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How Accurate are Value at Risk Model at Islamic Banks? An Approach of Berkowitz Model

by

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This work is dedicated to my beloved parents who supported me, encourage me, and prayed for me and to my respected supervisor Dr. Arshad Hassan, who has been a constant source of inspiration.

CERTIFICATE OF APPROVAL

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Abstract

The purpose of this study is to investigate the market risk of Islamic banks using a sample of 18 Islamic banks from different countries. Non Parametric model that include Historical Simulation, Parametric model that include Normal Distribution, and Time Varying Volatility models that include EWMA, GARCH and Berkowitz are applied to forecast the risk of Islamic banks. Back testing is done using violation ratio, volatility ratio, Kupiecs proportion of failure test, and Christoffersens independence test to know about the accuracy of each model. The study used the data from 2008 to 2018. By comparing all the models, the Historical Simulation is a good estimator of risk. Berkowitz model outperform out of Time Varying Volatility models. For determining the capital adequacy ratio, it is recommended that regulators should consider the risk of different Islamic bank separately, and then determine the capital requirement accordingly and necessary adjustment should be made to capital adequacy ratio.

Keywords: Non Parametric model, Parametric model, Time Varying Volatility model, Back testing, value at risk.

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Abbreviations

AFB	Affine Bank
ABBG	Al Baraka Banking Group
ABC	Arab Banking Corporation
ALCIB	Alliance Islamic Bank
ALMB	Alinma Bank
ABTK	Al Barak Turk Katilim
ARJ	Al Rajhi
AIB	Arab Islamic Bank
BAJZA	Bank AlJazira
BIB	Bahrain Islamic Bank
BISM	Bank Islam Malaysia
BISL	Bank Islami Limited
BSM	Bank Syariah Mandiri
DIB	Dubai Islamic Bank
EWMA	Exponentially Weighted Moving Average
GARCH	Generalized Autoregressive Conditional Hetroskedasticity
H.S	Historical Simulation
IMRH	Ihtimar Holding
N.Distribution	Normal Distribution
POF	Proportion of Failure
QIB	Qatar Islamic Bank
QIIB	Qatar International Islamic Bank
VaR	Value at Risk

Chapter 1

Introduction

The chapter cover theoretical background, research gap is identified, problem statement, objectives of research, research questions, significance of the study and plan of the study.

1.1 Theoretical Background

Risk is the uncertainty about future outcome, it is probability that actual outcome may be different from desired outcome, and it is the probability of loss. Companies usually face two types of risk operational risk and financial risk. Operational risk include legal risk, regulation risk, accounting risk, and model risk. Financial risk include foreign exchange risk, interest rate risk, credit risk, market risk, and liquidity risk. Legal is that legal position may change, regulation risk is that an unregulated sector may become regulated, accounting risk is that accounting methods may change, model risk is that financial model become obsolete. Foreign exchange risk is uncertainty about exchange rate, interest rate risk is uncertainty about future interest rate, credit risk is that the counter may default, market risk is uncertainty about future market behavior, and liquidity risk is uncertainty about future conversion to cash.

Risk management is the process of identifying the risk that an entity wants. Measuring the actual risk face by the entity and taking actions to bring actual level of risk to desired level of risk. It has nothing to do to eliminate the risk. It is a continuous process that actual risk remain within target level.

Risk assessment is very important in todays business environment. Regulators and other stakeholders requires that companies should have their risk profile and use strategies to control risk. The first step in risk assessment is to identify the risk that a firm have. Second to create library of all risks that firm that firm face. Third there should be a person who is responsible for controlling the risk. In fourth step the control measures are identified to reduce the risk. In fifth step the potential of risk is identified. Lastly it is revised annually or more frequently if big changes occur.

Volatility in the financial market and need for regulation has changed the scenario in which the bank to operate. Not only banks are interested to manage their risk but regulators also wants banks to disclose their risk. Investors also want to know about the risk faced by the different banks to compare the risk by the banks for their investment decisions.

There has always been a relationship between risk and return. The decision about investment in a stock for a given level of return is always based on a given a given level of risk to assume. If the risk in a stock is high investors demand a high amount of return for that particular stock, and a low level of return may be acceptable for investors if the stock in which they are investing has low amount of risk. It mean there is always positive relationship between risk and return.

Traditionally certain tools are used by investors and other agencies to know about reliability and risk of financial institutions. The most commonly used method is ratios analysis. The most important ratios in that regard are liquidity ratios, leverage ratios, profitability ratios, asset management ratios, capital structure ratios, market related ratios. However the use of these ratios provide a lot of information about the financial health of any entity but the exit amount of risk cannot be assess using these ratios. Because these ratios are based on the information given in financial statement of any firm which are greatly subject to the view of finance manager and historical as well. Another method of risk measurement is standard deviation but the problem with standard deviation is that is depended on distributions (Horne & JR, 2004).

Recently developed measure of risk is value at risk. Value at Risk and Conditional value at risk are well known measures of risk. After the failure of big financial institutions in 1987 VaR become one of the important tool for market risk measurement. Value at Risk is the loss expected on investment in a given time horizon with given confidence level. VaR is a statistical measure of loss. VaR measures the losses resulting from normal market movement. VaR accumulate all the losses in portfolio into a single number that is suitable for reporting to regulators, management and for disclosure in annual report (Linsmeier & Pearson, 2000).

VaR models are allowed for measuring risk capital charge for big banks by U.S and other international banking regulators after the modification of 1996 Basel Accord for market risk estimation. After these development, VaR models have become a standard tool for market risk estimation used by financial and other nonfinancial entities as well (Berkowitz & OBrien, 2002).

The need for using VaR as a measure of risk started because last few decades suffer from high volatility in exchange rates, fluctuations in interest rates, and more volatility in stock prices and due to managing market risk by using derivatives. All these trends are accompanied by high volume of foreign trade and the international links between the companies. The increased use of derivatives are also accompanied by high volume of trading of securities and expansions of financing opportunities. The use of derivatives securities also increased due to high volume of foreign transactions among firms. As a result of these trends, the amount of risk in the companies portfolios significantly increased. Due to all these trends, the demand for a comprehensive measure of market risk increased to be used by manager to report to management (Linsmeier & Pearson, 2000).

There are three methods of VaR calculation one is Historical Simulation, second is Variance Covariance method and third is Monte Carlo Simulation. The disclosure of VaR has three main objectives. First it is used as market risk measure faced by the banks. Second objective is that VaR estimation can be converted into market risk capital charge to have sufficient fund for loss arising from adverse market conditions. Third objective is that it enable the regulators to investigate the banks internal VaR a process known as backtesting (Perignon, Deng, & Wang, 2008).

The value at Risk concept was first introduced by U.S investment Bank J.P Morgan. The chairman of the bank Dennis Weatherstone asked for a simple and comprehensive risk tool for risk measurement and risk management process. Using the Markowitz theory of portfolio VaR was developed. However, the origin of the name value at risk was unknown (Adamko, Spuchkov, & Valkov, 2015). In 1990 the different names were used for Value at Risk first name Dollar at Risk (DaR), second name Capital at Risk (CaR), third name Income at Risk (IaR), fourth name Earning at Risk (EaR), and the last Value at Risk also known VaR (Holton & MA, 2002).

According to international standards, domestics regulators demand all banks working in their own jurisdiction to calculate and disclose their VaR forecast. In Canada it is compulsory for the banks that they should disclose and report their VaR forecast since 1997. Most of the regulatory bodies allow banks to use their own internal model of VaR for measuring market risk instead of using a standard model of VaR for risk estimation. However this internal model of VaR for risk estimation will only be acceptable to regulators in case if the banks prove the accuracy of this internal model through external validation. Many market players are of the opinion that the high degree of independence given to banks in sitting their market risk charge has some misleading effects. Particularly the banks may be induced to underestimate their VaR forecast in order to reduce their market risk charge (Perignon et al., 2008).

Although VaR is very attractive approach for market risk estimation and management but it has some limitations. VaR models used by dealers and end users for risk estimation demonstrate varying results for the same types of portfolios. The effect of these inconsistencies are very important for the capital adequacy standard. These discrepancies in results mainly occur due to dependency of VaR methods on different parameters, differences in data, different assumptions and methodology (Beder, 1995).

VaR is very simple tool for market risk measurement but it suffers from some statistical problems. The Basel Committee on banking supervision uses VaR to determine capital adequacy standard for banks and other financial firms to cover their market risk facing due to normal operation. However if the underlying risk is not forecasted accurately this may lead the banks to underestimate or may overestimate the risk and as a result maintain extremely very high capital or very low capital. The ultimate effect of this will be the inefficient allocation of financial resources by the banks concerned (Engle & Manganelli, 2004).

There are two basic reasons to reject VaR as measure of market risk estimation. First value at risk is not doing well in case of aggregation of different risks therefore creating addition problems. Second value at risk does not encourage the use of diversification strategy but also sometime restrict diversification (Artzner et al., 1999). A major shortcoming of VaR is that it does not provide the tool to handle the loss that might occur beyond the threshold amount shown by this measure. It cannot distinguish between situation where the losses may be deem worse. It is also found that it has bias toward optimism rather than consevatism that should prevail in risk management (Rockafellar & Uryasev, 2002)

To overcome these shortcoming an alternative risk measure Conditional value at risk which is also known as expected shortfall is used. Expected shortfall also known as expected tail losses is a risk measurement technique that measure the lossess that a portfolio has beyond the VaR cutoff point. VaR shows the worst loss at given time horizon and also at a given confidence interval. Expected shortfall is the loss that may occur beyond the VaR thershold. In others word if the loss exceed the VaR threshold then conditional on that happening what will be the maximum amount of loss or Expected Shortfall is the loss conditional on the loss that exceed the VaR. Expected Shortfall is a very good risk measurement technique instead of VaR for financial risk management, and if correctly estimated is a reliable instrument for measuring relative riskiness (Acerbi et al., 2018).

Moreover VaR is not a coherent risk measure a risk measure is coherent if it meet the following four conditions nuber one monotonicity, number two positive homogeniety, number three subadditivity, and fourth nuber is tranlation invariance.

VaR does not meet the condition of subadditivity. All these conditions are fulfill by Expected Shortfall so this is a coherent risk measure.

Islamic banks works according to the basics laws of Shariah and their practices and policies must be Shariah compliant. Under the laws and principles of Shariah the taking and giving of Riba (interest) is illegal, and due to this bane the financial transaction of these banks are interest free. The financial instruments of these banks are Shariah compliant and are different from the conventional banks (Harzi, 2011).

Acting as financial intermediary, risk management is also very important for Islamic banks. Islamic banks also face sveral types of risks including market risk, credit risk, operational risk, and liquidity risk (Ariffin & Kassim, 2014). To remain alive and be successful greatly depend upon the ability of banks to manage these risk efficiently. Another consideration for Islamic banks is that risk management techniques adopted by these banks should not contradict the basic techings of Shariah (Khan & Ahmad, 2001).

The management of risk for Islamic banks is much important as compared to conventional banks. largely due to fact that Islamic banks are exposed to additional risk due to the specific nature of financial contracts, legal regulations, liquidity contracts and the goverence system of Islamic banks (Cihak & Hesse, 2010).

As a result of increasing pressure of globalization, a comprehensive risk management tool is very important for Islamic banks to cope with cross border financial movements. There are also arguments that Islamic banks profitability and performance is greatly affected because of allocation of more resources for reducing these risks (Ariffin & Kassim, 2014).

Same management techniques are used by Islamic banks as used by the conventional banks. The relationship between readiness and the resources needed for implementing the Basel II Accord for UAE banks are studied by Al-Tamimi. The study shows that banks in UAE are aware of the benefits, impacts and challenging related in implementing Basel II Accord. The study reveals the difference between the education level of UAE banks employee and the need for Basel II accord. The importance of education for Basel II Accord implementation is also revealed (Al-Tamimi, 2008).

According to Basel Committee, proper level of capital must be maintain by all banks to suffer the expected losses to remain as a going entity. During the last crises the amount of losses experienced by these banks was much greater the amount of capital appropriated for the purpose (Varotto, 2011).

1.2 Gap Analysis

VaR based models have been used to forecast the risk of banks. As Islamic banks are growing rapidly having operation in more than 75 countries with more than 300 institutions contributing to world economy. In Islamic banks there is limited work on VaR based models. The Berkowitz model was only tested for six large U.S banks. There is no such study on Islamic banks so this study bridge the gap by applying Berkowitz model on Islamic banks.

1.3 Problem Statement

Risk profile of Islamic banks is different due to diversified risk faced by Islamic banks. General perception about risk in Islamic banks is also different from traditional banks. Risk measurements techniques used by banks cannot cover the risk inherent in Islamic banks. Model based work is limited, specifically VaR based risk estimation in Islamic banks is less investigated. So the behavior of Islamic banks in the context risk is less addressed area and need detail investigation.

1.4 Research Questions

The research questions of this study are as under

- How do parametric VaR model perform in estimation of risk in Islamic banks?

- How do non parametric VaR model perform in estimation of risk in Islamic banks?
- How do time varying volatility based VaR model perform in estimation of risk in Islamic banks?
- Which model perform best in estimation of risk in Islamic banks?
- Is capital allocation proposed by Basel committee appropriate for Islamic banks?
- What should be the minimum capital allocation for Islamic banks?

1.5 Objectives of the Study

The objectives of this study are following

- To examine the market risk of Islamic banks using VaR techniques.
- To identify the best model for assessing the risk in Islamic banks.
- To determine the minimum capital requirement of Islamic banks.

1.6 Significance of the Study

Risk management is one of the important function of banks. This study is very important for investors, banks and regulators. Investors want to know about the risk faced by banks, as in investment decisions there is always relationship between the expected return and a particular level of risk to assume. This study is helpful for different investors such as individual, fund managers and financial institutions in managing the risk of the stocks of Islamic banks in their portfolios. As Islamic banks are growing rapidly and becoming more attractive for investors so the technique used provide great help to the investors in evaluation of risk and return of these Islamic banks.

The several techniques are used in this study for assessment of risk in Islamic banks and different methods of backtesting are used for determining the accuracy of these tchniques to help the Islamic banks in assessing of exact level of risk and mangement of risk. Many banks face bankruptcy due to not identifying the risks faced by them and determining the exact amount of loss to be faced as a result of risk. After knowing about the level of risks faced, these Islamic banks may allocate their resources more accurately and avoide the weak allocation of resources.

This study is also beneficial for regulators as the soundness of financial institutions and financial system is always a matter of major concern for them. The study is helpful for regulators in the context of determining the mininmum capital requirement for Islamic banks, and in setting of rules and regulations for these banks.

1.7 Plan of the Study

This study is comprised of five different chapters. Chapter 1 covers the main idea of the study. In this section main concepts of the study are presented followed by gap analysis, problem statement of the study, research question, after that objectives and significance of the study. In chapter 2 narration is given about theoritical aspects as well as empical analysis from past studies. In capter 3 different techniques used for estimation of risk are covered. The chapter 4 explains the emprical results and discuss the finding.

Chapter 2

Literature Review

Value at Risk is used as measure of risk estimation in the rcecent past years. After the 1987 financial crises, VaR emerged as one of the important tool of risk estimation in the financial institutions. Litrature shows that VaR is used as measure of risk by financial institutions such as banks and different insurance companies. VaR was widely used as measure of risk during 1990.

The origion of VaR can be traced back, when New York Stock Exchange imposed capital reqirement on its member banks. VaR also has evidence in portfolio theory of Markowitz and Ray (Holton & MA, 2002). There are different types of risks faced by the firms, VaR is a meaure of market risk. VaR is the loss expected on an investment with a given confidence level and also at a given time frame. Value at risk is used as a tool of risk management by financial and nonfinancial organizations due to the fact that VaR is very easy summary measure of risk, and also has an a very attractive basis (Bodnar, Hay, & Marston, 1998).

In another study by Basak and Shapiro (2001) ananlyze, the well known policies of vigorous portfolios and investment of wealth policies of the investors who are maximizing their wealth and are interested in reducing their exposure to market risk with the help of value at risk. It is observed that the manager using VaR select the most risky assets in their potfolios as compare to non risk managers and as result suffer heavy amount of losses when these losses happen. For overcoming the demerits of VaR an substitute risk managent models is also suggested on the probability of loss to occure. It was also identified that in time of down risk the risk is overstated by VaR risk manager when the market goes down and understated at the time of up market movement.

Beder (1995) state that VaR has achieved a very quick acceptance as a risk management tool and all VaR tools do not perform equally. The VaR calculations for the same portfolios exhibit different consequences. The causes of this differences is reliance of VaR techniques on differences of data, the different parametre used and as well as the differences in the methodologies of VaR calculations. In short the quantitative tools and VaR as well are the essentials tools of risk management. It is also found that the determination of regulatory capital is very lagely depended on the use of VaR.

The study done by Berkowitz et al., (2011) give fresh proofs on the projection of profit and loss and as well the value at risk for big international banks.The data set involves the real daily profit and loss produced within four distinct business line.These business lines are engaged in trading of stocks and each is witnessed every day at least for two days. With this distinctive set of data, the study present a unifying structure for the correct assessment of VaR estimation. The Monte Carlo Simulation is used to evaluate which test has the highest accuracy. The conditional autoregressive used for value at risk works well in all cases.

VaR is used as a measure of risk by many financial institutions and is calculated using the tchnique of historical simulation (Christoffersen & Pelletier, 2004). The study carried by Danielsson and Vries (2000) suggest a semi-parametric technique for unconditional value at risk assessment. The highest risk are indicated by parametric methods, however the non pararmetric models exhibited the lowest risk. The coparision of various technique for securities portfolios and returns of option, shows that risk assessment is very best at five percent level, however at high interval of probability the result become more weak. It heavily underestimate VaR, but the assessment made by semi parametric are more valuable.

In a study conducted by Perignon et al., (2008) claims that this is the first research that uses the daily data and value at risk of the banks risk management strategies. Using the data from the bigest six commericial banks in Canada, it is found that banks shows a systematic overstatement of conservatism during the estimation of VaR. There are only two exception found in total number of 7354 days, which mean these are the days where the actual loss are above the reported losses. It is exposed by each bank that risk is overstated in the range from 19% to 79% in each bank.This excess VaR is endorsed to various variable such as high vigilance and the impacts of diversification is minimized when the VaR is added for diverse line of business, and for several classes of risk. The VaR is also exaggerated due to social cost and as well due to economic cost used in is reference measure of risk.

Due to changes in nature of risks the methods used to measure these risk must adjust to these changes. Quantatitive risk measures are used as a vital risk management tool in parallel with models of returns. Investment decisions, the supervisory decisions, to determine the amount of safe capital, and regulatory decisions are largely based on these risk measures. In todays rapid changing fianancial world risk measures must be alert to news and should be easy to grasp in difficult situations.Value at risk is used as only standard measure of risk by these financial institutios and their regulators as well. The great fame of this measurement tool among financial players stem from the conceptual simplicity of this instrument. In ealy 1990 value at risk is introduced in financial industry to provide management a sigle number that could easily and rapidly include information about risk of portfolio. The cost of a position can be measured in term of risk using VaR, which help them to allocate resources in more best way (Engle & Manganelli, 2004).

According to Basel II Accord the banks and also other deposite accepting institutions are required to report their daily VaR forecast to the concern domestic authorities at the start of each trading day using one of the value at risk models to measure risk (Jimenez-Martn, McAleer, & Perez-Amaral, 2009).

The research by Kuester, Mittnik and Paolella (2006) compare the working of current techniques with various other fresh technique of value at risk for the purpose of forecasting risk. With the sample of more than thirty years of NASDAQ daily data of return it discover, that most of the techniques are working improperly, however multiple models are appropriate for model suitability under the present regulatory evaluation regulations. The model with best performance is GARCH and followed by Historical Simulation. The performance of conditional autoregressive VaR model is low.

The financial firms and nonfinancial firms as well use value at risk as measure of potential losses. The use of value at risk is at peak in financial firms where VaRs limits are used for trading operation and also fund management. VaR has been used by managers as a summary of market risk exposure. Due to widespread use of VaR it has become very important to study the impact on stock market and as well as on option market (Berkelaar et al., 2002).

One of the most important concept for estimation of risk in financial and nonfinancial firms is the likelihood based measure of risk which is called value at risk. The results presented by VaR are very easy to understand by all category of employees and at each area of organization. That is the main reason that VaR is implemented very quickly. Due to various financial damage VaR is considered in 1993. The growth of VaR begin in 1988 when the Central bank demanded all the banks to determine minimum catpital to insure safety against the trading risk in their operations. During 1993-1995 it is used as one of the key component of market risk assessment by banks. It is also used as a tool for internal risk management and also recommended by Basell Committee as technique for external regulatory reporting (Bohdalov, 2007).

According to Ufer (1996), the VaR model is obtaining acceptance quickely, patricularly in the fields of financial companies and is also arising as a benchmark for industry risk. In insurance companies the amount of risk is estimated according to depreciation for that year end. Sometimes risk is identified through method known as gap analysis accoding to which the comparison is made between the amount of assets and liabilities at different time intervals. The disadvantage in these methods is the problem of standardization, and hence cannot be used as comparison between different competing firms. These methods do not provide a clear understanding of risk, and cannot be used for identification of risk in complex portfolios such as options. Many large organizations have formulated ways to provide a very clear image of the risk in market. In Europe why these methods become popular in the recent past is that BIS has given the instructions to cope the market risk with the appropriate capital. A committee formulated by BIS indicate three methods used by firms for that purpose. The first of which is Historical Simulation Method, the second method include Variance-Covarianc approch and the third one is Monte-Carlo technique.

A very large portion of microeconomic theory has the association with formulating statistical methods for identifying risk in the calculation of insurance premimum. The concept with vast amount of use and having the best worldwide practice, the risk assessment is not merely reported by firms for the information of regulators, but for informatio of investors too. To know about the amount of movement in an asset or portfolio with movement in market conditions, VaR is the simplest method used for knowing the worst loss that has the probability of occurance at certain confidence (Majumdar, 2008).

The use of value at risk has arosed as tool of risk forecasting and also of risk management and at the same time becoming customary for market risk. The Group of thirty also called G30 and also by the Derivative Policy Group the VaR has been acknowledged as a technique of market risk estimation and for the purpose of reporting as well. VaR is nowdays adopted as basis of capital allocation according to Basel Committee Amendment regading accord of capital due to the market risk (Ball & Fang, 2006).

A study conducted by Yildirim (2015) measure the risk of foreign exchange inherent in insurance copanies. The foreign exchange risk is calculted through two model of VaR one of them is Historical Simulation and the other one is Monte Carlo measure of risk. After the analysis of the data it become evident that insurance companies are exposed to foreign exchange risk. The losses shown by Historical Simulation are on higher side compared to the losses represented by Monte Carlo tool.

The VaR is estimated for Dutch interest rate and the various model of VaR are used in this study, namely Monte Carlo method, the next one historical simulation and Variance Covariance as well. The result indicate that for holding period of ten days the method which outperform are Monte Carlo and the Variance Covariance with combination of GARCH. The most worse performance are shown by t-distribution (Vlaar, 2000).

Different modele of VaR are used by another study to identify risk. In this study the strength and weakness of different VaR based methods are identified. The backtesting technique are also applied to evaluate the performance of various approaches. The filtered Historical Simulation is found the best model. The results of parametric models are also very good when the assumption of independent and identically distributed return is ignored. The Parametric model can produce a very good results if the forecast of conditional variance are correct (Abada et al., 2014).

In another research by Orhan and Koksal (2012) examine the forecast of VaR estimation in time of crises under the assumption of GARCH. During the era of global fiancial crises the stock data from emerging and developed economies are collected and GARCH model is used to find VaR. The backtesting are then applied through Kupiec and Christofferson test, the results suggest that ARCH is performing well and the GARCH (1,1) is also doing well. The results are very worst presented by normal distribution.

In a study by Lin & Shen (2006), the accuracy of VaR is estimated through the use of t-distribution and then on the basis of backtesting procedure the result are investigated. It is found that the t-distribution appears the best when the confidence interval crosses 98.5% and identifying degree of freedom tail inex is used.

ROMERO et al., (2013) in a research implement many techniques of VaR to calculate VaR. From theporetical and from the practical point of view, their comparative strength and their weakness are identfied in regard of all of the methodologies. From practical point of view the literature demonstrate that the best technique for projection of VaR is the technique of Filter Historical Simulation. In addition the results of parametric technique is very attractive under the skewed and fat tail distribution, particularly if the supposition of identically and also the independent distribution is ignored. To know about the validity of VaR the backtesting also done.

Another research carried on in 2006 studies seven different GARCH models for estimation of value at risk accompanied by riskmetrics and as well as two GARCH long memory technique. Long and also short position in investment are regarded. These seven different models are implemented to 12 indices from different countries and four foreign exchange rate to estimate every model at different interval. The finding show that stationary and at the same time fractionally incorporated GARCH presented the reliable results than riskmetrics at 1% VaR. The performance of t-error models is good as compared to normal error model in case of long position, however not good in short position. However there is no asymmetry fount in exchange rate (So & Yu, 2006).

Rjiba et al. (2015) in study for a portfolio comprising of five assets they assess the analytical working of numerous VaR approaches. The traditional technique including Historical Simulation, with combination of bootstrap and also the Filter Historical Simulation are applied.The performance is judged on the basis of three different criteria, number one is Conditional Coverage test, the second criteria used is independence and conditional coverage, and the third one is the loss function. The results suggest that the classical techniques performed well in the departure of normality and the prediction are highly accurate in event of more losses.

Another study performed in 2000 propose the VaR and associated risk approaches for estimation of risk in hetroskedastic financial return, and when the probability of tail distribution is conditional. The current volatility is estimated through GARCH model, and the tail of distribution with extreme value theory. Through the backtesting applied on historical daily return, the estimation is stronger for one day. The Monte Carlo approch best perform in the forecasting of conditional quantile than the square root of time technique (McNeil & Frey, 2000).

The Karachi Stock Exchange, VaR assessment is done with the help of E-estimator of GARCH type of model. The stock data are split into three interval such as pre crises period, the second the period of crises and that of after the crises period for well comprehension of effect of global crises on KSE. The symmetric and as well as asymmetric GARCH models are applied to all these three periods and VaR are achieved in sample and for that of out of sample. The findings depicts that

E-estimator give precise and consistent forecaste of in low volatility period and also for that of high volatility period, and it is also found that asymmetric model outperform than symmetric model in case of KSE (Iqbal, 2017).

Ragnarsson (2011) compare the assessment of VaR for chosen GARCH model. The chosen GARCH (1,2) model is assessed againist the GARCH (1,1) and that against riskmetrics. The models are assessed at 1% and 5% for three sample, including one is full sample, and that the other is the sample before crises, and finally that sample with crises period. The findings demonstrate that it is not easy to pick one of these for all of the periods concerne. But the performance of GARCH (1,1) are very well for the full sample, for before crises the most recommended is riskmetrics, and GARCH (1,2) with best performance in crises sample.

A study conducted in 2016 observe the value at risk and the statistical characteristics of the daily price yield of valuable metals from 2000 to 2016, including gold,platinum, palladium and silver. The two different stage GARCH are applied, such as VaR is forecasted through the use of GARCH model and EVT is used to identfy the tail behavior. In th comparison of dynamic VaR it is reveald that gold has the very much steady and maximum VaR, this trend followed by platinum and silver, however the finding revealed that VaR is very much volatile in case of palladium. Through the result of backtesting it is found that it is not suitable techniques in precious metal risk management (Zhang & Zhang, 2016).

A study conducted in 2014 assesses the risk of banks with help of VaR methodologies in bank Three different techniques of VaR estimation are applied, including Variance Covariance, the other one is Historical Simulation, and Monte Carlo Simulation. The finding of all these methos are not in agreement for the VaR, and are very diverse from each other. The reliance on a single method can lead to misleading results (Saddique & Khan, 2015).

Another study apply the VaR models on nine distinct emerging markets daily return for the purpose of examining the comparative effiency of these models. The Historical Simulation and Variance Covariance model in combination with Etreme Value Theory at 95% and as well at 99% confidence are used to determine VaR. It is revealed that the properties of return distributions are distinct at left tails and at the right tails. In these market the risk and return are not similar (Gencay & Seluk, 2004).

Similarly, Nazir and Kumar (2018), conduct a study in main asian economies to emprically study estimation of VaR. The VaR is anticipate for Singapore, Hong Kong of China, Malaysia, South Korea, Indonesia, Taiwan of China, Philippines, Thailand, China, applying various opposing models. The backtesting process is applied , including unconditional coverage test and that conditional coverage test, to know which model is more appropriate for these economies. The result are blend with most authentic results of FIGARCH. The discrepencies in result are due to two reasons. First reason is that for future estimation of the VaR model the historical data of shares return is used. The second significant reason is that, the model is based on assumptions and estimates that does not remain the same for all the times. These variances in results indicate that, there are some problems associated with these approaches.

A study in 2018 scrutinize for the first time value at risk and the other related measures in Bit Coins to compare the results with S&P 500 and also with gold prices. The models which are applied GJR-GARCH in combination with pearson type-IV Distribution. The results indicate that there is very high volatility in Bit Coins and violations are very large for value at risk in Bit Coins compare to other assets. As per Basel Committee the capital requirements and also the capital allocation is very high for Bit Coins investors.

Cabedo and Moya (2003) in study suggest value at risk for oil price risk identification. The study implement three technique of VaR assessment, the standard measure of Historical Simulation, the other one is Historical Simulation with ARMA forecasts (HSAF) and the Variance-covariance technique, based on the assumption of autoregressive conditional Hetroskedasticity model of forecasts. The findings depicts that HSFA approach offers flexible VaR assessment, that fits the with movement of oil prices and give a more efficient risk assessment. VaR can be use to predict maximum oil prices and as well for desigining risk management policies.

Another study conducted in 2009 propose VaR as a very best tool of market risk disclosure in oil prices at given confidence level and consider it very crucial for risk management of oil prices. As oil prices becoming more instable and having a much effect on general price level.VaR model are used for both short and long position in oil market, to predict VaR through conditional and unconditional approaches. These models are also compared with other popular models including GARCH, and with Historical Simulation and that Filter Historical Simulation. The results of Historical Simulation are very effective. Another which produce strong results is GARCH (1,1) model. At last, the finding also reveal the significance filtering process (Marimoutou et al., 2009).

Similarly, in study by Fan et al. (2008) estimate VaR by applying GARCH type of model, based on the approach of Generalizes Error Distribution, for the both such as great downside and upside retuns in the crude oil spot market of WTI and Brent. The emiprical result suggest that GARCH based tool appear more attractive, than the most popular HSAF technique such Historical Simulation with that of ARMA forecast. This is comparatively much more reliable and precise than the model based on the approach of normal distribution used commonly. The results are beneficial for all those who are interested in the forecast and assessment of risk also in the oil markets.

A research in 2015 examine the value at risk and the related return for different European stock markets. The study exhibit that Sweden and UK, are the best suited markets for risk averse investors as they have highest risk return output in risk and return. The output of Greece and Holland are very bad on the basis of risk and return. However the return of Austria are significantly high with huge VaR. The result are beneficial in regard of different policies making specially in monetary policy (Iglesias, 2015).

A study in 2002 explore the retionship among the trading VaR, for a very little sample of U.S commercials banks and the following instability of their trading income, for the purpose to giving proofs on informativeness of this newly developed tool. Historical Simulation is used to forecast end of day position, in case of single position and for the collective positions also.

It is clear from the empirical finding that VaR discoveries are very much informative in identifying the trading profit variability. So, revelation of VaR can be used by the investors and as well as by the analyst for the purpose of relating the trading portfolios of different banks (Jorion, 2002).

In a study in 2001 the value at risk is used to forecast the risk of more than 80 banks. In this study first different methods are used to identify that the VaR techniques which are in practice are correct, and then selecting the best one on the basis of statistical techniques. VaRs are calculated on the basis of volatility based models, and then these models are compared with each others on the basis of backtesting (Christoffersen et al., 2001).

lez-Rivera et al. (2004) evaluate the predictive performance through different volatility based models of stock return for VaR. The loss function is selected, for which volatility evaluation is of great significane to compare their output. Two economic loss functions are estimated, such as option pricing function and other one is utility function, and two statistical loss functions, the first one goodness of fit for the determination of value at risk, and the second one predictive probability function. Three different test such as White, Hansen etc are very strong and unbiased measure for best predictive performance. The results show that simple models such as Riskmetrics and the Exponentially Weighted Moving Average, and that Simple Moving Average, are working better as others more advance techniques are doing for option pricing. The Asymmetric Quadratic GARCH appears to lead in case Utility base function, and the stochastic volatility is doing best in case of that VaR based loss function. The model of conditional standard deviation as compared to variance appears to be the leading in case of probability based function of loss.

A study by Vehvileainen and Keppo (2003) examine the risk management of de regulated market of electricity in Nordic electricity market. For power portfolio, the Monte Carlo Simulation is used. The findings of Historical Simulation provide the risk management techniques of the study concerned can also implemented to other electricity markets.

Sadeghi and Shavvalpour (2005) use two tools of value at risk forecasting.The first of them is Historical Simulatio with ARMA forecasting, and the second one is the variance covariance on the basis of GARCH model assumption. At 99% confidence, the finding recommend the HASF is offering the most reliable forecasting. However at 97.5% confidence the Value at risk is bigger than estimated with help of HASF approache.

A study conducted in 2016 use different empirical test to identify suitable model for foreign exchange risk. The parametric model which include variance covariance and that the non parametric model such as Historical Simulation are applied for forecasting value at risk in foreign exchange rate. Two different approaches of backtesting including kupiecs and the other one traffic light are used for the VaR accuracy determination. The findings depicts that risk is highly underestimated through the use of normality assumtion. The VaR assessment is found more realistic in case of students t distribution assumption (Swami et al., 2016).

Hammoudeh et al. (2013) use the value at risk to examine in six differents assets the downside risk, including four from valuable metals, petroleum and from S&P 500. The VaR is forecasted with the help of nine different models, including riskmetrics, the filter Historical Simulation, the GARCH type approach, and also approaches from extreme statistics. Three different techniques are used for the assessment of these models including unconditional coverage, second independence and last one conditional coverage. The findings exhibits that riskmetrics work inefficiently in case of individual assets and the best one is CEVT model. In case of individual assets the riskmetrics evaluation were mix for capital allocation purpose. However the riskmetrics is highly recommended in case potfolios for capital allocation purpose.

Similarly, a study in 2015 estimated value at risk and the Expected Shortfall in gold market with help of Generalized Pareto Distribution and the student t distribution in gold market. The backtesting is done with the help of Kupiecs test and also that Christoffersen test. The finding exhibit that GPD is the most appropriate model in case of gold prices than students t approach (Chinhamu et al. 2015).

Jackson et al. (1998) evaluate the emprical performances of various models of VaR through the data of fixed income securities, foreign exchange data and equity securities of U.K bank. The parametric and as well as nonparametric models are used to determine VaR. The simulation based model are strong incomparison to parametric model in case of tail return. However in case of time series behavior the parametric models are good.

In a research Hung et al., (2008) examine the the impact of fat tailed innovation with the help of three GARCH models including GARCH-N, and the GARCH-t and the third GARCH-HT on the results of one day onward VaR predictions. For identifying the correctness and proficiency of VaR models, the daily prices of five different power commodities are used including WTI crude oil, the Brent crude oil, Heating oil, the propane and as well as Gasoline regular. The outcomes of the research exhibit that when the return of assets have leptokutic and fat-tailed characteristics the VaR accuracy is very high forecasted through the GARCH-HT model for the high as well as low confidence. These outcomes also recommend that fat-tailed distribution is much appropriate for estimation VaR specifically in the occasion of power commodities.

Youssef et al., (2015) assess the crude oil and gasoline Value at risk and the expected shortfall. Three models of GARCH including FIGARCH, the HYGARCH, and the FIAPARCH are applied to know about volatility of power commodity. The extreme value theory is also applied on tail distribution instead of whole distribution. For one day onward VaR the FIGARCH model is strongly recommended on the basis of findings. The long memory GARCH and the Historical Simulation for low confidence were best performed as suggested by backtesting techniques. It is revealed by the results that for the energy market prices the long memory, asymmetry and the fat-tail and in combination with EVT are very important in risk management.

Similarly, in a research Aloui and Mabrouk (2010) examine crude oil, and gas products in case of short and long trading position as well the VaR and the expected shortfall. The traditional VaR determination with riskmetrics and their extension to like long memory, the asymmetry and the fat tail in the power market instability are applied. The three GARCH type of models containing FIGARCH, the HYGARCH and the FIPARCH are used in VaR computation. It is clear from the findings that for long as well short trading circumstances, asymmetry, the fat tail and the long memory anticipating the one day ahead VaR in the best fashion. The model which give the higest result is FIGARCH.

Sarma et al., (2003) conduct two case studies for model selection, one from S&P 500 index and the second from the NSE-50 index for both 95% and for the 99% level. The two stage slection process is used for model selection. The statistical accuracy is determine in the first step. If the various models are rejected, then in the second step the subjective loss function is applied for the selection of surviving models. The two stage pocess of selecting proves to be beneficial in selecting a VaR model, however addressing the issue incompletely. These case studies provide proofs about the strength and the constraints about the current information of VaR assessment and their testing as well.

For different VaR models the the projecting performance is assessed form various perspective such as the filtered and the unfiltered, the coventional and the extreme value approaches, the parametric and the nonparametric during the era of financial crises in Asian economy. The White reality test is applied to compare the performance of these models. On the basis of these results before the crises period and after crises the riskmetrics model is a good forecating technique. However, during the crises it is found that EVT based techniqes are working significantly. The predicting performance of various approaches are not same and are mix at different intervals, for diffent periods and even for different markets. So the results suggest that for different time periods, different technique should be used, as no single model is forecasting well during all periods (Bao et al., 2006).

Al-Zoubi and Maghyereh (2007) examine the comparative risk performance with the help of various VaR approaches, such as Riskmetrics, the Student-t, the APARCH and the skew Studen-t of the Dow Jone Islamic Index, and the Dow Jone World Index for the period 1996-2005. The Dow Jone World exhibit the bigger VaR as compare to DJIS.

Abdrashev (2016) use value at risk for the judgment of volatility in Islamic banks and as well in coventional banks securities. It is shown by the findings that the variable influencing risk in conventional banks securities are the same as for the Islamic banks.

The displayed commericial risk (DCR) for a sample of Islamic banks of Bahrain is calculated through the quantative technique. The VaR is implemented to know about the risk to identify the DCR-VaR and the capital adequacy ratio for the Islamic banks. First the circumstance which are exposed to risk on basis of actual return of Islamic banks are identified. And then at given confidence and also at given holding period the DCR-VaR and the capital adequacy is assessed (Toumi et al., 2018).

Ariffin and Kassim (2014) investigate the risk management approaches of main Islamic banks in Malaysia. It is revealed by findings that Islamic banks are applying all the techniques of risk management, such as credit rating, the gap analysis and all other less technically developed measures of risk. However, the use of highly developed measures of risk such as value at risk, the simulation approach are founded to be not most commonly used by Islamic banks.

Ariffin et al., (2009) conduct a study to know about the opinion of different CFO and the risk managers of 28 Islamic banks and from 14 countries about nature of risk, and the techniques of risk management and risk measurement as well. It is revealed by findings that Islamic banks are subject to same kinds of risk as the conventional banks. The finding also depics that less sophistecated tool of risk management including maturity matching, the gap analysis and the credit rating. The sophisticated tools of risk management, such as VaR, the PAROC and the simulation are not in high practice. This due to the reason that Islamic banks are new and also lack the resources for the implementation of the said techniques.

A research conducted in 2012 to explore in detail how the Islamic banks in MENA region measure and manage their risks. The finding indicate there is variation in degree of percetion of risk about different funding methods. It is found that conventional methods of risk alleviation are entensively used by the Islamic banks such as collateral and the guarantees. VaR is not widely used by Islamic banks for the measurement of market risk in the MENA region. Most banks in MENA does not use the more sophistecated methods of risk. The reason for not using the sophistecated techniques for assessment and monitoring of risk is that, it is not easy for Islamic banks working in the MENA region due to lack of data (Mokni et al., 2012).

A study in 2008 expose the UAE bnaks readiness for the implementation of Basel II. It is assessed from the results that UAE banks want to implement Basel II. The readness of UAE banks is due to the appropriate resources and also adequate level of employees education. (Al-Tamimi 2008).

Backtesting are the significant tools applied to assessed the precision of different VaR models in use. Backtesting tools are extensively used for the distinction of accurate model from inaccurate model. In the indian capital market, the assumption and characteristics of numerious backtesting techniques is investigated, and evaluated their precisions. For the period 2007-2008 the VaR is estimated for Nifty 50 stocks on the basis of closing prices. The results of different backtesting techniques are not in agreement for various VaR models, indicating the inefficiency of these techniques, for the identification of best model (Virdi, 2011).

After reviewing the literature it is clear that various models of VaR have been used by different individuals. There is no consensus on any single model . Different model have been proposed for different circumstances.Hence in this study the Berkowitz model is applied for the first time for the risk estimation of Islamic banks in combination with others models such as Historical Simulation, Normal Distribution, Exponentially weighted moving average and the GARCH model.

Chapter 3

Methodology

3.1 Data Description & Methodology

This chapter covers the data description and the research methodology adopted to explain the risk behavior of Islamic banks.

3.1.1 Data Description

The sample comprise of daily return of trading activities of 18 Islamic banks of the world. The daily return are based on position at the close of each day. The data is collected from 2007 to 2018 except Alinma bank, Qatar Islamic bank and Qatar international Islamic bank where data is available for the period from 2010 to 2018.

The banks include The Affine Bank, Al Baraka Banking Group, Al Baraka Turk Katilim, Alliance Islamic Bank, Alinma Bank, Al Rajhi Bank, Arab Banking Corporation, Arab Islamic Bank, Bahrain Islamic Bank, Bank Aljazira, Bank Islam Malaysia. Bank Islami Pakistan Limited, CIMB Islamic Bank Berhad Malaysia, Dubai Islamic Bank, Ihtimar Holding, Qatar International Islamic Bank, and Qatar Islamic Bank.

The return is calculated as under

$$R_t = log(P_t/P_{t-1}) \tag{3.1}$$

where

P_t is the price at the close of day t

P_{t-1} is the price at the close of day t-1

R_t is the return at the end of day t

TABLE 3.1: Sample Description

Bank Name	**Period**	**Number of Observations**
Affine Bank	2008 2018	2400
Al Baraka Banking Group	2008-2018	2851
Al Rajhi Bank	2008-2018	2745
Al Baraka Turk Katilim	2008-2018	2831
Alinma Bank	2010-2018	1658
Alliance Bank	2008-2018	2360
Arab Banking Corporation	2008-2018	2849
Arab islamic Bank	2008-2018	1921
Bahrain Islamic Bank	2008-2018	2849
Bank Aljazira	2008-2018	1398
Bank Islam	2008-2018	1398
Bank Islami Limited	2008-2018	2845
Bank Syariah Mandiri	2008-2018	2706
CIMB Berhad Malaysia	2008-2018	2377
Dubai Islamic Bank	2008-2018	2746
Ihtimar Holding	2008-2018	2848
Qatar Int Islamic Bank	2010-2018	2184
Qatar Islamic Bank	2010-2018	2185

3.1.2 Research Methodology

The methods used to estimate the VaR are broadly classified into three main types. The Non-parametric method, the parametric method, the time varying volatility model. The nonparametric model most commonly use the Historical Simulation approach. The Parametric models mainly used the Normal Distribution, and the

Student-t Distribution. The time varying volatility models commonly use the assumption of GARCH model, the Weighted Moving Average approach.

The historical Simulation is the most commonly used model because of its simplicity and ease. This model is based on the simplest assumption that the history repeat itself. So about the future returns the proposition is that it will be the same as in the past. There is no reliance on statistical tools. However, in the case of parametric model there is use of certain statistical assumptions about the distribution of return for the forecasting of VaR. The most common model including is Normal distribution and the student-t distribution. In time varying volatility it is supposed that the volatility will change over various period of time. The models forecasting VaR through the use of volatility most commonly include the GARCH and the EWMA. For VaR estimation of daily return of Islamic banks of acros countries all above models are applied.

The 250 day rolling window is used in case of all these models for the estimation of new VaR. To verify the reliability of the said models the violation ratios and the volatility ratios are calculated. The study also use the kupiecs and the Christoffersen test for backtesting that help in the comparison and identification of appropriate model.

3.1.2.1 VaR Estimation through Non-Parametric Approach

Non parametric is a sort of statistical techniques that do not require the specific distribution function. The return should not be dependent on certain parameters, the most popular of which is the normal distribution. The various characterics that are needed for the parametric method are not necessary for the non-parametric method. This method is normally used when the distribution of share prices are not known or when the sample is not very large in size. This method is also recognized as free from any distribution. The most commonly used approach of non-parametric is that of Historical Simulation.

Historical Simulation

Most commonly the VaR is calculated through the traditional approach of Historical Simulation. The historical prices of the stocks returns are used in this method for forecasting of the VaR. This method has the common proposition that history will repeat itself. So it is assumed that what has happened in the past will continue in future. This methods has some advantages and the certain disadvantages as well. The most simple and very easy application of this method is main advantages. The use of various parameters are also not considered in this method. One of disadvantage is that there is a large amount of data necessary for estimation of VaR under this approach, which may difficult in certain cases. There is also the probability of overestimation of risk under this approach, when extraordinary volatility is found during sample period.

The VaR at a given probability is just the negative $T * P^{th}$ value in distribution of return multiplied by the value of the portfolio.

The VaR is identified at a specified interval through the simulation technique is calculated as under

$$VaR_{t+1,a}^{HS} = quantile1 - \alpha(rt, rt - 1.....t - T + 1) \tag{3.2}$$

Where rt the stock return in t time.

3.1.2.2 VaR Estimation through Parametric Models

The parametric models uses some distribution assumption for the forecasting of VaR. The most commonly used assumption is Normal Distribution. However, in the prices of stocks there is some time fat tails behavior so another parametric model based on student-t distribution is applied.

VaR Forecasting through Normal Distribution

The most commonly used parametric models is the Normal Distribution or in which it is main assumption that the return are in compliance with normal distribution, such as the mean value of return is zero, and the standard deviation of return is equal to one. The variation that occur in the value of portfolio are free of the changes of the prices of assets founding that portfolio. For VaR measurement the following formula in time t + 1 is applied.

$$VaR^{ND}_{t+1,a} = \mu + \sigma_{Z_{1-a}} \tag{3.3}$$

Where μ represent the mean of the stock return concern, and σ is the standard deviation of that particular stock for the time period in consideration, where as $Z_{1-\alpha}$ is the quintile of Normal Distribution (Vasileiou, 2017).

This methods also has various advantages and also suffer from certain disadvantages. The primary benefit is that it is very easy and extensively applied in the market. The understanding of this technique and implementation are also the significant benefits. The disadvantages contain that it is not applicable in certain situation when data is not Normally Distributed. The most alarming is for fat tails, which results in underestimation of VaR at higher confidence interval.

3.1.2.3 VaR Estimation through Time Dependent Volatility Models

There are also various models which compare the volatility changing over time period. There are assets which has different volatility during different time period, such as less volatility at one time and higher volatility at other time. Three models are applied in this study including GARCH, Bekowitz and the EWMA to account for time varying volatility.

Exponentially Weighted Moving Average (EWMA) Approach

The first model that compare the time varying of volatility to anticipate VaR is the EWMA technique. Expected volatility exhibit that the later prices have effect on the volatility in future. When there is more quick changes in return, the volatility is large and vice versa (Danelsson, 2011).

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

Where lamda is the decay factor with a value 0.94. The univariat EWMA has the easy implementation. The unconditional volatility for the period of one day is $\sigma 1$.

VaR Through GARCH

Based on the assumption of consistent volatility throughout time, the volatility elements of stocks prices are not considered and the assessed VaR does not include the observed volatility in the return of securities, and consequently the model may not produce sufficient VaR estimations. In econometrics literature, numerious generalized conditional heteroskedastic model are proposed to forecast conditional volatility. The bollersive (1986), model is the most frequently used model of conditional hetroscedastity in the literature.This technique mesure the volatility in a better way, and simultaneously assess the models parametrer.

The GARCH model particulars has two fundamentals segments, such as the conditional mean element, that capture the changing aspects of the series of returns, as a past returns function and the conditional variance segment that produce the evolution of returns variability throughout time as function of past errors. The daily conditional mean is assumed to track first order autoregressive procedure.

$$r_t = \phi_0 + \phi_{1rt-1} + \varepsilon_t \tag{3.5}$$

Where the $rt-1$ is the lagged return,ϕ_0, ϕ_1 are the constant to be measured and the ε_t is the term of innovations.

For the GARCH (p,q) model the dynamic conditionel variance equation can be formulated by

$$\delta_t^2 = \alpha_0 + \Sigma_{i=1}^{p}\alpha_i\varepsilon_{t-1}^2 + \Sigma_{j=1}^{q}\beta_j\delta_{t-j}^2 \tag{3.6}$$

Where $\alpha_0 > 0, \alpha 1 > 0, \beta_i > 0$ are the positive parameters with the compulsory constraints to ensu-re finite conditional variance and also covariance stationarity. Empirical studies of financial econometrics literature shows that the GARCH (1,1) model is better and accurate forecast for volatility.

The GARCH method is very widely applied in modeling the conditional volatility in financial time series, and it undertake that good news and as well as bed news shocks have the same effect on conditional volatility, as it depends only on the square residuals of past.

For the GARCH model on the basis of normaly distributed invention, the value at risk can be computed as

$$VaR^p_{t+1/t} = \mu + \varphi\gamma_t + \phi(p)\delta_{t+1} \tag{3.7}$$

Where the $\varphi(p)$ is used to denote p_{th} quintile for the normal distribution.

3.1.2.4 Backtesting

After the calculation of VaR through different models it is necessary to know about the accuracy of model. The process through which the accuracy, and as well as the performance of models is examined is called backtesting. In backtesting actually the ex ante VaR results is taken for a specific model and comparison is made with the ex post realized return such that historical observations.

Backtesting is very helpful in recognizing the shortcoming of the risk predicting models and for giving suggestions for the model improvement, however fails to give information about reasons of the limitations. Backtesting however, can avoid undervaluing VaR, and thus certify that the banks have sufficient amount of capital. On the other hand the backtesting could, minimize the probability of overestimating VaR, that can result in unnecessary conservatism for the banks (Danielsson, 2011).

Violation Ratio

This ratio is applied as a tool to determine that how a particular model is actually performing in forecasting of risk. If on a given day, the real loss is less than the estimation of VaR, it is then said that the VaR limit have been violated. For calculating the violation ratio, the actual number of the observations are divided by the expected number of violations (Danelsson, 2011).

The most appropriate value for the violation ratio is one, however in most of the situations it is usually not possible to have exactly 1. A violation ratio greater than one is an indication of under forecasting of risk, and smaller than 1 is detection of over forecasting. Therefore as a rule of thumb a range between 0.80 to1.20 is considered appropriate. However, in most circumstance the violation ratio, is deem as good technique and the decisions are largely based on the violation ratio.

VaR Volatility

Volatility is another technique used for determination of reliability of VaR models, which indicate the related instability in that specific model. In this method the decision is normally basis on the amount of volatility, such that the greater volatility is detection of unreliable estimation, and the low volatility shows the appropriateness of the model. The parameter that is applied to test, the VaR volatility is the standard deviation. The volatility technique is mostly applied in the identification of best model, calculated under the assumption of normal distribution. One of the reason is that, the statistical properties of the said method are determined by setting the criteria of standard deviation and as well as mean.

Kupiecs POF Test

The kupiec test is proposed in 1995 as binomial test, which is also known as conditional coverage test. This test work with the approach of binomial distribution. This test uses a likelihood ratio to check whether or not the probability of exception is compatible with critical value p indicated by confidence interval. The likely-hood ratios are calculated for all the models, at different confidence interval, and compared with critical value of 3.84 for the 95% confidence and with critical value of 6.66 for 99% confidence interval. If LR is less than 3.84 for 95 percent the model is good and accepted, and for 99 percent the LR less than 6.66 is the acceptance region. The null hypothesis of the Kupiec test is rejected if LR value is more than the chi-square value and the model may not be used for the estimation of risk.

The statistic of POF test

$$LR_{POF} = -2log\left(\frac{(1-q)^{z-x}q^{x}}{(1-\frac{x}{z})^{z-x}(\frac{x}{z})x}\right) \tag{3.8}$$

Where x denote that no of times the model failed, z is the count of number of observations and q = 1 is VaR interval.

If the LR value calculated through the help of this formula is under the range of critical value with one degree of freedom, the null hypothesis is accepted and the model is correctly forecasting the risk.

The Kupiec test null hypothesis is as under

$$H_{op} = P = \frac{X}{T} \tag{3.9}$$

Where P= Proportion of the failure

P = Rate of the observed failure

X = Number of the exception

T = Number of the observation

Christoffersen Test

The christoffersen independence test is a back testing technique developed in 1998. This method is applied to determine, whether there is or not a clustering of volatility. To see whether the violations detected during a particular period, have been uniformly distributed throughout that time, or have happened one after another producing cluster. In this test too the LR is calculated and the comparison is made with that of benchmark chi square value, which value change as the confidence level change. If the LR calculated fall within the range of related chi square value, this mean that the null hypothesis is accepted, the violation that happen are free from each other and therefore no clustering has occur. However, if the LR value is greater than that this chi-square amount, the null hypothesis will be rejected and the violations that have been occur are not free from each other and are closely linked with each other and thus creating clustering.

The likelihood ratio is calculated as under

$$LR_{CCI} = -2log\left(\frac{(1-\pi)^{p00+p10}\pi^{p10+p11}}{(1-\pi)^{p00}\pi_o^{p01}(1-\pi_1)^{p10}\pi_1^{p11}}\right) \tag{3.10}$$

Where

- $p00$ indicate period of time having no failure, followed by period of time without any failure.
- $p10$ indicate period of time having failure, proceed by period of time with no failure.
- $p01$ shows period of time with no failure, followed by period of time having failure.
- $p11$ indicate period of time having failure, continue by period of time with failure.
- 1 indicate likelihood of failure at time t, provided that no failure happened on time $t1 = p01/(p00 + p01)$.
- 0 indicate likelihood of the failure at period t, giving that failure happened at the time $t1 = p11/(p10 + p11)$.
- π indicate the probability of failure for time $t, = (p10 + p11 + /(p00 + p01 + p10 + p11)$.

The null hypothesis have the assumption of no clustering, which mean violation for a day has no dependency upon the violation of preceding day. On the other hand the null hypothesis is rejected and there is clustering between violations throughout period of time.

The violations clustering shows that return instability vary in time to an extent not considered by the models. To further follow the possibility for anticipated volatility, the study set the substitute VaR model, determined from the ARMA (1,1), GARCH (1,1) model of return. So that, for rt we forecast the behind following condensed form model

$$rt = \mu + prt - 1 + \mu_t + \lambda\mu_{t-1} \tag{3.11}$$

Where μ_t is the iid innovation with mean zero and a variance σ_t. The process of volatility is explained as

$$\sigma_t = \omega + \theta\mu_{t-1}^2 + \phi\sigma_{t-1} \tag{3.12}$$

Where ω, θ and the ϕ are the parameters evaluated. We use the standard GARCH model in which innovation assumptions is conditionally normal. The parameters of ARMA and GARCH are forecasted and VaR is estimated and backtested.

Chapter 4

Data Analysis, Results and Discussion

This chapter presents the results of this study, conducted to evaluate the VaR model in Islamic banks. First the descriptive statistics for Islamic banks are presented. Then under different assumption the VaR is calculated and discussed, and finally the back testing process is conducted to evaluate the predictive performance of different models.

4.1 Descriptive Statistics

Table 4.1 shows the descriptive statistics of the daily return of Islamic banks included in the sample. The mean value shows the average daily return of each Islamic bank in the sample. The highest positive average return 0.0008 is earned by Bank Islam Malaysia. The lowest average positive return 0.00001 is earned by Affine bank. The highest negative average return is shown by Al Baraka Banking Group, and Arab Banking Corporation amounting to -0.0007 respectively. The maximum return earned per day, by Bank Aljazira, Bank Islam, Bank Islami Limited, Bank Syariah Mandiri, Al Baraka Turk Katlim, Qatar Islamic Bank, Bahrain Islamic Bank, and CIMB Bank, are 0.5708, 0.1976, 0.1869, 0.1823, 0.1823, 0.1664, 0.1640, and 0.1562 respectively. The maximum loss is incurred by Bank

Aljazira, Arab Banking Corporation, Ihtimar Holding, Bank Syariah Mandiri, Al Barak Turk Katleem, CIMB, Bank Islami Limited, Dubai Islamic Bank, amounting to -0.5591, -0.5328, -0.1743, -0.1568, -0.1568, -0.1495, -0.1476, -0.1455, and -0.1396.

The standard deviation depicts the risk of each stock in the sample. Bank Islami Limited is the most risky throughout the sample followed by Ihtimar Holding, Bank Aljazira, Bank Islam, Bank Syariah Mandiri, Dubai Islamic Bank, and Albaraka Turk Katilim, with standard deviation amounting to 0.0303, 0.298, 0.0253, 0.0247, 0.244, 0.0224, and 0.0200 respectively. The lowest risk is shown by the stock of QIIB, Qatar Islamic Bank, and Alliance Islamic Bank, having standard deviation of 0.0126, 0.0144, and 0.0155 respectively.

Table 4.1: Descriptive Statistics

Bank	**Mean**	**Max**	**Min**	**Std.Dev**	**Skew**	**Kurt**	**J.Bera**
AFB	0.00001	0.1206	-0.0956	0.0159	0.4599	12.38	8894
ABBG	-0.0070	0.0953	-0.1351	0.0177	-0.7221	17.93	26718
ARJ	0.00005	0.1044	-0.0946	0.0165	0.0564	11.15	7603
ABTK	0.00004	0.1823	-0.1495	0.0200	0.3282	11.79	9177
ALBM	0.0004	0.1542	-0.1082	0.0175	0.6715	15.90	11619
ALCIB	0.0001	0.0943	-0.1088	0.0155	-0.3093	8.25	2744
ABC	-0.0007	0.0953	-0.5328	0.0198	-7.2300	196.69	4478406
AIB	-0.0001	0.0892	-0.1237	0.0190	-0.0718	6.22	836
BIB	-0.0004	0.1640	-0.1090	0.0174	-0.2157	18.18	27402
BAJZA	-0.0002	0.5708	-0.5591	0.0253	0.1847	183.43	3723554
BISM	0.0008	0.1976	-0.1559	0.0247	1.2500	14.87	8571
BISP	0.0017	0.1869	-0.1455	0.0303	0.5909	6.72	1803
BSM	0.0007	0.1823	-0.1568	0.0244	0.3979	8.93	4040
CIMB	0.0002	0.1562	-0.1476	0.0162	-0.1947	16.43	17879
DIB	0.0001	0.1277	-0.1396	0.0224	-0.1613	12.36	10041
IMRH	-0.0006	0.1226	-0.1743	0.0298	-0.1169	6.38	1363
QIIB	0.0004	0.1279	-0.1053	0.0126	0.2383	17.71	19726
QIB	0.0005	0.1664	-0.0870	0.0144	0.7234	17.14	18388

The skewness give information about symmetry and asymmetry of data. The returns of Affine Bank, Al Rajhi Bank, Al Turk Katlim, Alinma Bank, Bank Aljazira, Bank Islam, Bank Islami Limited, Bank Syariah Mandiri, Qatar International Bank and Qatar Islamic are positively skewed. The reurns of Al Baraka Bank, Alliance Islamic Bank, Arab Banking Corporation, Arab Islamic Bank, CIMB, Dubai Islamic Bank, and Ihtimar Holding are negatively skewed. The conclusion is that the return are asymmetric.

The kurtosis shows the peakness and flatness of data. The kurtosis value of each bank in the sample is more than 3, which mean that the returns of all banks are leptokurtic, and the stock return are has fat tail distribution, and the data is not normally distributed. The bank with highest value of kurtosis is Arab Banking Corporation, followed by Bank Aljazira, QIIB, and Qatar Islamic Bank amounting to 196.69, 183.43, 17.71, and 17.14 respectively. The high values of Jarqu Bera test also confirm that the stock data is not normally distributed.

4.2 VaR Estimation through Non-Parametric, Parametric and Time Varying Volatility based Models

In this study the VaR is forecasted under the assumption of Non-parametric method, which include the Historical Simulation approach. The second method is the Parametric model which include the Normal Distribution technique, and the third one is the Time Varying Volatility models consisting of EWMA, the GARCH, and Berkowitz assumption based model.

Table 4.2 illustrates the results of VaR forecasting under the non-parametric, the parametric model, and the Time Varying Volatility assumption based model at 95% confidence interval.

At 95% confidence level according to Historical Simulation approach, the Ihtimar Holding is the bank with highest risk of the sample with a VaR value of 5.2%. The inference is that there is 95% chances that the losses will not be more than 5.2% on a day. The second and the third risky bank under this approach are Bank Islami Limited, and Arab Islamic Bank, with the VaR amount of 4.8% and 3.1% respectively. Arab Banking Corporation appears as least risk bank of the sample having VaR of 1.4%. Followed by Qatar International Islamic Bank and Qatar

Islamic Bank, with VaR of 1.7% and 2% respectively. So, as per the Historical Simulation if the investors chooses to invest in the shares of Arab Banking Corporation, they have to face very less risk, and they will be exposed to the greatest risk if they make investment in stocks of Ihtimar Holding.

At a 95 percent confidence level, Normal Distribution based VaR provide that most risky stock in the sample, is Bank Islami Limited with 5% VaR. Ihtimar Holding and Bank Aljazira are the second and third risky bank out of the sample with VaR of 4.9%, and 4.1% respectively. Qatar International Islamic Bank is the lowest risk stock followed by Qatar Islamic Bank and Alliance Islamic Bank, with VaR figure 2%, 2.3%, and 2.5% respectively. As reported by this approach at 95% confidence the highest risk stock is Bank Islami Limited, and least risk is shown by QIIB. This method suggest that much loss will be suffered by investors if they invest in Bank Islami Limited, and will be suffering minimum risk if the investment is made in that of QIIB stocks.

Table 4.2: VaR at 95% under H.S, N.Dist, EWMA, GARCH,and Berkowitz assumption

Bank	**H.S**	**N.Dist**	**EWMA**	**GARCH**	**BERKOWITZ**
AFB	-0.0235	-0.0262	-0.0200	-0.0151	-0.0249
ABBG	-0.0217	-0.0290	-0.0148	-0.0234	-0.0281
ABTK	-0.0298	-0.0330	-0.0249	-0.028	-0.0318
ARJ	-0.0233	-0.027	-0.0653	-0.0651	-0.0248
ALMB	-0.0251	-0.0286	-0.0253	-0.0228	-0.0263
ALCIB	-0.024	-0.0255	-0.0157	-0.0169	-0.0242
ABC	-0.0145	-0.0325	-0.0164	-0.0293	-0.0326
AIB	-0.0314	-0.0312	-0.015	-0.0226	-0.0308
BIB	-0.0224	-0.0286	-0.0054	-0.0229	-0.0283
BAJZA	-0.0295	-0.0416	-0.0175	-0.0262	-0.0379
BISM	-0.0308	-0.0406	-0.0249	-0.0254	-0.0350
BISL	-0.048	-0.0515	-0.0313	-0.0365	-0.0486
BSM	-0.0371	-0.0402	-0.0262	-0.0262	-0.0362
CIMB	-0.0243	-0.0266	-0.0172	-0.0197	-0.025
DIB	-0.0306	-0.0369	-0.0587	-0.0509	-0.0329
IMRH	-0.0526	-0.0491	-0.0391	-0.0416	-0.0483
QIIB	-0.0172	-0.0207	-0.0129	-0.0154	-0.0192
QIB	-0.0201	-0.0236	-0.0187	-0.0192	-0.0218

According to EWMA method at 95 percent confidence level, with VaR amount of 6.5 percent Al Rajhi Bank is the highest risky bank in the sample. With VaR of 5.8% the Dubai Islamic Bank is on second number, and third high risk is faced by Ihtimar Holding having 3.9% VaR. Bahrain Islamic is reported as the lowest risky stock with a VaR figure of 0.5% by EWMA. The EWMA report that QIIB with 1.2% and Arab Islamic Bank 1.5% are the second and third less risky bank from the sample. Al Rajhi Bank is declared by EWMA top risky bank, and Bahrain Islamic Bank has low risk as reported by EWMA model.

As per the GARCH model at 95% confidence level, Al Rajhi Bank top the sample in the category of risky banks having 6.9% VaR value. Dubai Islamic Bank is the second risky bank showing VaR of 5%, and Ihtimar Holding with VaR amount of 4.1% is the third much risky bank. Lowest risk with VaR amount of 1.5%, is shown by Affine bank and QIIB followed by Alliance Islamic Bank presenting 1.6% VaR value. Al Rajhi Bank is on the top in the sample from high risk perspective, and from low risk angle the Affine Bank is on the top in the sample. So, the Investors will loss large amount if they invest in Al Rajhi Bank, and will be exposed to minimum risk if chooses Affine Bank stocks.

The Berkowitz Model at 95% level of confidence report that Bank Islami Limited is the most risky stock with 4.9% VaR. Ihtimar Holding with 4.8 percent VaR and the Bank Aljazira with 3.9% VaR is on number two and three in the list of high risk bank. The lowest risk 1.9% may be faced by QIIB, followed by Qatar Islamic Bank 2.2% and Alliance Islamic Bank 2.4%. The Berkowitz model suggest the most risky stock that of Bank Islami Limited, in the sample and the least risky bank as reported by Berkowitz model is QIIB. As per the Berkowitz method the risk of investor is on peak if they choose Bank Islami for their investment, and their risk will be small if QIIB is chosen for investment.

Al Rajhi Bank is reported by EWMA and GARCH model, as the riskiest stock. Bank Islami Limited is risky according to Normal Distribution and Berkowitz and second risky by Historical Simulation. Ihtimar Holding is reported risky by Historical Simulation, and second risky by Normal Distribution and Berkowitz and third risky by EWMA method. So, in the whole sample the Al Rajhi Bank,

Bank Islami Limited, and Ihtimar Holding are high risk stock at confidence level of 95%.

QIIB has lowest risk by Normal Distribution and the Berkowitz, second lowest risky by Historical Simulation, EWMA, and by GARCH model. Qatar Islamic Bank is third risky as per Historical Simulation, the N. Distribution and the Berkowitz declared it second risky. Alliance Islamic Bank is at third risky bank as per N. Distribution, GARCH, Berkowetz and EWMA. QIIB, Qatar Islamic Bank, and the Alliance is least risky, in the whole sample at 95% Confidence.

Table 4.3 shows the results of VaR estimation at 99% confidence level under the assumption of Historical Simulation, Normal Distribution, EWMA, GARCH, and Berkowitz model for all the banks in the sample.

According to Historical Simulation Model at 99% confidence level, in the category of high risk Ihtimar Holding with VaR of 9% comes first, Arab Banking Corporation 8.2% is on second number, and with 8% VaR Bank Islami Limited is on number three. As per Historical Simulation at 99% confidence QIIB with VaR of 3.4% is the least risky stock, Qatar Islamic Bank with 4.3% VaR is second less risky, and Alliance Islamic Bank 4.5% is the third riskiest stock.

The N. Distribution based model report that, Bank Islami Limited with VaR 7.3% is the most risky throughout the sample. The second risky is the Ihtimar Holding having 6.7% VaR followed by Bank Aljazira with VaR 5.8%. The minimum risk is found in QIIB as per the N.Distribution reporting only 2.9% VaR. The second bank with minimum risk 3.3% is Qatar Islamic Bank, followed by Alliance Islamic Bank reporting 3.6% VaR amount. The 7.3% highest VaR is reported for Bank Islami Limited, and 2.9% lowest VaR for QIIB at 99% confidence under the assumption of N.Distribution.

According to EWMA method Al Rajhi Bank is the highest risk stock at 99% confidence level, with a VaR of 9.2%. Dubai Islamic Bank, and Ihtimar Holding are the second and third risky stock depicts VaR of 8.3% and 5.5% respectively. Bahrain Islamic bank is reporting VaR of 0.07% is the least risky bank throughout the sample, followed by QIIB and Al Barka Bank reporting VaR of 1.8 % and 2%

Table 4.3: VaR at 99% under the H.S, N.Dist. EWMA, GARCH and Berkowitz assumption.

Bank	H.S	N.Dist	EWMA	GARCH	BERKOWITZ
AFB	-0.0487	-0.0371	-0.0282	-0.0214	-0.0349
ABBG	-0.0779	-0.041	-0.0209	-0.0332	-0.0392
ABTK	-0.0567	-0.0467	-0.0352	-0.0396	-0.0449
ARB	-0.0501	-0.0382	-0.0923	-0.0983	-0.0349
ALMB	-0.0491	-0.0405	-0.0358	-0.0323	-0.0373
ALCIB	-0.0452	-0.0360	-0.0222	-0.0239	-0.0343
ABC	-0.0822	-0.046	-0.0232	-0.0415	-0.0457
AIB	-0.0460	-0.0442	-0.0212	-0.0320	-0.0433
BIB	-0.0689	-0.0405	-0.0077	-0.0323	-0.0396
BAJZA	-0.0698	-0.0589	-0.0247	-0.0370	-0.054
BISM	-0.0735	-0.0575	-0.0352	-0.0359	-0.0496
BISL	-0.0803	-0.0729	-0.0443	-0.0516	-0.0688
BSM	-0.066	-0.0569	-0.0371	-0.0370	-0.0516
CIMB	-0.0458	-0.0377	-0.0244	-0.0279	-0.0355
DIB	-0.0608	-0.0523	-0.083	-0.0720	-0.0463
IMRH	-0.0909	-0.0695	-0.0553	-0.0588	-0.0678
QIIB	-0.0345	-0.0293	-0.0183	-0.0218	-0.0273
QIB	-0.0435	-0.0335	-0.0265	-0.0271	-0.0309

respectively. Al Rajhi Bank is in high risk category and from low risk perspective Bahrain Islamic Bank is bank with minimum value of risk.

According to GARCH approach AlRajhi bank (9.8%) is identified as the more risky in the entire sample at 99 percent confidence interval. The other risky stock are Dubai Islamic bank (7.2%) and Ihtimr Holding. Affine Islamic Bank with 2.1% VaR is on top of the low risk banks, at same confidence level. The next banks with minimum risk are Qatar International Islamic Bank, and Qatar Islamic Bank, reporting VaR of 2.2% and 2.7% respectively. GARCH model suggest Al Rajhi Bank as the highest risk stock in the whole sample, while the Affine Bank is found as most safe bank at 99% Confidence.

The Berkowitz model of Time Varying Volatility at 99% confidence interval, report that Bank Islami Limited with 6.8% VaR, as most risky stock throughout the sample. Similarly Ihtimar Holding (6.7%) VaR and Bank Aljazira (5.4%) VaR are the risky banks under the assumption of Berkowitz Model at the 99% confidence. The Berkowitz model depicts Qatar International Islamic Bank safest banks in the overall sample with VaR of 2.7% under the same confidence level. Qatar Islamic Bank (3%) VaR and Affine Bank (3.4%) are the other safe banks for investments. According to Berkowitz approach Bank Islami Limited is riskiest, while the QIIB is the most safe banks under 99% confidence interval. Berkowitz is the third model reporting the same banks as the highest and lowest risky from the sample for both confidence level 95% and 99% as well. Al Rajhi Bank is reported by EWMA and GARCH model as top risky stock in the entire sample. The N.Distribution and Berkowitz shows Bank Islami Limited the high risk bank and third risky by Historical Simulation. Ihtimar Holding is the riskiest bank as per Historical Simulation. N. Distribution and Berkowitz model declare it second riskiest. The QIIB is reported as low risk bank according to Historical Simulation, N. Distribution and as well by Berkowitz and second less risky by EWMA and GARCH model. Qatar Islamic Bank is second least risky bank as per Historical Simulation, N.Distribution and Berkowitz model. The Historical Simulation, the N. Distribution, and Berkowitz depicts third lowest risk bank. At 99% confidence level again the same banks remain the highest risk and low riskest banks.

4.3 Back Testing

After the calculation of value at risk through different model then it is necessary to evaluate accuracy of each model. Back testing is the producer used to determine the accuracy of various models. In this study, the violation ratio, the VaR volatility, the Kupiec test and the christoffersen test are applied for testing about validity of VaR models.

4.3.1 Violation Ratio

Violation ratio is calculated by comparing the observed number of violations in model, with the expected number of violations. The most suitable number of violation ratio is one. The violation ratio is one when the actual number of violation are equal to the expected number of violations. If the violation ratio is one the inference is that the model forecast the risk correctly. However, a violation ratio of greater than one is indication of under forecast of risk and smaller than one is indicating overforcast of risk.

Table 4.4 reports the violation ratios under the assumption of Historical Simulation, N.Distribution, the EWMA, GARCH and Berkowitz models at 95% confidence level.

TABLE 4.4: Violation Ratio @ 95%

Bank	**H.S**	**N.Dist**	**EWMA**	**GARCH**	**BERKOWITZ**
AFB	0.9771	0.7631	0.9213	0.9213	0.8340
ABBG	0.993	0.7929	1.13	0.8391	0.8289
ABTK	0.9221	0.8368	1.05	0.9066	0.8692
ARB	1.6	0.9939	1.27	1.17	1.03
ALMB	0.9943	0.7102	0.8522	0.7812	0.8328
ALCIB	0.7582	0.8815	1.03	0.872	0.941
ABC	0.7464	0.5309	0.6079	0.5463	0.5688
AIB	0.8862	0.8502	1.08	0.9820	0.9067
BIB	0.8622	0.816	0.9392	0.8622	0.7938
BAJZA	0.8496	0.513	0.7935	0.6973	0.6122
BISM	0.8020	0.7497	1.03	0.8369	0.8595
BISL	0.9868	0.8943	0.9483	0.9097	0.7949
BSM	0.9609	0.9201	0.9039	0.8713	0.8650
CIMB	0.8932	0.7522	0.8462	0.6958	0.8164
DIB	1.09	1.03	1.29	1.2000	1.05
IMRH	0.8929	1.08	1.24	1.15	1.15
QIIB	0.8066	0.6618	0.7755	0.7652	0.6596
QIB	1.01	0.7475	0.8686	0.8893	0.8428

At the 95% confidence level, the violation ratio for the Historical Simulation model range from 0.80 to 1.09 for most of the banks such that for17 banks out of 18 banks, including Affine Bank (0.9771), Al Baraka Bank (0.9930), Al Baraka Turk Bank (0.9221), Al Rajhi Bank (1.6), Alinma Bank (0.9943), Alliance Islamic Bank (0.7582), Arab Islamic Bank (0.8862), Bahrain Islamic Bank (0.8622), Bank Al-Jazira (0.8496), Bank Islam (0.8020), Bank Islami Limited (0.9868), Bank Syariah Mandiri (0.9609), CIMB (0.8932), Dubai Islamic Bank (1.09), Ihtimar Holding (0.8929), QIIB (0.8066), and Qatar Islamic Bank (1.01), except Arab Banking Corporation (0.7464). For 95% of the sample the Historical Simulation is strongest forecasting model. So, at that confidence the Historical Simulation may be recommended as a best risk estimation model.

The violation ratio, under the assumption of N.Distribution is blew one for six banks, including Alinma Bank (0.7102), Arab Banking Corporation (0.5309), Bank Al Jazira (0.5130), Bank Islam (0.7497), QIIB (0.6618), and Qatar Islamic Bank (0.7475). The 12 banks violation ratio comes under the appropriate level of 0.80 to 1.20 including Affine Bank (0.7631), Al Barak Bank (0.8368), Al Rajhi Bank (0.9939), Alliance Islamic Bank (0.8815), Arab Islamic Bank (0.8502), Bahrain Islamic Bank (0.8160), Bank Islami Limited (0.8943), Bank Syariah Mandiri (0.9201), CIMB (0.7522), Dubai Islamic Bank (1.03), and Ihtimar Holding (1.08). So, the conclusion is that for six banks the risk is overforecasted under the said assumption. However, 12 banks risk is estimated properly.

According to EWMA the violation ratio is at acceptable range from 0.80 to 1.20 for 14 banks, including Affine Bank (0.9213), Al Baraka Bank (1.13), Al Baraka Turk Katilim (1.05), Alinma Bank (0.8522), Alliance Islamic Bank (1.03), Arab Islamic Bank (1.08), Bahrain Islamic Bank (0.9392), Bank Al Jazira (0.7935), Bank Islam (1.03), Bank Islami Limited (0.9483), Bank Syariah Mandiri (0.9039), CIMB (0.8462), Qatar International Bank (0.7755), and Qatar Islamic Bank (0.8686), indicating proper estimation of risk. The violation ratio of three banks, AlRajhi Bank (1.27), Dubai Islamic Bank (1.29) and Ihtimar Holding (1.24) exceeds the acceptance region, indicating that risk is under estimated for these stock. The Arab Banking Corporation (0.60) indicate violation ratio under the acceptance criteria so the risk is overestimated.

The violation ratio calculated for the GARCH model, comply with acceptance (0.80 to 1.20), for 15 banks including Affine Bank (0.9213), Al Baraka Bank (0.8391), Al Barak Turk Katilim (0.9066), Al Rajhi Bank (1.17), Alima Bank (0.7812), Alliance Islamic Bank (0.8720), Arab Islamic Bank (0.9820), Bahrain Islamic Bank (0.8622), Bank Islam (0.8369), Bank Islami Limited (0.9097), Bank Syriah Mandiri (0.8713), Dubai Isalmic Bank (1.20), Ihtimr Holding (1.15).

Qatar International Islamic Bank (0.7652), and Qatar Islamic Bank (0.8428), showing proper risk estimation. Violation ratios for Arab Banking Corporation

(0.54), Bank Aljazira (0.69), and CIMB (0.69), is below the appropriate level, showing under estimation of risk. So, at 95% confidence the GARCH model may also be consider as a good model.

For Berkowitz model, the fifteen banks exhibits a violation ratio that is in compliance with the benchmark of 0.80 to 1.20 which include Affine Bank (0.8340), Al Baraka Bank (0.8289), Al Baraka Turk (0.8692), Al Rajhi Bank (1.03), Alinma Bank (0.8328), Alliance Islamic Bank (0.9410), Arab Islamic Bank (0.9067), Bahrain Islamic Bank (0.7938), Bank Islam (0.8595), Bank Islami Limited (0.7949), Bank Syariah Mandiri (0.8650), CIMB (0.8164), Dubai Islamic Bank (1.05), and Qatar Islamic Bank (0.8428), showing that the risk is accurately calculated for these banks. For Arab Banking Corporation (0.56), Bank Al Jazira (0.61) and QIIB (0.65) violation ratio fall below the range of acceptance such that 0.80 to 1.20, representing that the risk of all these banks is overcalculated. The Berkowitz model is the true forecasting technique for the 84% of the sample. So, the Berkowitz model as per violation ratio at 95 percent confidence is also a good method of VaR calculation for Islamic banks. The Arab Banking Corporation violation ratio under the Historical Simulation (0.74), N.Distribution (0.53), EWMA (0.60), GARCH (0.54), and Berkowitz (0.56) is blow one showing overestimation of risk.

Table 4.5 report the violation ratios at 99% confidence level calculated through the application of all models used in this study.

Applying the assumption of Historical Simulation, the violation ratios of 13 banks are falling between the acceptance benchmark of 0.80 to 1.20 such as Affine Bank (0.8841), Al Baraka Bank (0.7689), Al Baraka Turk Bank (0.8136), Al Rajhi Bank (0.9218), Alinma Bank (0.8522), Alliance Islamic Bank (0.7582), Arab Islamic Bank (0.9580), Bank Islam (0.7846), Bank Syariah Mandiri (0.8957), Dubai Islamic Bank (1.00), Ihtimar Holding (1.00), Qatar International Islamic Bank (0.7755), and Qatar Islamic Bank (0.8273),showing that Historical Simulation is proper model of risk identification in all that 13 banks. The violation ratio, of Bank Islami Limited (1.35), is higher than the range of acceptance indicating that the risk is under evaluated. The violation ratio for Arab Banking Corporation (0.53), Bahrain Islamic Bank (0.65), Bank Al Jazira (0.72), and CIMB (0.70) is not in agreement with the level of acceptance, and showing that the risk of these four stock is overestimated.

The violation ratios, under the asumption of N.Distribution of all Islamic banks such as Affine Banks (1.58), Al Baraka Bank (3.04), Al Barak Turk Katlim (1.43), Al Rajhi Bank (2.32), Alinma Bank (1.49), Alliance Islamic Bank (2.04), Arab Banking Corporation (1.96), Arab Islamic bank (1.49), Bahrain Islamic Bank (2.73), Bank Al Jazira (1.60), Bank Islam (1.39), Bank Islami Limited (1.77), Bank Syariah Mandiri (1.63), Dubai Islamic Bank (2.68), Ihtimar Holding (3), QIIB (1.55) and Qatar Islamic Bank (1.76) is much higher than the suitable target range indicating that N.Distribution as weak estimation for risk at the above level for the Islamic banks in the sample.

Applying EWMA model, the violation ratio is again greater than (0.80 to 1.20) the acceptance level in respect of all banks such as Affine Bank (2.46), Al Barak Bank (4.11), Al Baraka Turk Katlim (1.93), Al Rajhi Bank (2.48), Alinma Bank (1.84), Alliance Islamic Bank (1.89), Arab Banking Corporation (2.15), Arab Islamic Bank (1.38), Bahrain Islamic Bank (3.16), Bank Al Jazira (1.96), Bank Islam (1.39), Bank Islami Limited (1.58), Bank Syariah Mandiri (1.38), CIMB (1.97), Dubai Islamic Bank (2.56), Ihtimar Holding (2.77), QIIB (1.49), and Qatar Islamic (1.81), so EWMA model is also rejected at this confidence interval for estimation of risk in Islamic banks.

The violation as per GARCH model is again above the range of acceptance for the 17 banks including Affine Bank (1.95), Al Baraka Bank (2.96), Al Barak Turk Katilim (1.70), Al Rajhi Bank (2.32), Alinma Bank (1.63), Alliance Islamic Bank (1.71), Arab Banking Corporation (1.88), Arab Islamic Bank (1.56), Bahrain Islamic Bank (2.89), Bank Al Jazira (1.48), Bank Islam (1.66), Bank Syariah Mandiri (1.55), CIMB (1.93), Dubai Islamic Bank (2.44), Ihtimar Holding (3.00), QIIB (1.49), and Qatar Islamic Bank (1.45). However it is at appropriate level only for bank namely Bank Islami Limited (1.08), indicating a true risk estimation of that stock only. On the other hand for 95% of the sample the risk is not properly

Table 4.5: Violation Ratio @ 99% Confidence

Bank	**H.S**	AFB	**EWMA**	**GARCH**	**BERKOWITZ**
AFB	0.8841	1.58	2.46	1.95	1.7500
ABBG	0.7689	3.04	4.11	2.96	2.84
ABTK	0.8136	1.43	1.93	1.7	1.62
ARB	0.9218	2.32	2.48	2.32	1.89
ALMB	0.8522	1.49	1.84	1.63	1.68
ALCIB	0.7582	2.04	1.89	1.71	2.03
ABC	0.5386	1.96	2.15	1.88	1.93
AIB	0.9580	1.49	1.38	1.56	1.46
BIB	0.6543	2.73	3.16	2.89	2.77
BAJZA	0.7214	1.6	1.96	1.48	1.39
BISM	0.7846	1.39	1.39	1.66	1.15
BISL	1.35	1.77	1.58	1.08	1.13
BSM	0.8957	1.63	1.38	1.55	1.22
CIMB	0.7052	1.69	1.97	1.93	1.81
DIB	1.00	2.68	2.56	2.44	1.49
IMRH	1.00	3.0000	2.77	3.00	1.97
QIIB	0.7755	1.55	1.49	1.49	1.24
QIB	0.8273	1.76	1.81	1.45	1.69

forecasted, so at 99% confidence the GARCH model also fail to be used for risk determination of Islamic banks as shown by violation ratio.

The violation ratio calculated using Berkowitz Model, shows that 14 banks risk is overforecasted which include Affine Bank (1.75), Al Baraka Bank (2.84), Al Barak Turk Bank (1.62), Al Rajhi Bank (1.89), Alinma Bank (1.68), Alliance Islamic Bank (2.03), Arab Banking Corporation (1.93) Arab Islamic Bank (1.46), Bahrain Islamic Bank (2.77), Bank Aljazira (1.39), CIMB (1.81), Dubai Islamic Bank (1.49), Ihtimar Holding (1.97), and Qatar Islamic Bank (1.69), and is a clear indication of weaker model for the above banks. The following banks violation ratios are in confirmation with acceptance criteria including, Bank Islam (1.15), Bank Islami Limited (1.13), Bank Syariah Mandiri (1.22), and QIIB (1.24), indicating the risk of these four banks is properly estimated. The violation ratio suggest the Berkowitz model a weaker estimation of risk for the 78% sample and strong forecasting model for only 22% of the sample, so this model also does not qualify as best model for risk measurement of Islamic Banks at 99% confidence level.

4.3.2 VaR Volatility

Volatility is another technique used to know about the stability of a particular model. Volatility refers to inconsistency in financial markets. The lower the volatility in the model the most fit a model and vice versa.

Table 4.6 shows the VaR Volatility at 95% confidence calculated using Historical Simulation, N.Distribution, the EWMA model, GARCH, and the Berkowitz model.

Using the Historical Simulation, at this confidence level the highest volatility is shown by Al Barak Turk Bank (1.84%), followed by Bahrain Islamic Bank (1.53%) and Bank Islam (1.5%). The lowest volatility is found in two banks Arab Islamic Bank and QIIB amounting to 0.49% followed by Alliance Islamic Bank (0.60%), Affine Bank (0.71%), Qatar Islamic Bank (0.73%) and Al Baraka Turk Katelim (0.75%) The Volatility of rest of Islamic banks including Al Rajhi Bank 1.01%, Arab Banking Corporation 1.42% Bank Aljazira 1.14% Bank Islami Limited 1.35%, and Bank Syariah Mandiri 1.44% is around 1%. So, Volatility ratio recommend Histo rical Simulation as fair model.

The Volatility ratio calculated using N.Distribution, is high in case of Bank Islam amounting to 1.95%, Bank Aljazira 1.87%, and Dubai Islamic Bank 1.57%. The Al Baraka Bank 1.00%, Arab Banking Corporation 1.26%, Bank Islami Limited 1.27% Bank Syariah Mandiri 1.23% volatility is around 1% in respect of all these banks. The rest of the Islamic Banks volatility is below 1% including Affine Bank 0.76%, Al Baraka Turk Bank 0.72%, Alinma Bank 0.79%, Alliance Islamic Bank 0.58, Arab Islamic Bank 0.48%, Bahrain Islamic Bank 0.67%, CIMB 0.80%, QIIB 0.58%. Qatar Islamic Bank 0.80%. The Volatility ratio, at 95% confidence also recommend the N.Distribtion a very stable model.

The EWMA report the Volatility of Bank Al Jazira 2.45%, Arab Banking Corporation 2.15% Bank Islam 2.13%, Bank Islami Limited 2%, Dubai Islamic Bank 2.04%, Ihtimar Holding 1.79%, and Al Barka Banking Group 1.53%. The Volatility is approximately 1% in case of Affine Bank 1.03%, AlBaraka turk Katilim 1.14%. Al Rajhi Bank 1.33%, Alinma Bank 1.2% Bahrain Islamic Bank 1.34%,

Table 4.6: VaR Volatility @ 95% Confidence level

Bank	**H.S**	**N.Dist**	**EWMA**	**GARCH**	**BERKOWITZ**
AFB	0.0071	0.0076	0.0103	0.0102	0.0116
ABBG	0.0184	0.0100	0.0105	0.0154	0.0097
ABTK	0.0075	0.0072	0.0114	0.0136	0.0111
ARB	0.0101	0.0096	0.0133	0.0144	0.0134
ALMB	0.0087	0.0079	0.0129	0.0155	0.0125
ALCIB	0.006	0.0058	0.0074	0.0073	0.0083
ABC	0.0142	0.0126	0.0215	0.0162	0.0101
AIB	0.0049	0.0048	0.0088	0.0088	0.0087
BIB	0.0153	0.0067	0.0134	0.0117	0.0095
BAJZA	0.0114	0.0187	0.0245	0.0527	0.0276
BISM	0.0151	0.0195	0.0213	0.0195	0.0214
BISL	0.0135	0.0127	0.0200	0.0201	0.0183
BSM	0.0144	0.0123	0.0124	0.0126	0.0145
CIMB	0.0084	0.008	0.0102	0.0112	0.0103
DIB	0.0144	0.0157	0.0204	0.0234	0.0227
IMRH	0.0128	0.0097	0.0179	0.0162	0.0124
QIIB	0.0049	0.0058	0.0086	0.0101	0.0088
QIB	0.0073	0.008	0.0111	0.0126	0.0118

Bank Syariah Mandiri 1.24%, CIMB 1.02%, and Qatar Islamic Bank is 1.11%. However the volatility is less than 1% for all other Islamic Banks. So EWMA method is also indicated as suitable technique for risk forecasting by the volatility ratio at the 95% of confidence.

The volatility ratio calculated through the assumption of GARCH, depicts that the highest volatility in Bank Aljazira which is 5.27%. The next banks that have high volatility VaR are Dubai Islamic Bank (2.34%), Bank Islami Limited (2.01%), Bank Islam (1.95%), Ihtimar Holding (1.62%), Arab Banking Corporation (1.62%), Alinma Bank (1.55%), Al Baraka Banking Grope (1.54%). The minimum volatile Islamic Banks include Alliance Islamic Bank (0.73%), Arab Islamic Bank (0.80%). The Affine Bank (1.02%), Al Barak Turk Katlim (1.36%) AlRajhi Bank (1.44%), Bahrain Islamic Bank (1.176%), Bank Syariah Mandiri (1.26%), CIMB(1.12%) QIIB (1.01%), and Qatar Islamic Bank (1.26%) show volatility near to 1%.

Using the Berkowitz model, the volatility is high in case of Bank Al Jazira (2.76%), Dubai Islamic Bank (2.27%), Bank Islam (2.14%), and Bank Islami Limited (1.83%). Under the Berkowitz the volatility is below 1% of Arab Islamic Bank (0.87%), QIIB (0.88%), Bahrain Islamic Bank (0.95%), and Albaraka Bank (0.97%). Affine Bank (1.16%), Albarak Turk Bank(1.11%), Al Rajhi Bank (1.34%), Alinma Bank (1.25%), Arab Banking Corporation (1.01%), Bank Syariah Mandiri (1.45%), CIMB (1.03%), Ihtimar Holding (1.24%), Qatar Islamic Bank (1.18%), all these banks volatility is around 1%. The Berkowitz model is very better model on the basis of volatility at 95% confidence.

Table 4.7 explains the volatility at 99% confidence level under the Historical Simulation, the N.Distribution, EWMA, the GARCH and Berkowitz assumption.

As per Historical Simulation the Dubai Islamic Bank shows the highest volatility, of 4.22%, followed by Bank Islam (3.39%), Alinma Bank (2.51%), Bank Islami Limited (2.41%), Al Baraka Turk (2.01%). The Ihtimar Holding (1.10%), QIIB (1.40%), Qatar Islamic Bank (1.71%), Bahrain Islamic Bank (1.73%), depicts the less volatility. The Affine Bank (1.92%), Al Baraka Bank (1.83%). Al Rajhi Bank (1.92%), Alliance Islamic Bank (1.89%), Arab Banking Corporation (2.32%), Bank Al Jazira (1.86%), Bank Syariah Mandiri (1.87%), CIMB (1.65%), volatility is approximately 2%. Dubai Islamic Bank and Bank Islam volatility is more than 3% indcating as weaker model for that banks.

Volatility estimation using the N.Distribution, the Bank Islam depicts high volatility of 2.76%, followed by Bank AL Jazira (2.65%), Dubai Islamic Bank (2.23%). The volatility is smaller than one in case of Arab Islamic Bank (0.68%), QIIB, Alliance Islamic Bank (0.82%) and Bahrain Islamic Bank (0.95%). The volatility is near to one percent of Affine Bank (1.08%), Albraka Banking Group (1.42%), Al Barka Turk Katlm (1.01%), Al Rajhi Bank (1.36%), Alinma Bank (1.12%), CIMB (1.13%), Ihtimar Holding (1.38%), and Qatar Islamic Bank (1.14%). It is very close to two for Arab Banking Corporation (1.79%), Bank Islami Limited (1.79%), and Bank Syariah Mandiri (1.75%). The volatility ratio, suggest the N.Distribution a proper model at 99% confidence.

The EWMA method report 3.46% in Bank Al Jazira showing this model as weaker risk forecasting model in Bank Al jazira. Arab Banking Corporation (3.05%), and Bank Islam (3.01%), Dubai Islamic Bank (2.88%), Bank Islami Limited (2.83%) and Ihtimar Holding is (2.54%). The EWMA report below a two percent for rest of the banks including Affine Bank (1.46%), Al Baraka Bank (2.16%), Al Barka Turk Bank (1.615%), Al Rajhi Bank (1.88%), Alinma Bank (1.83%), Alliance Islamic Bank (1.05%), Arab Islamic Bank (1.25%), Bahrain Islamic Bank (1.90%), Bank Syariah Mandiri (1.75%), CIMB (1.44%), QIIB (1.22%), Qatar Islamic Bank (1.57%).

Table 4.7: VaR Volatility at 99% Confidence Level

Bank	**H.S**	**N.Dist**	**EWMA**	**GARCH**	**BERKOWITZ**
AFB	0.0192	0.0108	0.0146	0.0144	0.0165
ABBG	0.0183	0.0142	0.0216	0.0218	0.0138
ABTK	0.0201	0.0101	0.0161	0.0192	0.0157
ARB	0.0192	0.0136	0.0188	0.0203	0.0189
ALMB	0.0251	0.0112	0.0183	0.022	0.0177
ALCIB	0.0189	0.0082	0.0105	0.0103	0.0117
ABC	0.0232	0.0179	0.0305	0.023	0.0143
AIB	0.0249	0.0068	0.0125	0.0125	0.0122
BIB	0.0173	0.0095	0.019	0.0166	0.0134
BAJZA	0.0186	0.0265	0.0346	0.0786	0.0390
BISM	0.0339	0.0276	0.0301	0.0276	0.0303
BISL	0.0241	0.0179	0.0283	0.0284	0.0258
BSM	0.0187	0.0175	0.0175	0.0179	0.0205
CIMB	0.0165	0.0113	0.0144	0.0159	0.0145
DIB	0.0422	0.0223	0.0288	0.0331	0.0312
IMRH	0.011	0.0138	0.0254	0.0229	0.0175
QIIB	0.014	0.0082	0.0122	0.0143	0.0124
QIB	0.0171	0.0114	0.0157	0.0178	0.0167

The GARCH model volatility at 99% confidence level is highest for Bank Aljazira (7.86%), and Dubai Islamic Bank (3.31%), which mean GARCH method is worse risk estimator in stock of Bank Al Jazira and as well Dubai Islamic Bank. The Bank Islam (2.76%), Bank Islami Limited (2.84%) is around 3%. The Al Barak Bank (2.18%), Al Rajhi Bank (2.03%), Alinma Bank (2.20%), Arab Banking Corporation (2.30%), volatility is close to 2%. The rest of the sample is showing 1% volatility approximately.

Applying the Berkowitz model, the volatility is maximum in the stock of Bank Aljazira which is (3.9%), indicating the Berkowitz as improper model of risk evaluation. Dubai Islamic bank volatility is 3.12%, and Bank Islam volatility is 3.03%, and Bank Islami Limited volatility is 2.58% representing as other high volatile stock. The Berkowitz model is suitable for 95% of the sample. So it can strongly be recommended amongst the volatility based model as a method of risk forecasting on the basis of volatility ratio, at 99 percent confidence. Bank Aljazera volatility is 3.46% under EWMA, 7.86% under GARCH, and 3.90% under the Berkowitz model so all three model of volatility is not proper for this stock.

4.3.3 Kupiec's Test

Table 4.8 exhibits the Likelihood ratio, at 95% confidence interval forecasted using the assumption of Historical Simulation, N.Distribution, EWMA, GARCH and Berkowitz for all the 18 Islamic banks included in the sample.

The results in table 4.8 shows that, the LR of Affine Bank (0.06), Al Barak Bank (0.0065), Al Barak Turk (0.84), Al Rajhi Bank (0.44), Alinma Bank (0.00), Arab Islamic Bank (0.94), Bahrain Islamic Bank (2.72), Bank AL Jazira (3.12), Bank Islam (2.53), Bank Islami Limited (0.02), Bank Syariah Mandiri (0.19), CIMB (1.32), Dubai Islamic Bank (1.22) Ihtimar Holding (0.00), and Qatar Islamic Bank (0.02) under the Historical Simulation is below the chi-square value of 3.84, so indicating Historical Simulation a fair model for fifteen Islamic banks. The Alliance Islamic Bank (7.05), Arab Banking Corporation (9.60), and QIIB (4.06) LR are above the 3.84 criteria, suggesting inappropriate model for these 3 banks.

The value of LR under N.Didtribution, is below 3.84 criteria in case of ABTK (3.82), Al Rajhi Bank (0.00), Alliance Islamic Bank (1.62), Arab Islamic Bank (2.07), Bank Islami Limited (1.58), Bank Syariah Mandiri (0.84), Dubai Islamic Bank (0.15), and Ihtimar Holding (0.81), which is a clear indication of suitable model for all these 8 banks. The Affine Bank (6.87), Al Barak Bank (6.29), Alinma Bank (6.89), Arab Banking Corporation (36), Bahrin Islamic Bank (4.93), Bank Al Jazira (37.61), Bank Islam (4.12), CIMB (7.49), QIIB (13.15), and Qatar Islamic (7.26), LR is greater than 3.84 chi-square, so for these ten Islamic banks it is very weak method. For 56% it is true forecaster, while for 44% sample it not stable, so N.Disribution is no favorable model.

The LR under The EWMA for Affine Bank (0.7), Al Baraka Bank (2.28), Al Barak Turk Katlim (0.28), Alinam Bank (1.69), Alliance Islamic Bank (0..12), Bahrain Islamic Bank (0.52), Arab Islamic Bank (0.52), Bank Islam (0.05), Bank Islami Limited (0.37), Bank Syariah Mandiri (1.23), CIMB (2.79), and Qatar Islamic Bank (1.83), is falling under the critical value 3.84 so the Kupiecs test show EWMA method a perfect modeling for 12 Islamic Bank at 95% confidence. The LR of Al Rajhi Bank (8.63), Arab Bank Corporation (24.31), Bank Al Jazira (6.0), Dubai Islamic Bank (10.70), Ihtimar Holding (7.31), and QIIB (5.54) is not significant mean crossed the 3.84 chi-square. The EWMA for these 6 banks is a bad model. The Kupiecs test for 67% sample suggest the EWMA a true estimator, while for 33% of the sample it is rejected.

TABLE 4.8: Kupiec's Test at 95% Confidence Level

Bank	**H.S**	**N.Dist**	**EWMA**	**GARCH**	**BERKOWITZ**	**CHI**
AFB	0.06	6.87	0.72	0.72	3.68	3.84
ABBG	0.00	6.29	2.28	3.74	4.64	3.84
ABTK	0.84	3.82	0.28	1.22	2.66	3.84
ARB	0.44	0.00	8.63	3.62	0.11	3.84
ALMB	0.00	6.89	1.69	3.82	2.58	3.84
ALCIB	7.05	1.62	0.12	1.89	0.44	3.84
ABC	9.60	36.03	24.31	33.46	32.78	3.84
AIB	0.94	2.07	0.52	0.03	0.91	3.84
BIB	2.72	4.93	0.52	2.72	6.84	3.84
BAJZA	3.12	37.61	6.00	13.39	25.05	3.84
BISM	2.53	4.12	0.05	1.69	1.52	3.84
BISL	0.02	1.58	0.3700	1.14	6.75	3.84
BSM	0.19	0.84	1.23	2.23	2.71	3.84
CIMB	1.32	7.49	2.79	11.54	4.48	3.84
DIB	1.22	0.15	10.71	5.05	0.34	3.84
IMRH	0.00	0.81	7.31	3.13	3.02	3.84
QIIB	4.06	13.15	5.54	6.08	15.05	3.84
QIB	0.02	7.26	1.83	1.29	2.99	3.84

The LR under GARCH for Affine Bank is (0.72), Al Baraka Bank (3.74), Al Bark Turk Katlim (1.22), Al Rajhi Bank (3.62), Alinma Bank (3.82), Alliance Islamic Bank (1.89), Arab Islamic Bank (0.03), Bahrain Islamic Bank (2.72), Bank Islam (1.69), Bank Islami Limited (1.14), Bank Syariah Mandiri (2.23), Ihtimar Holding (3.13), and Qatar Islamic Bank (1.29), is compliance with chi-square

3.84 value, suggesting for 13 Islamic Banks the GARCH is authentic model of risk determination. Arab Banking Corporation LR is showing big value of 33.46, followed by Bank Al Jazeera (13.39), CIMB (11.54), Dubai Islamic Bank (5.05), and QIIB (6.08) that have crossed the 3.84 acceptance criteria, so indicating the GARCH as inappropriate model for 5 Islamic banks in the sample. The LR of Kupiecs suggest that fo 72% of the sample it is best, however 28% sample results is not reliable.

The Berkowitz model LR for Arab Banking Corporation, Bank al Jazira, and Qatar International Islamic Bank is 32.78, 25.05, 15.05 respectively suggesting clearly wrong model. Followed by Bahrain Islamic Bank (6.84, Bank Islami Limited (6.75), Al Baraka Bank (4.64), and CIMB (4.48), which is also not properly forecasted. The Berkowitz Model LR in case of Affine Bank (3.68), Al bark Turk Katelim (2.66), Al Rajhi Bank (0.11), Alinma Bank (2.58), Alliance Islamic Bank (0.44), Arab Islamic Bank (0.91), Bank Islam (1.52), Bank Syariah Mandiri (2.71), Dubai Islamic Bank (0.34), Ihtimar Holding (3.02), and Qatar Islamic Bank (2.99) suggesting Berkowitz the best suited model for 11 banks.

As per Kupiec test 15 Islamic Bank are correctly forecasted by Historical Simulation, 8 Islamic banks through N.Distribution, 12 by EWMA, 13 by GARCH, and 11 by Berkowitz. So Historical Simulation is on top of best model.

Table 4.9 exhibits the Kupiecs test Liklihood ratio through the assumption of Historical Simulation, Normal Distribution, EWMA, the GARCH, and Berkowitz for 18 Islamic banks included in the sample at 99 confidence of interval.

The Kupiecs LR using Historical Simulation, Affine Bank is 0.03, Al Barka Bank (1.03), Al Baraka Katilem (0.97), Al Rajhi Bank (0.16), Alinma Bank (0.33), Alliance Islamic Bank (1.3), Arab Islamic Bank (0.03), Bahrain Islamic Bank (2.77), Bank Al Jazeera (2.17), Bank Islam (0.58), Bank Islami Limited (2.88), Bank Syariah Mandiri (0.10), CIMB (2.08), Dubai Islamic Bank (6.47), Ihtimar Holding (0.15), QIIB (1.07), and Qatar Islamic Bank (0.62), explaining that is under 6.63 chi-square, so the Historical Simulation is ideal model as per the results of Kupiec test.

Table 4.9: Kupiec's Test at 99% Confidence Level

Bank	H.S	N.Dist	EWMA	GARCH	BERKOWITZ	CHI
AFB	0.03	6.25	33.14	15.47	11.17	6.63
ABBG	1.03	70.76	143.46	66.29	65.35	6.63
ABTK	0.97	4.32	17.98	10.69	9.40	6.63
ARB	0.16	32.19	39.33	32.19	17.58	6.63
ALMB	0.33	2.98	8.16	4.79	6.59	6.63
ALCIB	1.36	17.66	13.54	8.77	39.08	6.63
ABC	6.71	18.98	26.03	16.32	19.60	6.63
AIB	0.03	3.62	2.15	4.72	3.58	6.63
BIB	2.77	53.51	77.69	61.92	61.11	6.63
BAJZA	2.17	7.52	18.28	5.12	3.03	6.63
BISM	0.58	1.61	1.61	4.17	0.29	6.63
BISL	2.88	12.74	7.51	0.16	0.435	6.63
BSM	0.1	8.24	3.27	6.37	1.24	6.63
CIMB	2.08	8.53	15.89	14.54	12.69	6.63
DIB	6.47	48.95	43.07	37.47	5.87	6.63
IMRH	0.15	68.52	55.57	68.52	20.98	6.63
QIIB	1.07	5.08	4.23	4.23	1.15	6.63
QIB	0.62	9.16	10.33	3.44	8.81	6.63

Under the N.Distribution, the Al Baraka Bank (70.76), Ihtimar Holding (68.52), Bahrain Islamic Bank (53.51), Dubai Islamic Bank (48.95), Al Rajhi Bank (32.19), is reporting the LR much greater than 6.63 chi value, openly indicating as weaker performer model. The other rejected banks are Alliance Islamic (17.66), Bank Al Jazira (7.53), Bank Syariah Mandiri (8.24), CIMB (8.53), and Qatar Islamic bank (9.16) showing 67% sample weakly estimated. Affine Bank (6.25), Alinma Bank (2.98), Al Barak Turk (4.320, Arab Islamic Bank (3.62), Bank Islam (1.6), and QIIB (5.08) LR is within 6.63 range, showing N.Distribution a true forecaster of that bank and 33% sample is truly evaluated.

The EWMA method LR greatest in case of Al Barak Bank (143.46), followed by Bahrain Islamic Bank (77.69), Ihtimar Holding (55.57), Dubai Islamic Bank (43.07), Al Rajhi Bank (39), Affine Bank (33.14), Bank Al Jazira (18.28), Al Baraka Turk (17.98), CIMB (15.89), Alliance Islamic Bank (13.5), Qatar Islamic Bank (10.33), Alinama Bank (8.16), Bank Islami Limited (7.51), representing all 14 banks as forecasted inadequately by EWMA technique, and 78% sample showing poorest results. Only four banks Arab Islamic (2.15), Bank Islam (1.61), Bank

Syariah Mandiri (3.27), and QIIB (4.23) is falling under 6.63 chi-value, and only 22 % sample is forecasted perfectly.

The Kupiec LR, is highest at 99% confidence, through the GARCH technique for Ihimar Holding (68.52), followed by Al Barak Bank (66.29), Bahrain Islamic Bank (61.9), Dubai Islmic Bank (37.47), Al Rajhi Bank (32.19), Affine Bank (15.47), CIMB (14.54), Al Barka Turk Bank (10.69), and Alliance Islamic Bank (8.77), showing the model is not proper for 9 Islamic banks. However, the remaining 9 Banks LR is significant, including Alinma Bank (4.79), Arab Islamic Bank (4.72), Bank Al Jazira (5.12), Bank Islam (4.17), Bank Islami (0.16), Bank Syariah Mandiri (6.37), QIIB (4.23), and Qatar Islamic Bank (3.44), suggesting the GARCH, as the best technique.

Under the Berkowitz the Kupiec, LR is not significant in case of Al Baraka Bank (65.35), Alliance Islamic Bank (39.08), Ihtimar Holding (20.98), Al Rajhi Bank (17.58), CIMB (12.6), Affine Bank (11.17), Al Baraka Turk (9.40), and Qatar Islamic Bank (8.81), therefore indicating Berkowitz not reliable for 50% sample. The LR of Berkowitz is significant for following banks Alinma Bank (6.59), Arab Islamic Bank (3.58), Bank Aljazira (3.03), Bank Islam (0.29), Bank Islami Limited (0.435), Bank Syariah Mandiri (1.24), Dubai Islamic Bank (5.87), QIIB (1.15), and the model is best fitted for 50% of the sample.

4.3.4 Christoffersen (Independence Test)

Table 4.10 report the Chistoffersen LR results for entire Islamic banks, in the sample. For 95% confidence level the Christoffersen test LR of Historical Simulation is worse for thirteen Islamic banks which include, Affine Bank (17.16), Al Bark Bank (4.40), Al Bark Turk Bank (4.83), Al Rajhi Bank (11.90), Alinma Bank (137.48), Arab Banking Corporation (4.35), Bank Al Jazira (5.58), Bank Islam (20.11), Bank Syariah Mandiri (17.09), CIMB (19.07), Dubai Islamic Bank (19.15), QIIB (8.17), Qatar Islamic Bank (8.22). Only 28% of sample is forecasted correctly. So, the Historical Simulation, work in appropriately as per christoffersen results.

The Christoffersen LR is very high, for Ihtimar Holding (750.59), and rest 10 banks such as Affine Bank (12.11), Al Rajhi Bank (62.32), Alinma Bank (6.93), Arab Banking Corporation (6.43), Bank Aljazira (10.54), Bank Syariah Mandiri (22.60), CIMB (11.37), Dubai Islamic Bank (20.36), QIIB (7.77), and Qatar Islamic Bank (10.37) is also showing LR exceeding the chi-square 3.84, so the christoffersen test recommend N.Distribution a weaker model for the 61% of sample. The model is fair in case of Al Baraka Bank (1.95), Al Braka Turk Katilem (3.84), Alliance Islamic Bank (1.88), Arab Islamic Bank (0.32), Bahrain Islamic Bank (0.03), Bank Islam (1.04), Bank Islami Limited (3.93), so as per christoffersen only 39% sample is properly estimated, showing rejection of N.Distribution.

As per Christoffersen the EWMA appears good as only 5 Islamic Bank such as Bank Aljazira (7.35), Bank Syariah Mandiri (4.31), CIMB (178.49), QIIB (6.75), and Qatar Islamic Bank (4.35) is not forecasted properly. However 72% banks results are under 3.84 acceptance level, that are Al Baraka Bank (0.00), Al Braka Turk Katelm (2.12), Al Rajhi Bank (0.11), Alinma Bank (0.77), Alliance Islamic Bank (0.03), Arab Banking Corporation (0.15), Arab Islamic Bank (0.18), Bahrain Islamic Bank (0.64), Bank Islam (0.00), Bank Islami Limited (0.80), Dubai Islamic Bank (1.96), Ihtimar Holding (1.11) and the model is perfect for that banks. So, as per christoffersen test the EWMA is comparatively good model.

According to Christoffersen test, for 15 banks the LR fall under the significance level of 3.84 for the GARCH model, and the model is at top for good risk estimation. These banks are Al Braka Bank (0.04), Al Barak Turk Bank (0.09), Al Rajhi Bank (0.33),Alinma Bank (1.42), Alliance Islamic Bank (1.33), Arab Banking Corporation (0.53), Arab Islamic Bank (0.12), Bahr ain Islamic Bank (0.87), Bank Islam (1.70), Bank Islami Limited (1.24), CIMB (3.64), Dubai Islamic Bank (0.55), Ihtimar Holding (1.02), QIIB (2.96), and Qatar Islamic Bank (0.08). And only three banks LR is not significant including Affine Bank (7.40), the Bank Syariah Mandiri (7.74), and CIMB (17.56), and the GARCH is not perfect model only for 16

The christoffersen LR under the Berkowitz, is again in conformity with significance level of 3.84 chi-square for 15 Islamic banks representing the Berkowitz as best technique. The banks having LR below 3.84 are Al Baraka Bank (3.06), Al Baraka Turk Katilem (1.26), Al-Rajhi Bank (0.86), Alinma Bank (1.42), Alliance Islamic Bank (1.22), Arab Banking Corporation (1.09) Arab Islamic Bank (0.007), Bahrain Islamic Bank (0.06), Bank Al Jazeera (3.61), Bank Islam (0.15), Bank Islami Limited (1.31), Dubai Islamic Bank (0.03), Ihtimar Holding (0.22), Qatar Islamic Bank (1.09), and QIIB (0.16). And only 3 banks are out of chi-square 3.84.

TABLE 4.10: Christoffersen independence test at 95% Confidence Level

Bank	**H.S**	**N.Dist**	**EWMA**	**GARCH**	**BERKOWITZ**	**CHI**
AFB	17.16	12.11	17.28	7.40	50.43	3.84
ABBG	4.40	1.95	0.0095	0.04	3.06	3.84
ABTK	4.83	3.84	2.12	0.09	1.26	3.84
ARB	11.9	62.38	0.11	0.33	0.86	3.84
ALMB	137.48	6.93	0.77	1.40	1.42	3.84
ALCIB	2.49	1.88	0.03	1.33	1.22	3.84
ABC	4.35	6.43	0.15	0.53	1.09	3.84
AIB	0.12	0.32	0.18	0.12	0.00	3.84
BIB	0.16	0.03	0.64	0.87	0.06	3.84
BAJZA	5.58	10.54	7.35	4.16	3.61	3.84
BISM	20.11	1.04	0.00	1.70	0.15	3.84
BISL	3.21	3.93	0.8	1.24	1.31	3.84
BSM	17.09	22.60	4.31	6.04	7.74	3.84
CIMB	19.07	11.37	178.49	3.64	17.56	3.84
DIB	19.15	20.36	1.96	0.55	0.03	3.84
IMRH	0.87	750.59	1.11	1.02	0.22	3.84
QIIB	8.17	7.77	6.75	2.96	0.16	3.84
QIB	8.22	10.37	4.35	0.0085	1.09	3.84

Table 4.11 exhibits the Christoffersen test results calculated through the assumption of Historical Simulation, Normal Distribution, EWMA, the GARCH, and the Berkowitz, at 99% confidence level.

The Christoffersen test, under the Historical Simulation, show highest LR value 119.80 in Bank Aljazeera stock, followed by Bank Islami Limited (10.79), Dubai Islamic Bank (10.03), and Alinma Bank (8.74), which tell Historical Simulation, is not a very well suited estimater of these stock risk. However, for rest of the stock null hypothesis is accepted, including Affine Bank (6.61), AlBaraka Banking Group (0.001), AlBarka Turk Katelim (1.94), Al Rajhi Bank (1.44), Alliance Islamic Bank (2.56), Arab Banking Corporation (3.45), Arab Islamic Bank (2.15), Bahrain Islamic Bank (2.49), Bank Islam (3.23), Bank Syariah Mandiri (1.42), CIMB (2.81), Ihtimar Holding (1.03), QIIB (2.64), and Qatar Islamic Bank (2.41), and the model is consider as well suited risk forecaster.

Table 4.11: Christoffersens independence test at 99% Confidence level

Bank	**H.S**	**N.Dist**	**EWMA**	**GARCH**	**BERKOWITZ**	**CHI**
AFB	6.61	2.46	9.79	2.23	1.55	6.63
ABBG	0.001	6.35	0.55	0.19	0.20	6.63
ABTK	1.94	8.14	0.88	0.06	4.06	6.63
ARB	1.44	3.65	21.02	0.28	0.002	6.63
ALMB	8.74	4.33	2.85	11.08	0.46	6.63
ALCIB	2.56	1.11	0.07	0.21	11.99	6.63
ABC	3.45	5.45	0.46	10.42	0.69	6.63
AIB	2.15	0.75	0.97	0.65	0.63	6.63
BIB	2.49	1.79	0.15	0.31	0.85	6.63
BAJZA	119.8	12.83	9.11	2.39	0.35	6.63
BISM	3.23	1.33	1.34	0.85	1.64	6.63
BISL	10.79	10.57	17.5	1.03	7.89	6.63
BSM	1.42	17.48	0.46	0.27	3.38	6.63
CIMB	2.81	8.95	0.03	5.15	1.40	6.63
DIB	10.03	12.71	7.68	2.16	0.21	6.63
IMRH	1.03	9.22	0.64	0.06	2.35	6.63
QIIB	2.64	2.93	0.56	0.56	0.89	6.63
QIB	2.41	50.36	7.35	0.64	0.19	6.63

As shown by the Christoffersen test, at 99% confidence under the N.Distribution, the null hypothesis is accepted in case of 11 banks as the LR is below the 6.63 chi square. The banks indicating LR blew the 6.63 value are Affine Bank (2.46), Albaraka Banking Group (6.35), Al Rajhi Bank (3.65), Alinama Bank (4.33), Alliance Islamic Bank (1.11), Arab Banking Corporation (5.45), Arab Islamic Bank (0.75), Bahrain Islamic Bank (1.79), Bank Islam (1.33), QIIB (2.93), indicating the N.Distribution as good performer. The banks indicating LR above 6.63 are Al Baraka Turk Bank (8.14), Bank Al Jazira (12.83), Bank Islami Limited (10.57), Bank Syariah Mandiri (17.48), CIMB (8.95), Dubai Islamic Bank (12.71), Ihtimar Holding (9.22), and Qatar Islamic Bank (50.36), indicating that N. Distribution is not forecasting risk of these banks accurately.

As per the Christoffersen test LR, at 99% confidence level, under the EWMA the null hypothesis is accepted for 12 Islamic banks, as showing the LR below the cutoff point of 6.63 that are Al Baraka Bank (0.55) Al Barak Turk Bank (0.88), Alinma Bank (2.85), Alliance Islamic Bank (0.07), Arab Banking Corporation (0.46), Arab Islamic Bank (0.97), Bahrain Islamic Bank (0.15), Bank Islam (1.34), Bank Syariah Mandiri (0.46), CIMB (0.03), Ihtimar Holding (0.64), and QIIB (0.56). The Bank that fall out of range, mean not properly forecasted are Affine Bank (9.79), Al Rajhi Bank (21), Bank Al Jazira (9.11), Bank Islami Limited (11.70), Dubai Islamic Bank (7.86), and Qatar Islamic Bank (7.35).

The GARCH results are favorable, for 16 Islamic Banks comprising of Affine Bank (2.23), Al Baraka Bank (0.19), AlBaraka turk (0.06), Al Rajhi Bank (0.28), Alliance Islamic Bank (0.21), Arab Islamic Bank (0.65), Bahrain Islamic Bank (0.31), Bank Aljazira (2.39), Bank Islam(0.85) Bank Islami Limited (1.03), Bank Syariah Mandiri (0.27), CIMB (5.15), Dubai Islamic Bank (2.16), Ihtimar Holding (0.06), QIIB (0.56), and Qatar Islamic Bank (0.64). Only 2 Banks result are worst Alliance Islamic Bank (11.08), and Arab Banking Corporation (10.42), so christoffersen test suggest for 89% sample GARCH as best fitted.

As per Christoffersen test, for 89% sample the Berkowitz is true forecaster of risk. The LR is under the 6.63 chi-square for Affine Bank (1.55), Al Barak Bank (0.20), Al Barak Turk Katlim (4.06), Al Rajhi Bank (0.002), Alinma Bank (0.46), Arab Banking Corporation (0.69), Arab Islamic Bank (0.63), Bahrain Islamic Bank (0.85), Bank Aljazira (0.35), Bank Islami (1.46), Bank Syariah Mandiri (3.38), CIMB (1.40), Dubai Islamic Bank (0.21), Ihtimar Holding (2.35), QIIB (0.89), Qatar Islamic Bank (0.19). Only 11% sample is out of range of good criteria.

4.3.5 Capital Allocation for Islamic Banks

Table 4.12 report the capital allocation of Islamic banks, allocation made by bank itself, Historical Simulation, and Berkowitz model at 95% confidence level. As indicated by Historical Simulation and Berkowitz 15 Islamic banks over appropriated capital, including Affine Bank (19.30%), Historical Simulation 7.0%, Berkowitz 7.47%, Al Baraka Bank (12.5%), Historical Simulation 6.5%, Berkowitz 8.43%, Al Rajhi Bank (19.14%), Historical Simulation 6.99%, Berkowitz 7.44%, Alinma Bank (21.05%), Historical Simulation 7.53%, Berkowitz 7.89%, Alliance Islamic Bank 15.42%, Historical Simulation 7.2%, Berkowitz 7.26%, Arab Banking Corporation 18.1%, Historical Simulation 4.35%, Berkowitz 9.78%, Arab Islamic Bank (19.4 0%), Historical Simulation 9.42%, Berkowitz 9.24%, Bahrain Islamic Bank (17.11%), Historical Simulation (6.72%), Berkowitz 8.49%, Bank Al Jazira (26.3%), Historical Simulation 8.85%, Berkowitz 11.37%, Bank Islam 16.9%, Historical Simulation (14.4%), Berkowitz 14.58%, Bank Syariah Mandiri (21.6%), Historical Simulation 11.13% , Berkowitz 10.86%, CIMB (18.36%), Historical Simulation 7.29%, Berkowitz 7.5%, Dubai Islamic Bank 14.0%, Historical Simulation 9.18%, Berkowitz 9.87%, QIIB 16.42%, Historical Simulation 5.16%, Berkowitz 5.76%, Qatar Islamic Bank (18.8%), Historical Simulation 6.03%, Berkowitz 6.54%. Bank Islami Limited 15.10%, is appropriate as per Historical Simulation 14.4% and Berkowitz 14.58%. Two Islamic under appropriated capital including Al Baraka Turk Katilim 7.56%, Historical Simulation 8.94%, Berkowitz 9.54%, Ihtimar Holding (13.39%,), Historical Simulation 15.78%, Berkowitz 14.49%.

TABLE 4.12: Capital allocation at 95% confidence level

Bank	**Allocation of Bank**	**H.S**	**BERKOWITZ**	**Current Aallocation Status**
AFB	19.30%	7.05%	7.47%	Over
ABG	12.50%	6.51%	8.43%	Over
ABTK	7.56%	8.94%	9.54%	Under
ARJ	19.14%	6.99%	7.44%	Over
ALMB	21.05%	7.53%	7.89%	Over
ALCIB	15.42%	7.20%	7.26%	Over
ABC	18.10%	4.35%	9.78%	Over
AIB	19.40%	9.42%	9.24%	Over
BIB	17.11%	6.72%	8.49%	Over
BAJZA	26.30%	8.85%	11.37%	Over
BISM	16.90%	9.24%	10.50%	Over
BISL	15.10%	14.40%	14.58%	Appropriate
BSM	21.60%	11.13%	10.86%	Over
CIMB	18.36%	7.29%	7.50%	Over
DIB	14.00%	9.18%	9.87%	Over
IMRH	13.90%	15.78%	14.49%	Under
QIIB	16.42%	5.16%	5.76%	Over
QIB	0.19%	0.06%	0.07%	Over

Table 4.13 report capital allocation of Islamic banks at 99% confidence level, according to Historical Simulation and Berkowitz ten Islamic over appropriated capital. Four Islamic banks under appropriated capital. Four Islamic under appropriated according to Historical Simulation, and over appropriated as per Berkowitz model.

Table 4.13: Capital allocation at 99% confidence level

Bank	**Allocation of Bank**	**H.S**	**BERKOWITZ**	**Current Aallocation Status**
AFB	19.37%	14.61%	10.47%	Over
ABG	12.50%	23.37%	12%	Under
ABTK	7.56%	17.01%	13.47%	Under
ARB	19.14%	15.03%	10.47%	Over
ALMB	21.05%	14.73%	11.19%	Over
ALCIB	15.42%	13.80%	10.29%	Over
ABC	18.10%	24.66%	13.70%	Under
AIB	19.40%	13.80%	12.99%	Over
BIB	17.11%	20.67%	11.88%	Under
BAJZA	26.30%	20.67%	16.20%	Over
BISM	16.90%	22.05%	14.88%	Under
BISL	15.10%	24.09%	20.06%	Under
BSM	21.60%	19.80%	15.48%	Over
CIMB	18.36%	13.74%	10.65%	Over
DIB	14.00%	18.24%	13.89%	Under
IMRH	13.90%	27.27%	20.34%	Under
QIIB	16.42%	10.35%	8.19%	Over
QIB	18.18%	13.05%	9.29%	Over

Chapter 5

Conclusion

5.1 Conclusion

In this chapter after the analysis of whole process of chapter 4, the conclusion and some recommendations are given on the basis of that analysis.

5.1.1 Conclusion

In recent years the financial institutions experienced a huge of losses, due to which many organizations went to bankruptcy. So, there a was need to know about the potential of these losses, to protect them from future insolvency. Value at risk emerged as tool, to know about the chances of happening of these losses. In this study value at risk, was proposed on the basis of different assumptions such that Historical Simulation, N. Distribution, EWMA, the GARCH, and Berkowitz, and also at both confidence level such that, 95% and 99% as well.

One of the objectives, of this research is to identify the market risk faced by Islamic banks. As per Historical Simulation, at 95% confidence level most of the Islamic banks are facing 2% to 3% market risk, except Bank Islami Limited, and Ihtimaar Holding, having 4.8% and 5.26%. While the same method show, that Islamic banks are going to bear 6% to 7% market risk, except Arab Banking Corporation 8.2%, Bank Islami Limited 8.03% and Ihtimar Holding 9.09%. At 95% the N.distribution, show 2 to 3% market risk, except 3 Islamic banks, Bank al Jazira 4.16%, Ihtimaar Holding 4.91%, and Bank Islami Limited 5.15%. However, at 99% the VaR is 4% to 5%, besides Ihtimaar Holding 7%, and Bank Islami Limited 7.3%. The EWMA, GARCH and Berkowitz model, at 95% also the same percentage of risk, with the exception of two to three Islamic Banks that are exposed around 5% market risk. At 99% the EWMA and GARCH is showing 3% for majority of the sample, and Berkowitz 4% for many banks, with the exception of two to 3 Islamic banks that is 7% to 9%. The VaR is at maximum level, under the Historical Simulation, for both of confidence level 95% and also 99%.

The second purpose of the study, is to know about the best model for assessing the market risk faced by Islamic banks. For this purpose various tool, of back testing are applied including Violation ratio, the VaR Volatility, Kupiec test, and the Christoffersen test.

Using the criteria of Violation ratio, the Historical Simulation is true predictor in case 17 Islamic banks, N.Distribution 12 Islamic banks, the EWMA is good for 14 Islamic banks, and the GARCH and Berkowitz is performing well for 15 Islamic banks, at 95 % the Historical Simulation is leading model. At 99% violation ratio, Historical Simulation is good enough, for 13 Islamic banks, the N.Distribution, EWMA, and GARCH is 100% rejected, and Berkowitz is perfect only for 4 banks. So, violation ratio criteria give the Historical Simulation top rank. VaR volatility, at 95% confidence the VaR volatility suggest that all methods are equally good except GARCH. At 99% confidence level, volatility ratio is good for all model.

Proceeding to Kupiecs POF test, at 95% of confidence, the Historical Simulation is top performer, good for 83% banks, N.Distribution for 44%, EWMA for 66%, GARCH 72%, and Berkowitz 61% of the banks. The Historical Simulation is again 100% true forecaster at 99% confidence, the N.Distribution and as well EWMA is only reliable for 4 Islamic banks, GARCH is estimating 8 and Berkowitz 9 Islamic Banks adequately. The Historical Simulation, as per Kupiecs is again at both confidince is highest performer.

Next comes to Christoffersen independence test, which mainly used to know about clustering, such that there is any relation of former clustering with that of later clustering. At 95% it is found that, clustering is at peak in case of Historical Simulation only 17% is free of clustering. The null hypothesis, is accepted for 7 Islamic banks. However the clustering is at minimum, in GARCH 83% free and Berkowitz 83% of sample is independent. The Historical Simulation, declared 78% free from clustering, at 99 % confidence. The N.Disrtribution 50% free and 50% is showing clustering. The EWMA is showing high level clustering 77%, in sample. As shown by christoffersen test, there is no clustering in 90% under the tool of GARCH, and the Berkowitz too. So, the Christoffersen, give the highest accuracy in all five model to GARCH, and Berkowitz too.

After the analysis of all four technique of model validation, Historical Simulation rank top by three out of four methods, so the overall best technique is Historical Simulation. However, if using the time varying volatility approaches, then Berkowitz is recommended as the best one.

The third purpose of the study, is to set minimum capital requirement of Islamic banks. The basel committee, that setout rules and regulation, require all banks to set aside a minimum of 12% capital based on the risk weighted asset to insure the sustainability of banks and prevent them from bankruptcy. The Basel accord, also specifies that the daily capital charge (DCC), must be determine at rate equal to or greater than three times of the average VaR of the last 60 working days (Chang et al, 2019). Using the criteria above, and according to model identified as to be the best suited for risk estimation of Islamic banks, such as the Historical Simulation, after VaR is multiplied by 3, 83% of Islamic banks of the sample are under the threshold of 12%. However Bank Islami Limited (14%) and Ihtimar Holding (15.78%) are crossing the minimum 12% requirements.

5.1.2 Recommendations

The results of this study shows, that the model with highest accuracy at 95% and 99% too is the Historical Simulation. So, on the basis of this study Historical Simulation is recommended for market risk measurement of Islamic banks. However, using the time varying volatility model, the Berkowitz model, is the best in all of three models used in this study.

Another recommendation on basis of results of this study is that, the Basel Committee has set the minimum 12% limit for all banks, which is justified in most of the cases. However, individual banks may have high risk profile so additional condition for equity may be imposed to make it equal to 3 times of the VaR. In other words 12% or three times of VaR whichever is high.

Chapter 6

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