	11.4282	24.3657	14.1628	10.9753	2.79
Boubyan Bank	6.0599	61.3521	10.5925	54.7729	3.1769
Dubai Islamic Bank	3.2041	27.1349	9.1716	8.8874	0.1731
Khaleeji Commercial Bank	0.043	1.0341	4.71	9.2917	0.0087
Kuwait Finance House	4.7941	58.2812	18.6218	34.9906	6.177
Kuwait International Bank	9.6618	33.3151	18.5972	32.1975	3.1006
Masraf Al Rayan	8.8526	8.5301	4.8407	1.5232	0.0084
Qatar Intl Islamic Bank	5.7231	17.1201	9.1571	1.158	2.6828
Qatar Islamic Bank	0.6933	22.5726	4.3709	3.8754	0.293
Sharjah Islamic Bank	0.5218	5.2522	11.04	7.3771	0.88
Warba Bank	8.4558	9.1028	17.5226	10.0521	5.7949
ISLAMIC BANKS IN PAKISTAN					
BankIslami Pakistan Ltd	1.2357	0.9398	9.8337	2.8331	2.2633
Meezan Bank Limited	1.3539	1.7386	2.3101	2.4737	2.7731

Summarizing the above discussion, it can be said that based on Christofferson independence test, GARCH model shows best results among all the VaR estimation models under discussion at 99% confidence interval too.

4.2.3 Conditional VaR (Expected Shortfall) Estimation

Conditional Value at Risk (CVaR) is the weighted average expected loss that exceeds the VaR estimates. VaR considers a threshold and extreme losses exceed this threshold. Therefore to study the losses beyond VaR threshold, CVaR is estimated, which is also called Expected Shortfall (ES).

4.2.3.1 ES Estimation via Non-Parametric and Parametric Methods

Table 4.10 represents the results of ES estimation under the non-parametric and parametric assumptions based models for both 95% and 99% confidence intervals. In non-parametric assumption, Historical Simulation model is used, whereas in the parametric assumptions based models, N-Distribution and T-Distribution models are used.

At 95% confidence interval, in the Historical simulation approach we can see that the most risky bank to invest from the GCC banks is Bahrain Islamic Bank with an ES of 8.50%, followed by Al Baraka Banking Group (7.80%) and Khaleeji Commercial Bank with an estimated ES of 7.54%. The least risky based on the ES estimation turn out to be Warba Bank with an ES of 3.38% followed by Abu Dhabi Islamic Bank and Kuwait Finance House with 4.10% and 4.13% respectively.

At 99% confidence interval the highest risk is reported by Al Rajhi Bank with 16.53% ES. On second and third ranks are Bahrain Islamic Bank (14.39%) and Qatar International Islamic Bank (13.69%). And the least risky being, Warba Bank (5.48%), Kuwait International Bank (7%) and Kuwait Finance House (7.19%).

Table 4.10: Conditional VaR Estimation through Non-Parametric and Parametric Methods

Bank Name	Historical Simulation		N-Distribution		Student t-Distribution	
	95%	**99%**	**95%**	**99%**	**95%**	**99%**
ISLAMIC BANKS IN GCC						
Abu Dhabi Islamic Bank	0.041	0.0755	0.0347	0.0448	0.0341	0.0961
Ahli United Bank (Kuwait)	0.0486	0.095	0.0419	0.0541	0.0586	0.1247
Al Baraka Banking Group	0.078	0.113	0.0589	0.0762	0.0368	0.154
Al Rajhi Bank	0.0618	0.1653	0.1322	0.1708	0.0566	0.2019
Alinma Bank	0.0424	0.0729	0.0357	0.0462	0.0465	0.1134
Bahrain Islamic Bank	0.085	0.1439	0.0721	0.0932	0.1019	3.7943
Bank AlBilad	0.0567	0.0948	0.0457	0.059	0.0629	0.1843
Bank Aljazira	0.055	0.1002	0.0567	0.0733	0.0618	0.136
Bank Nizwa	0.0614	0.1136	0.0485	0.0626	0.0585	0
Barwa Bank	0.0572	0.0956	0.0465	0.0601	0.0327	0.1564
Boubyan Bank	0.0534	0.0943	0.0459	0.0593	0.0498	0.1847
Dubai Islamic Bank	0.0534	0.092	0.0464	0.06	0.0515	0.1701
Khaleeji Commercial Bank	0.0754	0.1103	0.0607	0.0784	0.0474	1.22E+47
Kuwait Finance House	0.0413	0.0719	0.0378	0.0489	0.0407	0.0766
Kuwait International Bank	0.0458	0.07	0.0416	0.0537	0.0416	0.0908
Masraf Al Rayan	0.0451	0.0815	0.0387	0.05	0.0629	0.1347
Qatar Intl Islamic Bank	0.0592	0.1369	0.1121	0.1449	0.0049	0.3793
Qatar Islamic Bank	0.0496	0.083	0.0418	0.0539	0	0.1708
Sharjah Islamic Bank	0.0541	0.0765	0.0484	0.0625	0.7838	0.1172
Warba Bank	0.0338	0.0548	0.0314	0.0406	3.67E+18	0.0766
ISLAMIC BANKS IN PAKISTAN						
BankIslami Pakistan Ltd	0.0582	0.0859	0.0591	0.0763	0.0342	0.1358
Meezan Bank Limited	0.0394	0.059	0.0391	0.0505	0.06	0.0611

Looking into the N-distribution approach, at both 95% and 99% confidence intervals, the most risky and the least risky remain the same. The highest risk is reported by Al Rajhi Bank with an ES of 13.22% and 17.08% for 95% and 99% confidence intervals respectively. Second most risk in both confidence intervals are Bahrain Islamic Bank with an ES of 11.21% and 14.49% for 95% and 99% confidence intervals respectively and Qatar International Bank with an ES of 7.21% and 9.32% for 95% and 99% confidence intervals respectively. The least risky banks here are the same for both 95% and 99% confidence intervals. The least ES is reported by Warba Bank with an ES of 3.14% and 4.06% for 95% and 99% confidence intervals respectively, then is Abu Dhabi Islamic Bank with an ES of 3.47% and 4.48% for 95% and 99% confidence intervals respectively and Alinma Bank with an ES of 3.57% and 4.62% for 95% and 99% confidence intervals respectively.

At 95% confidence interval, using student t-distribution approach, the top three risky banks include Warba Bank, Sharjah Islamic Bank (78.38%) and Bahrain Islamic Bank (10.19%). The most stable out of the sample include Qatar Islamic Bank (0%), Qatar International Islamic Bank (0.49%) and Barwa Bank (3.27%). At 99% confidence interval, the highest risk is reported by Khaleeji Commercial Bank. Second most risk in both confidence intervals are Bahrain Islamic Bank with an ES of 379.43% and on third stands Qatar International Bank with an ES of 37.93%. The least risky banks here for 99% confidence intervals are reported by Bank Nizwa with an ES of 0%, then is Kuwait Finance House (7.66%) and then Warba Bank with an ES of 7.66%. From the banks in Pakistan, the most risky is BankIslami Pakistan Limited according to all the approaches and the less risky is Meezan Bank Limited. Hence the most risky lot from the banks in the GCC includes Khaleeji Commercial Bank, Bahrain Islamic Bank and Qatar International Islamic Bank and the least risky lot includes Warba Bank and Kuwait Finance House.

In Pakistani Banks the more risky is BankIslami Pakistan Limited under all the three methods at 99% confidence interval and at 95% confidence interval

BankIslami Pakistan Limited is the riskier one under Historical Simulation and N-distribution but Meezan Bank reported a higher ES via Student t-distribution.

4.2.3.2 ES Estimation through Time Dependent Volatility Methods

At 95% confidence interval, EWMA approach exhibits that the most risky bank to invest from the GCC banks is Khaleeji Commercial Bank, followed by Bahrain Islamic Bank (6.25%) and Abu Dhabi Islamic Bank with an estimated ES of 5.04%. The least risky based on the ES estimation turn out to be Kuwait Finance House with 1.48% ES. On second and third ranks are Ahli United Bank (Kuwait) (1.67%) and Dubai Islamic Bank (1.67%).

At 99% confidence interval the highest risk is reported by Khaleeji Commercial Bank. The second most risky bank, according to EWMA approach is Bahrain Islamic Bank with 8.07% ES. On third rank is Abu Dhabi Islamic Bank (6.51%). The least risky based on the ES estimation turn out to be Kuwait Finance House with 1.91% ES. On second and third ranks are Ahli United Bank (Kuwait) (2.16%) and Dubai Islamic Bank (2.16%).

Looking into the GARCH approach, at both 95% and 99% confidence intervals, the most risky and the least risky remain the same. The highest risk is reported by Bahrain Islamic Bank with an ES of 6.73% and 8.69% for 95% and 99% confidence intervals respectively. Second most risk in both confidence intervals are Warba Bank with an ES of 6.38% and 8.25% for 95% and 99% confidence intervals respectively and Khaleeji Commercial Bank with an ES of 5.30% and 6.85% for 95% and 99% confidence intervals respectively. The least risky banks here are also the same for both 95% and 99% confidence intervals. The least ES is reported by Ahli United Bank (Kuwait) with an ES of 2.03% and 2.63% for 95% and 99% confidence intervals respectively, then is Dubai Islamic Bank with an ES of 2.39% and 3.09% for 95% and 99% confidence intervals respectively and Kuwait International Bank with an ES of 2.43% and 3.14% for 95% and 99% confidence intervals respectively.

Table 4.11 represents the results of ES estimation under the time dependent volatility approach based models for both 95% and 99% confidence intervals that include EWMA and GARCH methods.

TABLE 4.11: Conditional VaR Estimation through Time Dependent Volatility Methods

Bank Name	**EWMA**		**GARCH**	
	95%	**99%**	**95%**	**99%**
ISLAMIC BANKS IN GCC				
Abu Dhabi Islamic Bank	0.0504	0.0651	0.0489	0.0632
Ahli United Bank (Kuwait)	0.0167	0.0216	0.0203	0.0263
Al Baraka Banking Group	0.0295	0.0381	0.0437	0.0564
Al Rajhi Bank	0.0268	0.0347	-	-
Alinma Bank	0.0327	0.0423	0.0305	0.0394
Bahrain Islamic Bank	0.0625	0.0807	0.0673	0.0869
Bank AlBilad	0.0331	0.0428	0.0303	0.0392
Bank Aljazira	0.0306	0.0395	0.045	0.0582
Bank Nizwa	0.0334	0.0432	0.0419	0.0541
Barwa Bank	0.0241	0.0311	0.0321	0.0414
Boubyan Bank	0.0242	0.0313	0.0318	0.0411
Dubai Islamic Bank	0.0167	0.0216	0.0239	0.0309
Khaleeji Commercial Bank	0.0848	0.1095	0.053	0.0685
Kuwait Finance House	0.0148	0.0191	0.0246	0.0317
Kuwait International Bank	0.019	0.0246	0.0243	0.0314
Masraf Al Rayan	0.0293	0.0379	0.0361	0.0467
Qatar International Islamic Bank	0.0195	0.0252	-	-
Qatar Islamic Bank	0.0275	0.0355	0.0277	0.0358
Sharjah Islamic Bank	0.0289	0.0373	0.0405	0.0524
Warba Bank	0.0386	0.0499	0.0638	0.0825
ISLAMIC BANKS IN PAKISTAN				
BankIslami Pakistan Limited	0.0416	0.0537	0.0495	0.0639
Meezan Bank Limited	0.0375	0.0485	0.0406	0.0525

From the banks in Pakistan, the most risky is BankIslami Pakistan Limited according to all the approaches and the less risky is Meezan Bank Limited.

Hence the most risky lot from the banks in the GCC includes Khaleeji Commercial Bank, Bahrain Islamic Bank and Warba Bank and the least risky lost includes Ahli United Bank (Kuwait), Dubai Islamic Bank and Kuwait International Bank.

4.3 Estimation through Extreme Value Theory (EVT) Methods

All the previously studied VaR estimation methods study the entire distribution of returns in order to estimate VaR. However the extreme risks, that occur in cases of crisis, appear in the extreme tails of any distribution. Hence, in order to study the extreme tails, EVT is used. It has a huge importance in risk estimation and management as it is used to identify and prevent extreme losses from occurring.

In EVT there are two main methods for estimation. One is Block Maxima in which maxima (or minima) over blocks of time are studied and the second one is called Peak-Over-Threshold in which all the values over and above a certain level are selected for the study. The first method uses the Generalized Extreme Value (GEV) distribution whereas the second one uses the Generalized Pareto Distribution (GPD). The GPD method is further sub-divided into two using static and dynamic distribution.

4.3.1 VaR Estimation

In case of block maxima model under GEV approach, the results are generated only for left tail of return distribution (VaR) as the research motive is to estimate expected extreme loss. In this approach, the data consisted of maximum return for each block to compute GEV. The BMM suggest that if value of ξ (shape parameter) is greater than 1, which states that data follows Frechet distribution and this is the case for our 2 banks from Pakistan and 20 banks from the GCC. Also if the shape parameter less than 1, then it is Weibull distribution, which is the case with 2 banks in the GCC in our sample, named Abu Dhabi Islamic Bank and Al Baraka Banking Group.

The study estimates VaR for both tails of distributions at 95% and 99% confidence levels. The study uses "rolling-window" concept with window size of 250 observations. According to this concept, the one period ahead return forecast is calculated using the data from the previous 250 observations.

Table 4.12 reports the estimated VaR under the EVT approaches, GEV, GED (Static) and GPD (Dynamic) under 95% and 99% confidence intervals.

At 95% confidence interval, using the GEV approach, from the banks in the GCC, expected potential loss under BMM is maximum at 18.56% as reported by Bahrain Islamic Bank. On second number rests Bank Nizwa with 13.99% risk and then is Qatar International Islamic Bank with an estimated VaR of 13.40%. The least risky banks in the sample are Warba Bank, Kuwait International Bank and Kuwait Finance House with VaR values of 6.05%, 7.47% and 7.65% respectively.

At 99% confidence interval, for the banks in the GCC and under the GEV approach, the top three risky banks are Bahrain Islamic Bank (31.72%), Qatar International Islamic Bank (31.09%) and Al Rajhi Bank (31.01%), whereas the least risky banks include Warba Bank (9.87%), Abu Dhabi Islamic Bank (10.25%) and Kuwait International Bank (10.44%).

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

Using the GPD (Static) approach, at 95% confidence interval, the most risky banks from the GCC include Khaleeji Commercial Bank, Bahrain Islamic Bank and Sharjah Islamic Bank with their estimated VaRs as 4.93%, 4.78% and 3.88% respectively. The bottom three banks on the basis of VaR estimation are Al Baraka Banking Group (Kuwait), Warba Bank and Abu Dhabi Islamic Bank with estimated VaRs of 1.53%, 1.98% and 2.25% respectively.

At 99% confidence interval, the most risky banks in the GCC on the basis of VaR estimation through GPD (Static) approach are Al Baraka Banking Group, Bahrain Islamic Bank and Khaleeji Commercial Bank with VaR estimation of 10.09%, 9.89% and 9.39% respectively, whereas the least risky banks include Warba Bank, Kuwait Finance House and Alinma Bank with estimate VaR values of 4.39%, 5.21% and 5.33% respectively.

TABLE 4.12: VaR Estimation through EVT Methods

Bank Name	GEV (BMM)		GPD (Static)		GPD (Dynamic)	
	95%	**99%**	**95%**	**99%**	**95%**	**99%**
ISLAMIC BANKS IN GCC						
Abu Dhabi Islamic Bank	0.0805	0.1025	0.0225	0.0606	0.0007	0.001
Ahli United Bank (Kuwait)	0.0984	0.1985	0.0258	0.0613	0.0005	0.0006
Al Baraka Banking Group	0.1306	0.1675	0.0153	0.1009	0.0002	0.0009
Al Rajhi Bank	0.1211	0.3101	0.025	0.0558	0.001	0.0011
Alinma Bank	0.0906	0.1703	0.0244	0.0533	0.001	0.0012
Bahrain Islamic Bank	0.1857	0.3172	0.0478	0.0989	0.0019	0.0028
Bank AlBilad	0.1162	0.2419	0.0325	0.0778	0.0009	0.0014
Bank Aljazira	0.1146	0.1947	0.0314	0.0609	0.0003	0.0012
Bank Nizwa	0.1399	0.254	0.0234	0.0854	0.0005	0.0014
Barwa Bank	0.1061	0.1857	0.0341	0.0776	0.001	0.0016
Boubyan Bank	0.1084	0.2714	0.0299	0.0672	0.0007	0.0012
Dubai Islamic Bank	0.1042	0.1835	0.0308	0.0688	0.0014	0.0021
Khaleeji Commercial Bank	0.1263	0.1735	0.0493	0.0939	0.0014	0.002
Kuwait Finance House	0.0765	0.1293	0.0246	0.0521	0.0001	0.0001
Kuwait International Bank	0.0747	0.1044	0.0313	0.0549	0.0007	0.0011
Masraf Al Rayan	0.0928	0.166	0.0249	0.061	0.0012	0.0015
Qatar International Islamic Bank	0.134	0.3109	0.0279	0.06	0.0097	0.0169
Qatar Islamic Bank	0.0922	0.1388	0.0299	0.0593	0.0009	0.0016
Sharjah Islamic Bank	0.0894	0.124	0.0388	0.064	0.0009	0.0014
Warba Bank	0.0605	0.0987	0.0198	0.0439	0.0005	0.0001
ISLAMIC BANKS IN PAKISTAN						
BankIslami Pakistan Limited	0.0946	0.1293	0.0423	0.0679	0.0028	0.0033
Meezan Bank Limited	0.066	0.0917	0.0285	0.046	0.002	0.0025

Under the GPD (Dynamic) approach on 95% confidence interval the top three and bottom three GCC banks in this order are Qatar International Islamic Bank, Bahrain Islamic Bank, Khaleeji Commercial Bank, Kuwait Finance House, Al Baraka Banking Group (Kuwait) and Bank Aljazira with reported VaR values of 0.97%, 0.19%, 0.14%, 0.01%, 0.02% and 0.03% respectively.

At 99% confidence interval, for the banks in the GCC and under the GPD (Dynamic) approach, the top three risky banks are Qatar International Islamic Bank (1.69%), Bahrain Islamic Bank (0.28%) and Dubai Islamic Bank (0.21%), whereas the least risky banks include Warba Bank (0.01%), Kuwait Finance House (0.01%) and Ahli United Bank (Kuwait) (0.06%).

For the Islamic Banks in Pakistan, at 95% confidence interval, under all the approaches, i.e. GEV, GPD (Static) as well as GPD (Dynamic) BankIslami Pakistan Limited is more risky with a VaR value of 9.46%, 4.23% and 0.28% respectively, whereas Meezan Bank showed a lower risk with VaR values of 6.60%, 2.85% and 0.20% respectively under the above mentioned approaches.

Also at 99% confidence interval, the Pakistani Islamic banks show a similar risk levels with BankIslami Pakistan Limited reporting a VaR of 12.93%, 6.79% and 0.33% under GEV, GPD (Static) and GPD (Dynamic) respectively, whereas Meezan Bank Limited reported 9.17%, 4.60% and 0.25% respectively under the approaches mentioned above.

It can also be seen from the table that the VaR reported through GPD (Static) are higher than the one reported through GPD (Dynamic) and the also VaR reported through GEV is greater than the VaR reported through GPD (Static). This means either one of these is overstating the risk or the other is understating the risk.

Summarizing the above discussion, if we observe and compare all these three models together, the most risky banks in the GCC include Qatar International Islamic Bank and Bahrain Islamic Bank, whereas the least risky include Warba Banka and Kuwait Finance House.

4.3.2 Backtesting for EVT Methods of VaR Estimation

Back testing here again is done by estimating the Violation Ratio as well as VaR Volatility.

4.3.2.1 Violation Ratio

Table 4.13 reports the violation ratios under the GEV, GPD (Static) and GPD (Dynamic) approach at both 95% and 99% confidence intervals. As mentioned above, the ideal ratio here would be close to 1, i.e. within the range from 0.8 to 1.2. This is because this is a comparison of the total observed violations and the total expected violations. The more the violation ratio is close to 1, the better is the model considered for VaR estimation.

From the values reported in the table below it can be seen that only 6 out of 22 banks show an appropriate violation ratio when calculated via GEV at 95% confidence interval. This makes only 27% of the total banks in the sample. With GPD (Static) 91% of the banks show the violation ratios close to 1 and for GPD (Dynamic) none of the banks reported an appropriate violation ratio, hence failing the model.

According to this, at 95% confidence interval GPD (Static) can be considered a good model for VaR estimation for Islamic banks in Pakistan and for all of the Islamic banks in the GCC (in the sample) except for Alinma Bank (0.78) and Al Baraka Banking Group (3.34). For these two banks no other EVT approach shows an appropriate violation ratio either.

At 99% confidence interval, if we look at the values reported through GEV and GPD (Dynamic), none of the banks, whether in the GCC or in Pakistan, reported an appropriate violation ratio, hence failing these both models for VaR estimation. However for GPD (Static) 73% of the banks reported an appropriate violation range, i.e. close to 1.

Table 4.13: Violation Ratio for EVT Methods of VaR Estimation

Bank Name	**GEV (BMM)**		**GPD (Static)**		**GPD (Dynamic)**	
	95%	**99%**	**95%**	**99%**	**95%**	**99%**
ISLAMIC BANKS IN GCC						
Abu Dhabi Islamic Bank	0.061	8.3143	1.0374	0.9916	8.7262	43.5545
Ahli United Bank (Kuwait)	0.8948	5.3768	1.0283	0.9812	6.7347	33.281
Al Baraka Banking Group	0.0352	8.7951	3.3421	1.2313	6.0334	30.1671
Al Rajhi Bank	1.1455	6.654	1.0444	1.0318	8.2712	39.9453
Alinma Bank	0.591	4.0523	0.7767	0.7176	8.2735	40.6923
Bahrain Islamic Bank	0.5384	4.5305	0.998	0.9192	6.5397	32.3047
Bank AlBilad	1.0325	6.383	1.0325	1.0638	9.2866	45.9324
Bank Aljazira	0.5298	4.2678	1.0007	0.883	8.6534	41.9426
Bank Nizwa	0.5082	3.3632	0.9865	1.719	4.559	22.7952
Barwa Bank	0.7259	4.8168	0.9159	1.0176	9.0773	44.6404
Boubyan Bank	1.1986	6.5157	0.9895	1.0453	6.1045	30.5226
Dubai Islamic Bank	0.8381	5.881	1.0381	1	8.7	42.2143
Khaleeji Commercial Bank	0.0298	2.1593	0.9829	0.7446	6.0759	30.3797
Kuwait Finance House	0.7267	4.9394	1.0401	1.0211	6.3025	31.5127
Kuwait International Bank	0.1237	2.9741	1.0136	0.9279	6.562	32.8099
Masraf Al Rayan	0.5752	4.1389	0.8558	0.9821	8.4041	41.8099
Qatar International Islamic Bank	0.9024	5.419	0.974	1.0504	6.6746	32.275
Qatar Islamic Bank	0.2908	4.1706	1.0439	1.0248	0	40.8484
Sharjah Islamic Bank	0.2385	3.2368	1.1414	1.1073	7.598	37.9898
Warba Bank	0.4976	3.6364	0.8995	0.7656	7.1579	35.7895
ISLAMIC BANKS IN PAKISTAN						
BankIslami Pakistan Limited	0.0886	2.1418	0.7976	0.7386	8.8183	43.9439
Meezan Bank Limited	0.2595	3.0534	1.0382	1.0687	8.4427	41.6031

From the above discussion it is evident, that out of the three EVT methods used for VaR estimation, on the basis of violation ratio, GPD (Static) ranks better as compared to other two, but still this method cannot be applied to all the Islamic banks in our sample.

4.3.2.2 VaR Volatility Ratio

There is no volatility in VaR for GEV and GPD (Static) at both 95% and 99% confidence intervals, but there is VaR volatility ratio calculated for GPD (Dynamic). But since values are constant for two models, hence we cannot compare these models based on the VaR volatility ratio.

4.3.2.3 Kupiec POF (Unconditional Coverage) Test

The results of unconditional coverage test also known as Kupiec POF test are reported in Table 4.14.

It is evident that likelihood ratio for only 14% (3 out of 22) of the banks fall within the acceptable chi-square range of 3.84 for 95% confidence interval under the GEV approach. As far as GPD (Dynamic) approach is considered none of the banks showed favorable results. Only GPD (Static) approach shows better results with 91% banks having their likelihood ratios within the acceptable range.

This makes 20 out of 22 banks and this shows that none of the EVT approach is favorable for VaR estimation for Alinma Bank and Al Baraka Banking Group whose reported likelihood ratios turned out to be 6.71 and 209.34 respectively.

Similarly for 99% confidence interval, under both GEV and GPD (Dynamic) approaches, all banks show likelihood ratios beyond the acceptable range of chi-square, i.e. 6.64 and for GPD (Static) method this ratio for 100% of the banks fell within the range. Hence out of the three EVT approaches, GPD (Static) can be considered the best approach for VaR estimation both for the banks in the GCC and the Pakistani Islamic banks.

Table 4.14: Kupiec POF Test for EVT Methods of VaR Estimation

Bank Name	**GEV (BMM)**		**GPD (Static)**		**GPD (Dynamic)**	
	95%	**99%**	**95%**	**99%**	**95%**	**99%**
ISLAMIC BANKS IN GCC						
Abu Dhabi Islamic Bank	103.721	277.204	0.095	0.001	1706.828	3478.393
Ahli United Bank (Kuwait)	1.536	242.856	0.106	0.009	2058.490	4602.715
Al Baraka Banking Group	99.050	264.748	209.344	0.572	744.216	1782.797
Al Rajhi Bank	5.065	676.397	0.487	0.048	5612.077	11139.192
Alinma Bank	24.296	126.297	6.712	2.117	2800.964	5705.453
Bahrain Islamic Bank	20.378	102.897	0.000	0.103	1163.756	2635.837
Bank AlBilad	0.176	421.732	0.176	0.129	4652.644	9146.092
Bank Aljazira	18.946	80.991	0.000	0.196	1742.819	3417.225
Bank Nizwa	20.619	46.682	0.013	5.750	496.918	1393.468
Barwa Bank	12.831	225.836	1.129	0.009	4120.080	8100.754
Boubyan Bank	5.618	393.343	0.017	0.059	1921.673	4576.931
Dubai Islamic Bank	6.117	475.506	0.317	-	5438.589	10658.534
Khaleeji Commercial Bank	119.517	13.692	0.021	0.971	891.104	2127.281
Kuwait Finance House	18.223	339.368	0.353	0.019	2998.434	7031.993
Kuwait International Bank	268.000	108.208	0.041	0.226	3232.414	7438.304
Masraf Al Rayan	31.756	159.109	3.272	0.009	3467.951	7136.589
Qatar International Islamic Bank	2.170	405.384	0.151	0.106	3327.363	7240.272
Qatar Islamic Bank	152.382	238.051	0.419	0.026	417.659	10160.886
Sharjah Islamic Bank	51.033	37.346	1.184	0.132	1187.771	2563.340
Warba Bank	16.895	43.755	0.574	0.631	946.551	2095.063
ISLAMIC BANKS IN PAKISTAN						
BankIslami Pakistan Limited	97.2334	13.4346	3.1264	1.0281	1,796.47	3,638.28
Meezan Bank Limited	53.0056	36.0632	0.0993	0.0611	1,606.79	3,256.09

4.3.2.4 Christofferson (Independence) Test

Table 4.15 below shows the likelihood ratios for all the banks at both 95% and 99% confidence intervals. If we look into the results reported by this table, for 95% confidence interval, with GEV approach followed, 5% of the banks accept the null hypothesis and have their likelihood ratios within the chi-square range, and show that there is no clustering. For the remaining, the alternate hypothesis is accepted. For GPD (Static), in 23% of the banks, null hypothesis is accepted and in 45% of the banks the null hypothesis is accepted with GPD (Dynamic) approach.

This shows that comparing these three EVT models, GPD (Dynamic) ranks better than the other two but still it shows clustering in cases of Sharjah Islamic Bank, Kuwait International Bank, Qatar International Islamic Bank, Ahli United Bank (Kuwait), Qatar Islamic Bank, Boubyan Bank, Abu Dhabi Islamic Bank, Warba Bank, Kuwait Finance House and Alinma Bank from the banks in the GCC, and for Pakistani banks both Meezan Bank Limited and BankIslami Pakistan Limited.

However, for the banks in Pakistan, GPD (Static) however shows that there is no clustering as per this test.

At 99% confidence interval, for 32% and 36% of the banks, null hypothesis is accepted using the GEV and GPD (Static) approach respectively. However, again using GPD (Dynamic) the banks report better likelihood ratios as in 55% of the banks, the ratio falls within the acceptable range of 6.64, hence meaning there is no clustering in these banks over the period studied. This means this is a stable model for these banks in the GCC, except Sharjah Islamic Bank, Kuwait International Bank, Qatar International Islamic Bank, Ahli United Bank (Kuwait), Qatar Islamic Bank, Boubyan Bank, Al Rajhi Bank, Abu Dhabi Islamic Bank and Warba Bank. However, for the banks in Pakistan, both GEV and GPD (Static) report no clustering with 99% confidence interval.

Table 4.15: Christofferson Independence Test for EVT Methods of VaR Estimation

Bank Name	**GEV (BMM)**		**GPD (Static)**		**GPD (Dynamic)**	
	95%	**99%**	**95%**	**99%**	**95%**	**99%**
ISLAMIC BANKS IN GCC						
Abu Dhabi Islamic Bank	15.5917	15.9405	27.8534	6.6446	8.5498	8.7979
Ahli United Bank (Kuwait)	28.3317	39.5782	30.7137	1.1705	15.2965	12.9607
Al Baraka Banking Group	7.766	4.0745	1.0673	5.8594	0.4363	0.4363
Al Rajhi Bank	69.5522	74.7216	60.21	30.6595	3.4654	9.0709
Alinma Bank	37.6502	26.9906	29.5657	2.2417	5.6591	5.6619
Bahrain Islamic Bank	7.5042	5.5805	7.5587	13.1293	0.5898	0.4161
Bank AlBilad	69.4224	64.7725	69.4224	17.4659	3.6688	4.4783
Bank Aljazira	16.9411	11.065	9.1457	7.6358	1.6393	1.4803
Bank Nizwa	0.0038	0.2881	1.8309	0.5275	2.4552	2.4552
Barwa Bank	58.5041	90.8955	84.9993	46.5485	3.1844	3.9974
Boubyan Bank	70.6856	67.7289	71.9758	18.8862	11.477	11.477
Dubai Islamic Bank	66.2934	76.3622	71.199	62.5569	0.3744	0.2864
Khaleeji Commercial Bank	8.0973	1.7473	7.3933	8.9286	2.092	2.092
Kuwait Finance House	67.8316	67.9605	63.4286	46.0839	5.8359	5.8016
Kuwait International Bank	33.1365	94.1556	78.8217	43.2866	19.7557	19.7557
Masraf Al Rayan	33.4806	40.249	41.1202	20.1839	2.3662	2.1478
Qatar International Islamic Bank	87.4026	100.597	94.1818	26.0923	26.5144	18.2333
Qatar Islamic Bank	26.9351	48.2212	63.5093	10.4616	13.1398	12.5993
Sharjah Islamic Bank	11.6293	1.6978	3.6278	12.482	31.4321	31.4321
Warba Bank	17.1038	8.8231	17.1632	3.2628	6.9092	6.9092
ISLAMIC BANKS IN PAKISTAN						
BankIslami Pakistan Limited	4.7148	0.1321	0.9656	3.0001	4.9202	5.5528
Meezan Bank Limited	5.0146	3.9092	0.0294	1.8513	12.2765	12.6174

So summarizing the above discussion, again GPD (Dynamic) showed better results for 45% of the banks at 95% confidence interval and 55% of the banks at 99% confidence interval, as compared to GEV and GPD (Static) but it has failed in the earlier tests.

4.3.3 Expected Shortfall Estimation via EVT Methods

Table 4.16 reports the results of ES estimation under the EVT based models for both 95% and 99% confidence intervals. EVT methods studied include GEV, GPD (Static) and GPD (Dynamic) approaches.

TABLE

From the above results it is evident that at 95% confidence interval, and GEV approach, the highest ES is reported by Al Rajhi Bank (27.95%) followed by Qatar International Islamic Bank and Boubyan Bank with their reported ES of 26.51% and 25.20% respectively. The least risky as per this approach turn out to be Abu Dhabi Islamic Bank with an ES of 7.01% and the second and third least risky banks are Kuwait International Bank (8.01%) and Warba Bank (8.06%).

For GPD (Static) approach, at 95% confidence interval, the highest ES is reported by Bahrain Islamic Bank with an ES of 8.42%, followed by Khaleeji Commercial Bank (7.52%) and Bank Nizwa (6.39%). The least three risky banks to invest in, on the basis of ES are Warba Bank with 3.38%, Kuwait Finance House with 4.12% and Abu Dhabi Islamic Bank with a reported ES of 4.12%.

For GPD (Dynamic) at both 95% and 99% confidence intervals the top three and least three risky banks remain the same. Sharjah Islamic Bank, Barwa Bank and Qatar Islamic Bank report as ES of 161.53%, 150.29% and 150.02% respectively at 95% confidence interval and 161.57%, 150.34% and 150.08% respectively at 99% confidence interval, whereas the least three risky banks are Bank Aljazira, Abu Dhabi Islamic Bank and Bahrain Islamic Bank having their reported ES as 0%, 0.01% and 0.01% respectively under both 95% and 99% confidence intervals.

At 99% confidence interval, using GEV approach the top three most risky banks, on the basis of ES are the same as GEV, i.e. Al Rajhi Bank, Boubyan Bank and

Qatar International Bank with their ES reported as 71.60%, 63.10% and 61.48% respectively. Also the three least risky banks are the same as calculated through GEV approach too, i.e. Abu Dhabi Islamic Bank with an ES of 8.92%, Kuwait International Bank (11.20%) and Warba Bank (13.16%).

The most risky banks, at 99% confidence interval, using GPD (Static) are Bahrain Islamic Bank, al Rajhi Bank and Khaleeji Commercial Bank with their reported ES as 50.28%, 13.75% and 11.97% respectively. The least risky banks as per GEV turn out to be Warba Bank, Kuwait International Bank and Kuwait Finance House with their reported ES as 5.43%, 7.07% and 7.15% respectively.

Table 4.16: Conditional VaR Estimation through EVT Methods of VaR Estimation

Bank Name	**GEV (BMM)**		**GPD (Static)**		**GPD (Dynamic)**	
	95%	**99%**	**95%**	**99%**	**95%**	**99%**
ISLAMIC BANKS IN GCC						
Abu Dhabi Islamic Bank	0.0701	0.0892	0.0412	0.0749	0.0001	0.0001
Ahli United Bank (Kuwait)	0.1656	0.3343	0.0487	0.0938	0.0002	0.0002
Al Baraka Banking Group	0.123	0.1578	0.0505	0.0995	-0.0016	-0.0016
Al Rajhi Bank	0.2795	0.716	0.0515	0.1376	-0.0007	-0.0007
Alinma Bank	0.1364	0.2563	0.0423	0.0732	0.0003	0.0003
Bahrain Islamic Bank	0.246	0.4203	0.0842	0.5028	0.0001	0.0001
Bank AlBilad	0.204	0.4246	0.0569	0.0942	1.463	1.4633
Bank Aljazira	0.1543	0.262	0.0537	0.0988	0	0
Bank Nizwa	0.1902	0.3453	0.0639	0.1112	1.1625	1.1632
Barwa Bank	0.1496	0.2616	0.0571	0.0947	1.5029	1.5034
Boubyan Bank	0.252	0.631	0.0534	0.1012	1.4598	1.4601
Dubai Islamic Bank	0.1431	0.2521	0.0534	0.0915	1.3741	1.3747
Khaleeji Commercial Bank	0.1321	0.1815	0.0752	0.1197	-0.0012	-0.0012
Kuwait Finance House	0.1039	0.1757	0.0412	0.0715	0.0006	0.0006
Kuwait International Bank	0.0801	0.112	0.0458	0.0707	1.4571	1.4573
Masraf Al Rayan	0.1312	0.2347	0.0451	0.0812	0.0002	0.0002
Qatar International Islamic Bank	0.2651	0.6148	0.0518	0.1033	1.0728	1.0772
Qatar Islamic Bank	0.1052	0.1583	0.0496	0.0826	1.5002	1.5008
Sharjah Islamic Bank	0.0991	0.1374	0.0541	0.0763	1.6153	1.6157
Warba Bank	0.0806	0.1316	0.0338	0.0543	-0.0009	-0.0009
ISLAMIC BANKS IN PAKISTAN						
BankIslami Pakistan Limited	0.102	0.1394	0.0581	0.0858	0.0007	0.0007
Meezan Bank Limited	0.0753	0.1046	0.0394	0.0595	0.0007	0.0007

Chapter 5

Conclusion and Recommendation

This chapter includes the conclusion of this study, the recommendations on the basis of this study, some limitations of this study and some ideas for future research.

5.1 Conclusion

Value at Risk is a tool to measure the maximum potential risk in an asset, class of asset or a portfolio of assets. Different companies use this tool for future risk estimation. There are various models to estimate VaR, which use the historical returns to forecast future risks. Purpose of this research is to identify the best suited model, out of several models, to estimate VaR in the top 20 Islamic banks of the GCC and the listed Islamic banks in Pakistan. This study contributes to the application of VaR estimation techniques in the Islamic Banking industry, which is still unexplored for risk management in that industry.

VaR has been estimated using the five conventional methods that include non-parametric (Historical Simulation), parametric (student t- distribution and N-distribution) and time dependent volatility methods (GARCH and EWMA). Further the EVT methods have been used to estimate VaR that include GEV, GPD (Static) and GPD (Dynamic) to study the extreme left tails of the distributions at 95% and 99% confidence intervals. The descriptive statistics revealed non-normality of the entire data, which indicates fat tails of the distributions.

According to VaR estimation by conventional methods, the highest VaR is reported by normal distribution at both 95% and 99% confidence intervals for all banks in the GCC as well as the banks in Pakistan and the lowest risk is reported through EWMA approach at both 95% and 99% confidence intervals in both GCC and Pakistani banks. From the banks in the GCC, highest risk is reported by Al Rajhi Bank and the minimum risk is reported by Kuwait Finance House. From the banks in Pakistan BankIslami Pakistan Limited is more risky as compared to Meezan Bank Limited. Violation ratio and VaR volatility ratio has also been calculated and back-testing has also been applied to see which model is best suited for VaR estimation.

As per the results reported by Violation Ratio, it is evident that out of the five conventional methods used for VaR estimation, EWMA reported the least deviation from the expected violations at both 95% and 99% confidence interval for the banks in the GCC, by reporting 100% suitability for all the banks at 95% confidence interval and suitability to 90% banks in the GCC at 99% confidence interval. However for the banks in Pakistan, as per the violation ratio, both Historical Simulation and EWMA reported satisfactory (100% suitability) results, hence making these both models suitable for VaR estimation at both 95% and 99% confidence intervals.

Next comes the VaR Volatility ratio. Calculating this ratio for all the banks in the sample also indicates that EWMA is better than the other conventional methods as it reported lower volatility as compared to the other models at 95% confidence interval, as 95% of the banks reported the least volatility under this method in the banks from GCC. At 99% confidence interval, however, N-distribution reported better results for the banks in GCC, as 91% of the banks reported the least volatility under this method. For the banks in Pakistan, n-distribution, student t-distribution and EWMA reports minimum volatility at 95% confidence interval whereas at 99% confidence interval the volatility is minimum reported by N-distribution method only.

Kupiec (1995) point of failure (POF) test is applied to check the accuracy of the results reported by the VaR estimation, to all the banks in the GCC as well as Pakistan. At 95% confidence interval, EWMA reports the best results as 85% of the banks in the GCC and 100% banks in Pakistan fall under the benchmark range, hence making this model the most suitable for VaR estimation at 95% confidence interval. The only exceptions here are Al Rajhi Bank and Dubai Islamic Bank, for which better results are reported under Historical Simulation method, for which their violation ratio is reasonable too. Also for banks in Pakistan, Historical Simulation as well as GARCH also reports reasonable results, against both of which models, the violation ratio is also reasonable. At 99% confidence interval, student t-distribution and EWMA both report that 90% of the banks in the GCC fall under the benchmark range, hence these models can be used for their risk estimation. For banks in Pakistan, in 100% banks, the null hypothesis is accepted for Historical Simulation, N-distribution, EWMA and GARCH methods.

Christoffersen (1998) Independence test is conducted to evaluate whether the observed violations are linked to the previous period, hence forming a cluster, or whether they are independent of the other violations. Tests reveal that, at 95% confidence interval, for the banks in the GCC, the best results are reported under GARCH as in 70% of the banks, the null hypothesis is accepted. At 99% confidence interval, for the same category of banks, the null hypothesis is accepted for 100% banks under the GARCH method. According to Christofferson test, severe clustering is found by Historical Simulation, N-distribution, Student t-Distribution and EWMA approach at 95% confidence interval for the banks in GCC as well as by N-distribution and Student t-Distribution at 99% confidence interval. For the banks in Pakistan, at 95% confidence interval, the null hypothesis is accepted by the calculation done via all the conventional methods, whereas at 99% confidence interval, in all the methods except student t-distribution, the null hypothesis is accepted.

VaR considers a threshold and extreme losses exceed this threshold. Therefore, to study losses beyond the VaR threshold, the study estimates Conditional VaR or Expected Shortfall (ES). Estimating the ES for the banks in the sample, using the same conventional methods, it explains that the results of ES are consistent with the outcomes of VaR at both confidence intervals.

The next step of this study has been to estimate the VaR using the EVT methods. Two approaches are used in this study, i.e. GEV approach and GPD approach. Under GPD approach, further two methods are used to estimate VaR, i.e. GPD (Static) and GPD (Dynamic). After estimation of VaR, the same procedure is applied by calculation of Violation Ratio, VaR Volatility and back-testing using Kupiec and Christofferson tests.

From the results it is evident that the maximum risk on the extreme left tail is reported through the GEV approach for both 95% and 99% confidence intervals and for both groups of banks, i.e. in the GCC and in Pakistan. At both confidence intervals, the highest risk is reported by Bahrain Islamic Bank and the least by Kuwait Finance House in the GCC banks and for banks in Pakistan, higher risk is reported by BankIslami Pakistan Limited and the lesser by Meezan Bank Limited.

Next step in this research is the calculation of violation ratio. The violation ratios calculated under both confidence intervals, using the EVT approaches revealed that at 95% confidence interval 90% of the banks in the GCC and 100% banks in Pakistan show suitable results under GPD (Static) method. At 99% confidence interval, again GPD (Static) approach is the best as 75% banks in the GCC and 50% banks in Pakistan comply with the requirement and suggest that this model be used for VaR estimation out of the EVT approaches studied here.

After that comes the Kupiec Point of Failure Test for EVT methodologies. This test reveals that at both 95% and 99% confidence intervals GPD (Static) ranks as the best model for VaR estimation for both GCC banks and Pakistani Banks as in 90% of the GCC banks and 100% of Pakistani banks, the null hypothesis is accepted at 95% confidence interval and in 100% of the GCC banks and 100% of the Pakistani banks, the null hypothesis is accepted at 99% confidence interval. This test clearly rejects GPD (Dynamic) and GEV approaches for VaR estimation because of extremely insignificant values.

Christofferson test applied on EVT reveals that the least clustering is reported by GPD (Dynamic) model, whereby in 50% of the GCC banks, the null hypothesis is accepted at 95% confidence interval and in 55% of GCC banks, it is accepted at 99% confidence interval. The maximum clustering is reported by GEV approach for GCC banks. For Pakistani banks, in both 95% and 99% confidence intervals, in 100% banks, the null hypothesis is accepted using GPD (Static) approach.

From ES using the EVT approaches, it is evident that the maximum risk on the extreme left tail beyond VaR, is reported through the GPD (Dynamic) approach for both 95% and 99% confidence intervals and for the banks in GCC and through the GEV approach for the banks in Pakistan at both confidence intervals. At both confidence intervals, the highest risk is reported by Sharjah Islamic Bank and the least by Bank Aljazira in the GCC banks and for banks in Pakistan, higher risk is reported by BankIslami Pakistan Limited and the lesser by Meezan Bank Limited.

Another objective of this research is to test the adequacy of capital requirement as per the BASEL accord for capital regulations, given by the Basel Committee on Banking Supervision (BCBS) according to which all international banks to reserve at least 8% of capital based on their risk-weighted assets (BCBS, 2019). Also the BASEL accord states that the Daily Capital Charges (DCC) should be set at a value higher than or equal to 3 times of average VaR of the previous 60 business days (Chang et al., 2019). According to this, using the model finalized above for calculation of VaR, i.e. EWMA at 95% confidence interval, if we multiply VaR with 3, for all the Islamic Banks in the GCC, we see that 80% of the banks fall within the range to be maintained, i.e. 8%, however Bahrain Islamic Bank (14.9%), Warba Bank (9.2%), Khaleeji Commercial Bank (20.3%) and Abu Dhabi Islamic Bank (12.1%) go beyond the threshold limit. Also for the Islamic Banks in Pakistan 100% go beyond the threshold. On average if we look into the adequacy of capital to be maintained by the Islamic banking industry in the GCC, it comes out to be 7.7% which is fairly within the threshold limit of 8%. Similarly for the Islamic banking industry in Pakistan, on average it comes out to be 9.5%, which is greater than the requirement as recommended by BCBS.

5.2 Recommendations

The findings indicate that the EWMA method has highest accuracy in risk estimation under 95% and 99% of confidence level for both the banks in GCC and in Pakistan, therefore EWMA approach should be used to estimate VaR. The results are more satisfactory at 95% of confidence level as compared to 99%, therefore the value at risk of whole distribution should be estimated at 95% of confidence interval for both GCC and Pakistani Islamic banks.

In case of extreme events, value at risk should be estimated by using GPD (Static) approach should be used by both GCC Islamic banks and Pakistani Islamic banks because this model provides better forecasting of risk in extreme left tail of distribution. Also, as similar to VaR through conventional methods, the results here are more satisfactory at 95% of confidence level as compared to 99%, therefore the value at risk of tail distribution should also be estimated at 95% of confidence interval for both GCC and Pakistani Islamic banks.

Comparing all the eight methods discussed in this research with each other, and the two shortlisted methods recommended above, EWMA at 95% confidence interval from the conventional methods and the GPD (Static) at 95% confidence interval from the EVT methods, if we have to pick one, it should be EWMA at 95% confidence interval, since 100% of all the GCC banks as well as Pakistan banks show a violation ratio within range as compared to GPD (Static) at 95% confidence interval, where 90% of the GCC banks and 50% of Pakistani banks show a reasonable violation ratio within the range.

Comparing the risk profile of the Islamic banks in Pakistan and GCC, using the model shortlisted, i.e. EWMA at 95% confidence interval it is evident that the overall risk calculated for GCC banks is 2.56% and those of Pakistani banks is 3.16%. Hence it is concluded that the Islamic banks in the GCC are less risky and for anyone to decide where to invest from these two regions, should invest in the Islamic banks in GCC.

Considering the adequacy of capital requirements as mentioned in the conclusion section above, it is also recommended that the regulators should take into account the individual risks of the financial institutions and accordingly make necessary amendments to the capital requirements.

5.3 Ideas for Future Research

Uylangco and Li (2016) stated that VaR is not the best method for risk estimation, since it concerns mainly with the central values of a distribution and not with the extremes. In financial markets, where there are generally fat tails, the values in the extreme tails need equal weightage and attention, which VaR does not give them. the VaR approach has been subject to some criticism in the past too. Jorion (1996) stated that majority of the parametric methods use a normal distribution approximation in VaR, due to which the risk of high quantile is underestimated. Some studies have also tried to use different approximations, using student t-distribution assumptions of a mixture with normal distribution, but at the end, these methods focus on the central values of any distribution and not on the values in the extreme tails, which occur in extreme crisis situations. Therefore the issue of giving equal weightage to all the values in a distribution, be it in the center or in the tails, still remains unresolved.

As far as EVT methods are concerned, since they are applied on the tail distributions, where values occur rarely, therefore, it is important to have a larger sample size to be able to estimate the risk better and hence provide appropriate mitigation startegies.

As a future direction to scholars conducting research of risk management, the back-testing of the ES is an area they can put their efforts on. It is going to be better as they would be able to compare the results of VaR and ES and then recommend a better model for risk estimation for the Islamic Banking Industry. Moreover different methodologies including the Monte Carlo simulation, different approaches in the GARCH family, variance and covariance methods can be used to estimate VaR and ES. Also sample data can be enriched by taking Islamic Banks from another region of the world and comparing them with other Islamic Banks of the world in order to better visualize the outcome of these VaR estimation approaches.

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