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Seasonal Behavior in VaR and VaR Exceptions: Evidence from the Stock Indices of Islamic Countries

by

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This work is dedicated to my parents for their endless support and motivation and to my honorable supervisor Dr. Arshad Hassan who has been a source of motivation for me.

CERTIFICATE OF APPROVAL

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Abstract

This study compares the models, namely normal distribution, historical simulation, EWMA and GARCH for VaR estimation by considering daily stock returns of ten Islamic countries i.e. Pakistan, Saudi Arabia, Iran, Oman, Turkey, UAE, Bangladesh, Egypt, Indonesia and Malaysia for the period 2000 to June 2018. At 95% and 99% confidence interval normal distribution and historical simulation method performed best for risk estimation. Monthly and daily seasonal behavior is observed by using regression equation. A consistency of monthly and daily seasonal behavior in VaR is observed in monthly and daily data for all the ten Islamic countries whereas, for VaR exceptions, seasonal behavior is not present in all days and months of the year but differs among countries and across days while in Bangladesh and Malaysia the presence of seasonal behavior on VaR exceptions is very limited.

Keywords: Value at Risk, Stock returns, Seasonality, VaR exceptions

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Abbreviations

EMH	Efficient Market Hypothesis
EWMA	Exponentially Weighted Moving Average
GARCH	Generalized Autoregressive Conditional Heteroscedasticity
HS	Historical Simulation
ND	Normal Distribution
POF	Proportion of Failures
VAR	Value at Risk
VR	Violation Ratios

Chapter 1

Introduction

This section provides the introduction, theoretical background, statement of problem, questions, objectives, research gap and significance of the current study.

1.1 Theoretical Background

Efficient market hypothesis states that markets are rational and all available information is fully revealed by the prices of stocks and prices reflect all readily available information in the market. The securities prices rapidly adjust to the new information. But behavioral finance argues that observed anomalies present in market are ignored by such kind of efficient market. Market anomalies affect random pattern of the market by its unusual occurrence or abnormality in the stock market.The expected behavior of the stock market is opposed by the action of market prices. Some financial anomalies may disappear after appearing only once, but presence of some anomalies may be noticed consistently throughout historical chart analysis. Investors and traders can use this type of unusual market behavior to find opportunities in the the stock markets and due to lack of the information about this unusual occurrence their investments may be affected badly. In stock returns, these seasonal patterns have been observed across the globe by considering daily, weekly and annual return frequencies.Under globalization and international market integration, exploring seasonality in equity markets is necessary for portfolio managers and individual investors to timely restructure their portfolios. Anomaly is something that is exceptional and is defined by (Frankfurter and McGoun, 2001) as irregularity or a deviation from natural order or common condition. Probabilities of price drops and price rises are one of the most familiar risk-factors in finance.

The studies are conducted on traditional market hypothesis testing with the focus on prototype exists in stock returns which are commonly known as calendar anomalies, cyclical anomalies or calendar effect. Some of these anomalies are month of the year effect, week of the month effect, January Effect, Monday effect, and many more. Seasonality of stock return is economically and statistically significant phenomenon and existence of the seasonal behavior in return and volatility of different international stock markets may be considered as a symbol of non integrated financial markets. The seasonality in the stock market returns has encouraged numerous researchers to examine seasonal volatility patterns to illuminate seasonal returns with the help of different models like GARCH and ARCH models.

Arora and Das (2007) use Augmented Dummy Regressive model to study the day or the week effect in the Indian National Stock Exchange from the period ranging 1994 to 2007; they found the Friday and Monday effect. A research conducted by Aly et al. (2004) report Monday effect in the Egyptian stock market from the period ranging 1998 to 2001. Das and Jariya (2009) conduct a research on Srilankan stock exchange by using autoregressive model to test the day of the week effect for the period 1985 to 2004 and find the day-of-the-week effect in the Colombo Stock Exchange, Other day's returns are lower as compared to Friday. Bepari et al. (2009) find the April and July effects in Dhaka Stock Market from the period across 1993 to 2006. International studies similarly report evidence of patterns in daily returns, although significant positive or negative returns are reported on Mondays and Tuesdays respectively for several Asian markets, including Thailand and Malaysia (Brooks and Persand, 2001). December effect is revealed by Ignatius (1998) by using F-test in Indian and US stock markets from the period ranging

1979 to 1990. Previous findings have serious inferences for financial markets in which it is shown that the trade-off between risk and return commonly forms the basis for financial decisions. The appearance of such anomalies violates the efficient market hypothesis because these are predictable on some calendar effects. Hence, allowing the investors to develop trading strategies to earn an abnormal profit.

To know about risk is beneficial as we can change our behavior to avoid it. VaR has become a standard tool for assessing market risks, due to its conceptual simplicity, ease of computation, and readily applicability. To accurately forecast VaR, reasonable modelling of financial returns is critical. The main point that is required by this study is if Var has implication on the risk and returns of the stock markets then VaR must be affected by the seasonality that exists in the stock market. VaR is the technique that is widely used and is prominent too for computing price or market risk by using a single real number and assists to detect the price risk. VaR was promoted by J.P Morgan as a risk measure named as Risk Metrics during early period of 1990s. For many years, large number of variants of this measure have been introduced as a widespread measures of risk. That's why the VaR has become a popular measure, as early as 2001, for the risk management system of enterprises for the estimation of risk (Christoffersen et al., 2001).

Risk can be broadly defined in terms of volatility in empirical finance and may be consider as an unexpected outcome. Whatever the nature of operation organizations have they must expose to some sort of risk and it may occur due movement of prices in the financial market and have an overwhelming effect on the investments or on the financial markets. So the application and development or risk management tools have extensively increased around the globe and VaR on one of the tools to deal with this risk. VaR can be considered to quantifies the amount of financial risk within a firm, portfolio or position over a specified time frame. This technique is most commonly used by the firms to determine the occurrence ratio and of possible losses in their organized portfolios. To measure the risk and to avoid and control the risk exposure level, VaR is usually used by the risk managers and its calculations can be applied to specific positions, portfolios or to measure firm-wide risk. VaR model is defined by Saunders and Allen (2002), as a quantitative tool that is used to assess the possible loss suffered by a financial institution over a given time horizon and for a definite portfolio of securities i.e.in case tomorrow is defined as a statistically bad day, it quantifies the market value exposure of a financial instrument. VaR produces the equilibrium among the risk measures that are available and therefore constructs practical and robust risk models. Different VaR models are derived due to ever increasing availability and access to the financial world data and developments in information technology so that these are applicable for the risk management profession.

For estimating VaR, traditional approaches of Volatility assume that asset returns are normally distributed. Although this statement significantly simplifies the computation of VaR but it is not consistent with the pragmatic evidence in stock returns, which finds that the distribution of returns is negatively skewed by French et al. (1987) fat-tailed studied by Bollerslev et al. (1987) and peaked around the mean (Engle and Gonzalez-Rivera, 1991). This shows that extreme negative returns are much more expected to occur in practice than would be forecasted by the symmetric thinner tailed normal distribution. Thus, numerous studies have tested with fat-tailed and asymmetric return distributions for VaR estimation. Bali and Theodossiou (2008) compare different GARCH specifications and provides strong evidence that skewed fat-tailed distribution yield a more accurate and strong approach in VaR calculations than the normal distribution. Bali et al. (2008) investigate that VaR forecasts for US stock returns are better with the skewed generalized t distribution by using the role of high order moments in the VaR estimation. It is presumed by earliest studies that assets returns are distributed normally, but now at large it is accepted that asset returns show stylized effects i.e. leverage effect, fat tail return distribution and volatility clustering. These three stylized effects exhibit three important facts, i.e. (1) Bad news tends to exhibit more effect on stock returns than good news, (2) The excess kurtosis and time series of assets returns is used to measure fat tail phenomenon and is known as leptokurtic in nature, (3) Small changes exhibit small returns while large changes exhibit large returns. Volatility models are being used to exhibit VaR to capture these stylized facts. Bollerslev (1986) introduced autoregressive conditional heteroscedasticity (ARCH) models. By permitting the conditional variance as a function of time varying past errors to capture the correlations in squared returns VaR models are really helpful. Many more methods like ARMA GARCH, T-GARCH, E-GARCH, FIGARCH, GARCH, JGR GARCH are used by many researchers in the same aspect of study.

Ideally Accuracy Assessment of VaR forecasts must be done by considering the model performance in the future by using operational criteria. As long period of time would be required because violations are normally observed infrequently so backtesting inspects that how VaR forecasts or a VaR model performed across the time. To check the precision of the measure and distribution of returns backtesting models are being used. A simple back test checks the actual distribution of returns against the return distributions run through the model by comparing the actual loss exceptions with the expected number of exceptions. VaR models are worthwhile only if their prediction for future risks is precise. For the evaluation of the accuracy of the VaR measures, appropriate methods should always be used for the backtesting of those VaR measures that are been already used. Number of various testing procedures have been projected for the purpose of backtesting. Basic tests, like Kupiec's (1995) POF-test that is used to observe the frequency of losses in excess of VaR. Christoffersen's forecast test is a conditional test which covers the violation rate and also the independence of exception. Jorion (2000) states these tests rightly as 'reality checks'. If the VaR estimations are not precise, the models should be reassessed for incorrect assumptions, wrong parameters or imprecise modeling. If the back testing values are not accurate for the risk predictions, VaR can be reassessed and recalculated. So the main purpose here of back testing in this study is dual: (1) to evaluate the performance of the model and its estimation for risk measurement, and to compare relative performance of the models and methods because it is a tool for the confirmation process which is crucial for financial risk management.

1.2 Gap Analysis

Although the number of studies have been concluded on market anomalies, value at risk and VaR exceptions in case of market stock prices of different countries, commodity prices, returns of banks and other financial institutions but the presence of seasonality in VaR exceptions is still unexplored in case of stock indices around the globe except one study by Gupta and Rajib (2018) in case of commodity prices. The purpose of this study is to explore whether VaR exceptions in stock indices of Islamic countries are affected by the seasonality contributed in that specific market. Based on findings it is believed that there is a gap regarding the relationship between VaR exceptions and seasonality and this study provides a gateway for future research.

1.3 Problem Statement

Previous Studies provide that markets are not efficient and are facing unusual occurrences and abnormalities due to presence of anomalies which disturb the random pattern of the market returns. Earlier findings have serious inferences for financial markets in which it is shown that the trade-off between risk and return commonly forms the basis for financial decisions. VaR has become a standard tool for assessing market risks, due to its conceptual simplicity, ease of computation, and readily applicability. To accurately forecast VaR, reasonable modelling of financial returns is critical. The main point that require this study is if VaR has implication on the risk and returns of the stock markets then VaR may be affected by the seasonality exists in the stock market. This study is conducted to investigate about that either VaR exceptions exhibited seasonal behavior in stock market of Islamic countries. It will be helpful for further studies to cope up with probability of losses that occur due to Seasonality, so investors can revise their behavior to avoid the risk.

1.4 Research Questions

There are seven main questions that need detailed investigation in stock markets of Islamic Countries.

1. Which method is better to estimate VaR?
2. Whether GARCH based models are appropriate to identify seasonal behavior in the market?
3. Whether conventional model is appropriate to identify seasonal behavior in the market?
4. Does VaR is effected by the seasonality in the stock markets of Islamic countries?
5. Do VaR exceptions are effected by the seasonality in the stock markets of Islamic countries?
6. Does day of the week effect exist in VaR exceptions?
7. Does month of the year effect exist in VaR exceptions?

1.5 Research Objectives

1. To evaluate the various methods for the estimation of VaR
2. To identify the seasonality on VaR in market indices of Islamic countries.
3. To identify the seasonality on VaR exceptions in market indices of Islamic countries.
4. To explore day of the week effect in VaR exceptions.
5. To explore month of the year effect in VaR exceptions.

1.6 Significance of the Study

Risk management is the process of identifying possible risks,tragedies or problems before they happen and if it is truly managed it permits investors to set up procedures to minimize the impact of risk, taking measures that how to avoid the risk, or at least it assists to manage with its impact. There is robust relationship between risk and return in the stock markets. Commonly it is considered as greater the risk, greater the return.

It is vital to reflect the effects of seasonality when examining stocks of any market because it can have a big impact on an investor's returns and portfolio. This specific study deals with the measurement of risk and returns of the stock indices of islamic countries, although there are number of studies which measure overall risk of the market by using VaR and also debate that which method is appropriate to calculate VaR. But the point that is missing in the previous studies is that is this VaR same for each day of the week, or for each month of the year? The main thing that current study is contributing towards, finding out the element of seasonality in VaR and VaR exceptions and also to know in which specific day of the week or month of the year, VaR is increased or decreased.

Moreover, it is also significant to know that if this seasonal behavior exists in the market then it is essential from the investors perspective that they should adjust their risk profile accordingly and to maximize their returns.

1.7 Plan of the Study

This research is planned and divided into five chapters.

Chapter 1: It comprises of the introduction, theoretical background, gap analysis, statement of problem, plan and significance of the study.

Chapter 2: This chapter covers review of several studies of existing literature and provides way to the relevance and outcome of this study.

Chapter 3: It is based on methodology explaining about methods to estimate VaR, uses back testing techniques to check accuracy of VaR models and finally checks the empirical relationship between VaR exceptions and seasonality.

Chapter 4: This chapter comprises of results and interpretations.

Chapter 5: Summarizes all findings, discuss limitations of this study and have few recommendations for further future studies.

Chapter 2

Literature Review

This Part of the study contains literature review on seasonality that exists in the market and VaR approaches to find the previous work done on the returns and volatility.

2.1 Anomalies

Seasonality can be identified on daily, weekly and on monthly basis and has become an attractive research topic because it gained a significant attention in the literature. Malkiel and Fama (1970) developed the efficient-market hypothesis (EMH) which highlights on rational expectations of the investors and shows that whenever new information arises, the expectations of investors will be influenced. Some investors overreact while others underreact by following a normal distribution pattern. Basing on this information, market will move toward efficiency. Problem found with the EMH is that there is no reaction of new information in the prices of securities. However, a specific pattern is followed by the person, which gives them the opportunity to make an abnormal profits leading to inefficiency of the market. Behavioral economists explain that imperfection in the market is because of these patterns. These errors are predictable and they influence the reasoning and information processing. These are called anomalies and are very dangerous element for the equity market, as owing to the predictability of the trends.

Number of studies have been conducted on these seasonal behaviors that exist in market worldwide and disturb the common pattern of the market. Gupta and Rajib (2018) observed seasonality in Indian commodity market and reveal that if there is the impact of seasonality in the market, it ultimately causes VaR exceptions. Tse (2018) studies currency futures for the period 1973 to 2015 and find seasonality of returns in the foreign exchange market. The study conducted by Seif et al. (2017) tests five seasonal anomalies i.e. day-of-the-week, holiday, week 44, other January and the month of the year effect and report the efficiency of advanced emerging markets and except the other January effect this research is consistent with all of these seasonal anomalies, so it is in favor of the argument that emerging markets are not perfectly efficient. The countries where the tax year ending in December, In January for those all the G10 currency futures represent negative returns. Whereas, returns offered in April are positive. This study uses a seasonality strategy to exploit these anomalies, and select the portfolios on the basis of their historical returns based on months of the same calendar. The research of Ali et al. (2017) report that our study has tried to separate the impacts of Gregorian calendar anomalies from Muslim holy days to prove that their research outcomes are particularly a result of Muslim holy days only. To check this underlying effect, pooled fixed/random effect panel regression is being used in their study. Their findings are declaring that the only holy day, which has significant positive effect on stock returns of Asian markets is Eid.ul.Fiter holiday whereas, all the other holy days are leaving no effect and the only Gregorian calendar anomaly is Friday, which exists in Asian markets so their results support the fact that both Gregorian calendar and Islamic anomalies prevail in Asian markets. Another recent study reported by Andrieş et al. (2017) provides that the aim of that study is to investigate three seasonal anomalies, both in return and volatility i.e. the month of the year effect, week of the month effect and day of the week effect for eleven countries from Central and Eastern Europe area from 2000 to 2015 by using a conditional variance approach. The results of the study provide that the efficient market hypothesis does not hold for all the markets that have been surveyed. Additionally, the seasonal effects are also present in the volatility equations. Therefore, these markets are not efficient, giving rise to arbitrage opportunities. So, the investors may take advantage of these anomalies by scheming profitable trading strategies which account for transaction costs and make abnormal returns. Elhaj and Chowdhury (2016) examine the day of the week, turn of the month and turn of the year and provided that how the cross-sectional volatility of the Jordanian stock market may change due to these effects. Findings represent evidence of reduction of volatility on Thursday compared to Sunday, and report significantly lower volatility on the first three days of the month compared to the third day before the last day of the month. Thus, for the better understanding of the this finding is crucial for investors. Fiore and Saha (2015) indicate about risk and return trade off in their study and provide evidence that this trade off holds in all the months but not in summer and it outperforms both in the terms of risk adjusted returns and obsolute returns. Buy and hold strategy as well as Sell in the May strategy for switching to treasury bills in summer.

Another study reported by Banjumin et al., (2011) examines 34 international equity markets for the period ranging from January 1988 to December 2010 to check the monthly seasonality and it is reported that there are significantly positive and larger anomalies across the majority of these markets for April and December and it does not discover a significant January effect except for 3 markets. Besides, there is an indication of the presence of significant negative anomalies for June, August, and September in most of the global markets that are included in the sample. According to Balaban et al. (2001) the nature of the day of the week effect on returns and their conditional volatility is different among various countries and across days. Thirteen countries exhibit seasonality. Seven countries exhibit this seasonal behavior in either mean returns, or volatility exhibited by eight countries or both by two countries. Each day is reported at least once that is exhibiting significant positive and negative results in both volatility and mean having and exception that there is no positive impact in volatility and no negative impact on mean returns on Wednesdays.

Dzhabarov and Ziemba (2010) use futures data for the period 1993-2009 and 2004-2009 for small-cap stocks that are measured by the Russel 2000 Index and for large-cap stocks too that are measured by the S&P 500 Index and examine traditional seasonal anomalies, such as monthly effect, the January effect, turn-of-the-month effect, holiday effect and phenomenon of sell in May and go away and provides that it is still exist in the turbulent markets of the early part of the 21st century.It indicates still these anomalies matter. In small-cap stocks the effects are seem to be stronger so their findings are useful for investors who wish to invest in portfolios and for speculators who want to trade the effects. Hussain et al. (2011) conduct a study on Karachi stock exchange (KSE) and show that the market is inefficient and exhibit abnormal behavior towards returns. Chen and Singal (2003) observe the contribution of short sales to weekend effect. A study conducted by Al-Saad* and Moosa (2005) investigates the nature of seasonality in the monthly stock returns of the Kuwait Stock Exchange. A structural time series model including stochastic dummies reveals that seasonality exists but it is deterministic as shown by the dependability of the monthly seasonal factors over the sample period.

Two conventional models that use these deterministic seasonal dummies confirm these results. Furthermore, seasonality effect is found in the month of July, as contrasting to the familiar January effect. This finding is endorsed to the summer holidays effect. A very interesting study based on seasonality is conducted by Hirshleifer and Shumway (2003), they find that sunny weather is associated with upbeat mood so they examine the relationship between daily market index returns and morning sunshine in the city of a country's leading stock exchange and for 26 countries for the time frame 1982 to 1997. It further observes that stock returns and sunshine have significant strong correlation with each other. After controlling for sunshine, the study notice that snow and rain are not related to the returns. Considerable use of strategies that are based on weather is ideal because of lower transaction costs. Though these strategies are having frequent trades, fairly modest costs reduce desirable gains. These results are harder to integrate with the price setting that is fully rational. Another study conducted by Corhay et al. (1987) reports the presence of seasonality effect in the Fama and MacBeth estimate of the CAPM based risk premium in four stock exchanges: Paris, Brussels, London and NYSE. It also provides that, in Belgium and France, risk premium is negative for the whole year while positive in January only. There is no effect of January exists in the U.K. risk premium and observe a positive seasonal effects for April and for the rest of the year a negative average risk premium is declared. In the U.S the pattern of risk-premium seasonality and the pattern of stock-return seasonality coincides with each other. Both are positively significant in January. This study also reports that the risk premium of January in the U.S. is considerably greater as compare to those which are being observed in the markets of Europe. Interestingly, it specifies that in European equity markets, patterns of risk premium seasonality do not fully related to the patterns observed of stock returns seasonality in these specific markets. like while considering U.K, in January and April the average stock returns are significant and positive, however in the month of April the market risk premium is significantly positive. Wachtel (1942) is the first to observe seasonality in the Dow Jones Industrial average for the period 1927-1942. From 15 years of his study he observes frequent bullish tendencies from December to January and find this effect for 11 years out of the sample. Wachtel declare certain factors as the possible causes for the higher return in January, one of which is tax year end loss selling. A study by Agrawal and Tandon (1994)observe or negative or lower mean returns on Mondays and Tuesdays respectively while positive and higher mean returns from Wednesday to Friday in almost all countries.

Bayar and Kan (2012) report that there is a higher pattern of seasonality around the middle of week i.e. on Wednesday and Tuesday and it is provided that there is a lower trend exhibit towards the end of the week i.e. on Thursday and then on Friday. The highest volatility is observed on Mondays and lowest on Tuesdays. The seasonal pattern of returns is also examined by another study that declares the excess returns in January are connected to both long term and short term performance of past, and also to the market returns of previous year (De Bondt and Thaler, 1987). Gultekin and Gultekin (1983) provide the evidence of stock market seasonality in major industrialized countries of the world.It is reported that there are strong seasonality's in the return distributions of stock market in most of the capital markets across the globe. When this pattern of seasonality exists, it appears to be caused by the excessively large January returns in most of the countries and there is evidence of April returns in the U.K except Australia, where these months are too connected with the turn of the tax year.

Due to inability to trade on weekend short sellers close their position on Friday and reconstruct new short positions on Monday, which causes stock prices to fall on Monday and rise on Friday. All these studies shows that seasonality effect exists in the stock market, commodity market and currency market which effects the behavior of the investors regarding risk and returns.

2.2 Value at Risk (VaR)

VaR is being used as a leading measurement tool of portfolio risk especially in financial markets. Extant literature on use of VaR for the measurement of market risk exists. VaR is no longer an optional risk management tool, but it became mandatory. In empirical distribution, VaR is an estimation of the tails i.e. left tail or right tail. It is anticipated by some of the previous assessments of VaR that asset returns are not normally distributed which results in an overestimation or underestimation of the true VaR measures as it is well presented that asset returns reveal excess kurtosis and skewness.

For oil prices by assuming standard normal asset returns, Cabedo and Moya (2003) compare three measures of VaR assuming standard normal returns for oil prices. Method used in their study are variance and covariance method,historical simulation standard approach and historical simulation with ARMA forecast. The findings promote that the historical simulation with ARMA model as the most effective alternative for the risk quantification. Gupta (2018) in his recent study in Indiacompare three models named as APARCH, ARMA-GARCHRisk Metric's EWMA with normal and Student's t-distribution. These models have been applied to spot prices of seven commodities namely Gold, Aluminum, Copper, Guar seed, Cardamom and Soyabean. Daily VaR has been figured out for these seven commodities, for different time horizons,moreover VaR exceptions have been estimated at 99% confidence interval. Then the comparison is drawn between these three models on the basis of number of VaR exceptions and loss function. It is shown that the commodity prices tend to reveal higher volatility during certain time of the year due to presence of seasonality in production and consumption.

Goldman and Shen (2018) explore properties of asymmetric generalized autoregressive conditional heteroscedasticity (GARCH) models in the TGARCH family and suggest a more general Spline-GTARCH model that is used to capture low-frequency macroeconomic volatility, high-frequency return volatility as well as it measures an asymmetric response to past negative news in both GARCH and autoregressive conditional heteroscedasticity (ARCH) terms. Based on maximum likelihood estimation of S&P/TSX returns, S&P 500 returns and Monte Carlo numerical sample, the study project that more general asymmetric volatility model has better precision, higher persistence of negative news, higher degree of risk aversion and significant effects of macroeconomic variables on the low frequency volatility component. Nieto and Ruiz (2016) claimed that when considering at the enough alternative processes for measuring VaR forecasts, the results of a certain test may fluctuate depending on the number of out of the sample observations and the specific period that is being examined. There is no indication of a single method that clearly outperforms the others with the exception of the EGARCH model with Skewed-Student errors, all of them are rejected by at least one test in at least one out of the sample period. It is provided that relative to simple forecasts based on modelling, the evolution of the conditional variance using asymmetric leptokurtic errors and GARCH type models are among the most competitive ones. Saddique and Khan (2015) reports that the prior studies didn't favor the VaR estimation by using only one method because it may over or under estimate risk. Usually it is suggested to use more than one method for risk forecasting. Moreover, when the organizations are risk averse,they may rely on historical simulation method as it provides higher value for VaR. The Monte-Carlo simulation and historical simulation perform better in risk averse organizations, as returns are normally distributed but the risk takers favored to use methods that provide smaller VaR estimation. According to Abad and Benito (2013), Filtered Historical Simulation and Extreme Value Theory are the best methods for examining VaR. The parametric method under fat tail and skewed distributions also assure promising results particularly when there is an assumption that the standardized returns are identically distributed, are independent and is set aside and when time variations are considered in conditional high-order moments. Finally, it is reported that some asymmetric extensions of the CaViaR method also offer promising results. Saltoglu et al., (2006) report the predictive performance of several types of value at risk (VaR) models in various dimensions i.e. filterd versus unfiltered VaR models, conventional versus extreme value distributions, parametric versus nonparametric distributions, and quantile regression versus inverting the conditional distribution function. By using the reality check test of White (2000), it relates the predictive power of alternative VaR models in terms of the empirical coverage probability and the predictive quantile loss for the stock markets of five Asian economies that exhibit financial crises from 1997-1998. The findings that are based on these two criteria are largely compatible and show some empirical regularities of risk forecasts. The risk metrics model performs reasonably well in soothing or calm periods, whereas some extreme value theory (EVT) based models exhibit better results in the period of crises.

The study by Huang et al. (2004) examines that for asset returns which reveal volatility clustering and fatter tails like the SGX-DT futures TAIFEX, the VaR values exhibited by the normal APARCH model at lower confidence levels are preferred. Though, at high level of confidence, the VaR forecasts measured by the Student APARCH model are more precise than those that are acquired by using either the Normal APARCH or Risk Metrics models. A multivariate switching regime model is introduced by Billio and Pelizzon (2000) for the estimation of VaR for 10 Italian stock markets and for several other portfolios that have been generated by them. The study uses two back testing measures for contrasting their models and conclude that switching regimes are more accurate than the other known methods like under normal and student-t distribution, GARCH (1,1) and risk metrics. The findings of Brooks and Persand regarding model choice for the performance of vale at risk are, the models contain considerable differences for the number of days on which the observed losses exceed the expected loss, the method which performed significantly better in many situations is based on quantile estimation rather than simple or complex parametric approaches. Secondly, the study states that the use of long run data as compare to the single trading year that is required by the BASLE Committee has an uncertain effect on the evaluation performance of the models and the effect depends on the model and the asset series under consideration. Thirdly, it finds that when critical values are used under parametric approach i.e. normal distribution but the actual data seems to be fat tailed then it may leads to a considerably imprecise VAR estimate. Giot and Laurent (2004) also uses skewed student distribution for the estimation of daily VaR for stock index returns and point out that this method accomplished better outcomes than the pure symmetric one, as it reproduces the characteristics of the empirical distribution more precisely. Value at risk approach is used by risk managers to measure, forecast about future risk and control the level of risk exposure. Measures of VaR can be applied to portfolios, particular positions or to measure risk exposure for the firms, Industries, stock markets etc. The use and general acceptance of VaR models laid an extensive literature on a large scale with statistical descriptions of VaR and analyses of different modeling issues and various VaR approaches (Jorion, 2000).

Chapter 3

Data Description and Methodology

This chapter discusses sampling criteria and different risk assessment methods i.e. Backtesting models like Kupeic POF and Christoffersens independence tests which are used to carry out this work. These research methods are employed to analyze the factor of daily and monthly seasonality on VaR and VaR exceptions.

3.1 Data Description and Sample

Stock indices of ten (10) Islamic countries are taken as sample to carry out this study. Daily data of these indices is obtained from different websites of the relevant markets.

Table 3.1 includes different information regarding sample i.e. countries, their indices, time frame and observations taken

In order to elaborate complete research methodology, different models for VaR estimation, backtesting of VaR models to find out the accuracy of risk estimation method and equations being used to identify daily and monthly seasonal behavior for the indices of sample and relationship between VaR, VaR exceptions and seasonality are discussed in later subsequent sections of this chapter.

Table 3.1: Sample Information.

S. No.	Countries	Indices	Time Frame	Observations
1.	Pakistan	KSE	2000-2018	4467
2.	Turkey	BIST	2000-2018	4541
3.	Egypt	EGX	2000-2018	4423
4.	Oman	FTSE	2000-2018	4352
5.	Saudi Arabia	TASI	2000-2018	4804
6.	Indonesia	JKSE	2001-2018	4409
7.	UAE	ADX	2001-2018	4403
8.	Iran	TSE	2009-2018	2413
9.	Bangladesh	DSE	2013-2018	1227
10.	Malaysia	KLCI	2010-2018	2030

3.2 Econometric Models

3.2.1 VaR Estimation

For VaR estimation, different approaches are used. These approaches include parametric assumption i.e. normal distribution, non-parametric assumption i.e. historical simulation and time varying volatility models like exponentially weighted moving average method (EWMA) and generalized autoregressive along with conditional heteroscedasticity model (GARCH) by using R program having window size of 500 observations. Mix of aforementioned different approaches are utilized to forecast the possibility of loss in stock returns of Islamic countries against each day. The formula that is being used by this study to calculate the returns of the stock indices is as follows:

$$L_N\left(\frac{p_t}{p_{t-1}}\right)$$

3.2.2 Non-Parametric Approach

While using non parametric assumption, sample statistics related to past asset returns are used to calculate VaR. In the context of market risk, it involves using the historical returns of the stock market indices of related Islamic countries.

3.2.2.1 Historical Simulation Method

VaR calculation through historical simulation method requires historical data to measure the impact of market pattern on a given portfolio. While using this technique, empirical distribution of past returns is utilized to calculate VaR. As current portfolio is subject to historically recorded market movements, therefore it is used to generate a distribution of returns on the portfolio. In the return, this method is used to find out the maximum possible loss having a given likelihood. Real data is used by historical simulation method so unexpected events and correlations can be captured by it which may not be predicted by a theoretical model.

$$\mathrm{VaR} = -\sigma\phi(r) \tag{3.1}$$

This method assumes that the history will repeat itself i.e. past returns are the good and complete indicators of expected future returns.This technique uses a sample from past data set, records the VaR from the specific sample and calculates returns of indices. This procedure is repeated over and over to record multiple sample VaR.

3.2.3 Parametric Approach

Parametric approaches follow the underlying probability distribution assumption to estimate the parameters of VaR calculation.

3.2.3.1 Normal Distribution

Normal distribution can be defined as a continuous probability distribution against a random variable, i.e. χ. If normal distribution is plotted on a graph this would be a normal curve having features listed below:

$$f\left(\frac{\chi}{\mu\sigma^2}\right) = \frac{1}{\sqrt{2\pi\alpha^2}}\rho - \frac{(\chi-\mu^2)}{2\sigma^2}\mu \tag{3.2}$$

μ = Mean / Expectation of distribution including Median and Mode

σ = Standard Deviation

α^2 = Variance

3.2.4 Time Varying Volatility Models

Time-varying volatility model is used to analyze the fluctuations in volatility against different time periods. This depicts that investors have the option to consider volatility of an underlying security during different time periods. Like during the summers, the volatility of certain assets may be lower due to holidays. Therefore, it is pertinent to mention that time-varied volatility measures may have influence on expectations of investments. In order to overcome statistical differences in price fluctuations across the period, such financial model play a vital role.

3.2.4.1 Exponentially Weighted Moving Average Method (EWMA)

Volatility is an instant standard deviation of a stock which is a common risk metric. Alternatively, this can be calculated by taking the variance square root. Variance can possibly be measured historically or implicitly i.e. implied volatility. Simple variance could be more convenient method to measure historical variance. Limitation against taking simple variance method is that all returns get same weightage. Therefore, classic trade-off happens in which researcher require more data. But as more data is acquired, calculations are being diluted by distant or less relevant data. Therefore, exponentially weighted moving average (EWMA) approach remains better option than simple variance through assigning weights to the periodic returns. This option facilitates to use sample size of large data and to assign more weight to the most recent returns.

$$\mathrm{EWMA}_t = \lambda Y_t (1-\lambda)\mathrm{EWMA}_{t-1} \quad \text{for} \quad t = 1, 2, \cdots n \tag{3.3}$$

EWMA = Mean of historical data

n = Number of observationS

Y_t = Observation at time t

$0 < \lambda \leq 1$ is a constant which determines the depth of memory of the EWMA.

The Value of λ is taken as 0.94 as required by Risk Matrices.

3.2.4.2 GARCH

Engle (1982) introduce generalized autoregressive conditional heteroscedasticity (GARCH) process. This approach is developed with a view to estimate financial markets volatility. Being autoregressive, GARCH processes mainly depend on past squared observations along with past variances to predict current variance. GARCH processes remain very effective in asset return modeling and inflation. Therefore, these are widely used in financial markets. These processes minimize forecasting errors in the asset returns through considering prior forecasting errors and eventually, enhance accuracy of ongoing predictions.

$$\gamma_t = \lambda_0 + \lambda_1 \gamma_t - 1 + \mu_t \tag{3.4}$$

$$\rho_t^2 = \pi_0 + \pi_1 \mu_{t-1}^2 + \pi_2 \rho_{t-1}^2 + \pi_3 M \tag{3.5}$$

3.3 Back Testing

VaR is an important risk management tool which itemize and monitors the risk which an investment portfolio carries. Calculation of VaR becomes very easy when correct related VaR methodology is being chosen. This phenomenon becomes more vital in case of financial institutions, where accuracy of VaR measures is more vital. Any laps in VaR measures may lead the financial institution to a substantial loss. Further, this particular loss shall not only hit that particular institution but their individual investors, depositors and corporate clients shall also be victimized. In order to overcome this issue, backtesting technique is being utilized by risk managers in order to validate the accuracy of VaR calculations.

Backtesting compares the loss which is forecasted by the VaR model with actual losses occurred by the end of specific time period. Through this comparison, specific period is being detected where the VaR was being underestimated or where the portfolio losses were greater than the expected VaR. VaR results should be revisited in case backtesting values are incorrect. In this study,backtesting is applied on all models being examined and more suitable model is chosen for the correct estimation of VaR in the context of Islamic countries. Kupiec (1995) and Christoffersons (1998) tests are used, in order to observe the accuracy of VaR calculations.

3.3.1 Violation Ratios

If on a particular day, financial loss exceeds the VaR forecast, VaR limit considered to be violated.

$$\mathrm{VR} = \frac{\text{Observed number of violations}}{\text{Expected number of violations}}$$

Through comparison of actual VaR with expected violations, it is ascertained that either the model is fair, overestimated or underestimated. The ideal value for violations ratio would be equal to 1 which indicates that the number of expected violations are equal to number of observed violations. However, in real world financial market's data, it is not always possible to get exactly 1. Danielson (2011) recommended the acceptance range of violation ratio between 0.8 to 1.2 so for this range, violation ratio remains the basic risk estimation tool.

3.3.2 VaR Volatility

Statistical measure of dispersion of returns is volatility for a given security or market index. Most of the time it is being observed that higher the volatility indicates riskier security. On the other hand, when the volatility is lower it indicates that value of the security does not rise or fall dramatically, therefore this may be considered more steady. This can be reflected as range and speed of price movements. Analysts usually use these approaches to observe volatility in a market, an index and specific securities. By examining volatility, it is possible for investor or risk manager to estimate the risk. This term is highlighted during economic instability periods. Situations where uncertainty among investors increase may drive stock market volatility. On the other hand, security is prone to higher volatility level when the prices of shares fluctuate rapidly and its value change dramatically in a short span of time. Standard deviation of the returns is used to measure volatility. This could be more suitable option for the risk estimation when the data is considered as normally distributed.

3.3.3 Kupeic POF Test

Proportion of Failures (POF) test is introduced by Kupeic (1995) which is actually variation on the binomial test. Binomial distribution approach is required to be used with the POF test. Moreover, likelihood ratio is also required to be used to test either the chances of exceptions are synchronized with the probability p implied by the VaR confidence level. If the results show the difference between probability of exceptions p, the VaR model would be rejected. This test is χ^2 distributed and use likelihood ratios for the measurement. Being a statistical test, Likelihood-ratio computes the ratio among the maximum probabilities of a result under two alternative hypotheses. Under null hypothesis, numerator defines the maximum probability of the perceived result. While denominator illustrates the maximum probability of happening the observed result under the other hypothesis. In fact,this ratio indicates that the LR-statistics would be larger if this ratio is smaller. If the value is large enough in comparison to the critical value of χ^2 distribution, null hypothesis is rejected. The POF test statistic is given as:

$$\mathrm{LR}_{\mathrm{POF}} = -2\log\left(\frac{(1-p)^{N-x}\,p^{x}}{\left(1-\frac{x}{N}\right)^{N-x}\left(\frac{x}{N}\right)^{x}}\right) \tag{3.6}$$

N = Number of observations

x = Number of failures

p = 1-VaR level

3.3.4 Christoffersen's Independence Test

In order to measure the probability of observing an exception on a specific day depends to ascertain that whether an exception occurs. Christoffersen (1998) propose a test that is called Christoffersen test. Unlike the unconditional probability of observing an exception, this framework illustrates that either the reason for not passing the test is caused by inaccurate coverage, clustered exceptions or even by the both. It measures the dependency among consecutive days only. This test also uses the likelihood ratios along with independence of exceptions or violation statistics. The number of exceptions today are independent of the impact of violations of last day. Null hypothesis is accepted in this model if this condition exists. Otherwise null hypothesis will lie in the rejection area. The formula to be used for evaluating the correctness of sample results would be as under,

$$P\gamma_{t-1}\left(R_t < -\mathrm{VaR}_t\left(\rho\right)\right) = \rho \tag{3.7}$$

P = Predetermined coverage rate

t = Post returns

$\mathrm{VaR}_t(\rho)$ = Volatility forecasts

3.4 Seasonality

When the stock market performs better or worse during certain times of the year, it is said that seasonality persists in stock market. Therefore, seasonal effects of the stock market refer as the tendency for certain periods during the year to gain or lose value historically."This plays very important role in technical analysis where the investments repeat their pricing patterns or cycles. While trading or investing, investors may gain a slight advantage if they have understanding about how these trends work. Day of the week and month of the year effect are considered to be common seasonality anomalies. This analysis is based on the hypothesis that the yields produced by each security are not independent of these two seasonal effects. This study examines both effects individually with the help of the following equations.

3.4.1 Daily Seasonality on VaR

$$\text{VaR}_t = \beta_1\text{Mon}_t + \beta_2\text{Tue}_t + \beta_3\text{Wed}_t + \beta_4\text{Thu}_t + \beta_5\text{Fri}_t + \beta_6\text{Sat}_t + \beta_7\text{Sun}_t + \epsilon_t \quad (3.8)$$

3.4.2 Daily Seasonality on VaR Exceptions

$$\text{VaR(Exception)}_t = \beta_1\text{Mon}_t+\beta_2\text{Tue}_t+\beta_3\text{Wed}_t+\beta_4\text{Thu}_t+\beta_5\text{Fri}_t+\beta_6\text{Sat}_t+\beta_7\text{Sun}_t+\epsilon_t \quad (3.9)$$

Here β shows the average return for each day.

Dummy variables are taken for seven working days of the week, i.e. Monday, Tuesday, Wednesday, Thursday, Friday, Saturday, and Sunday.

ϵ_t is the error term.

Same sequence of equation will be followed to find out month of the year effect.

3.4.3 Monthly Seasonality on VaR

$$\text{VaR}_t = \beta_1 M_{1t} + \beta_2 M_{2t} + \beta_3 M_{3t} + \beta_4 M_{4t} + \cdots \beta_1 2 M_{12t} + \epsilon_t \quad (3.10)$$

3.4.4 Monthly Seasonality on VaR Exceptions

$$\text{VaR(Exception)}_t = \beta_1 M_{1t} + \beta_2 M_{2t} + \beta_3 M_{3t} + \beta_4 M_{4t} + \cdots \beta_1 2 M_{12t} + \epsilon_t \quad (3.11)$$

Here M represents dummy variable for each month of the year.

This equation is useful in finding out any relationship between VaR, VaR exceptions and daily as well as monthly seasonality which may have impact on stock indices of the countries.

Chapter 4

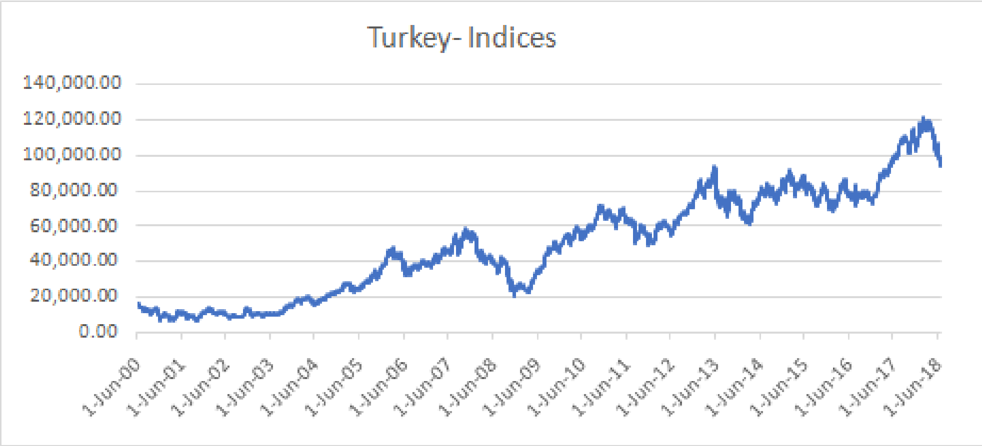
Results and Discussion

This chapter is designed to summarize the collected data and elaborate its statistical treatment, and to discuss the mechanics of analysis. It Includes the results and interpretation of value at risk at 95% and 99% confidence interval. After the measurement of VaR, back testing has been conducted to conclude that which method is better for the risk forecasting for which violation ratios, volatility of returns and likelihood ratios of Kupeic and Christoffersen's test are used at 95 and 99% confidence interval for normal distribution, historical simulation, EWMA and GARCH methods and then on the basis of each back testing technique, most suitable method is recommended for risk estimation.

Then Seasonality which is the main concern of this chapter has been tested. The focus is to deal with month of the year effect and day of the week effect on VaR and monthly and daily seasonality on the VaR exceptions.

4.1 Graphical Representation of Stock Indices and Returns of the Countries

This study used graphical representation to know the behavior of the indices of markets and their returns and this representation clearly indicates the pattern exists in the markets of all the ten countries which is shown below.


Turkey- Indices
140,000.00
120,000.00
100,000.00
80,000.00
60,000.00
40,000.00
20,000.00
0.00
1-Jun-00
1-Jun-01
1-Jun-02
1-Jun-03
1-Jun-04
1-Jun-05
1-Jun-06
1-Jun-07
1-Jun-08
1-Jun-09
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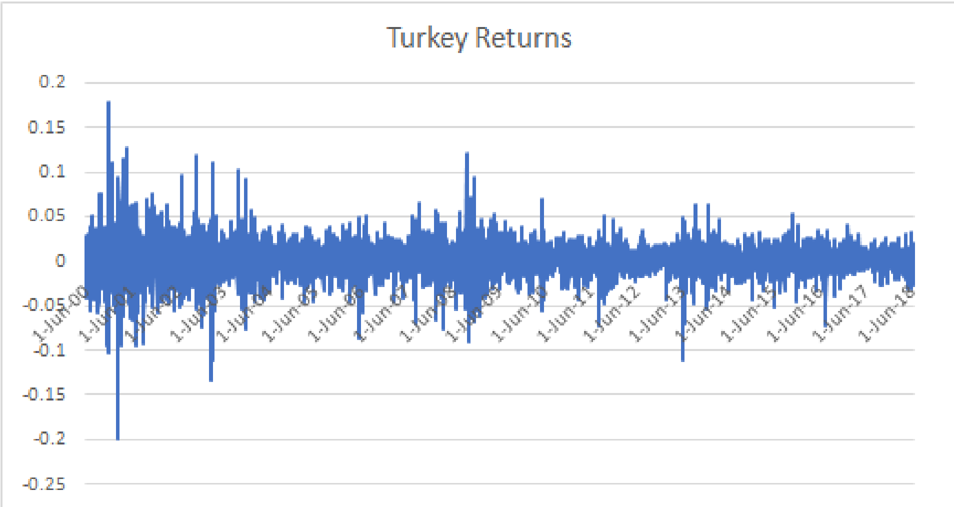
1-Jun-17
1-Jun-18


Turkey Returns
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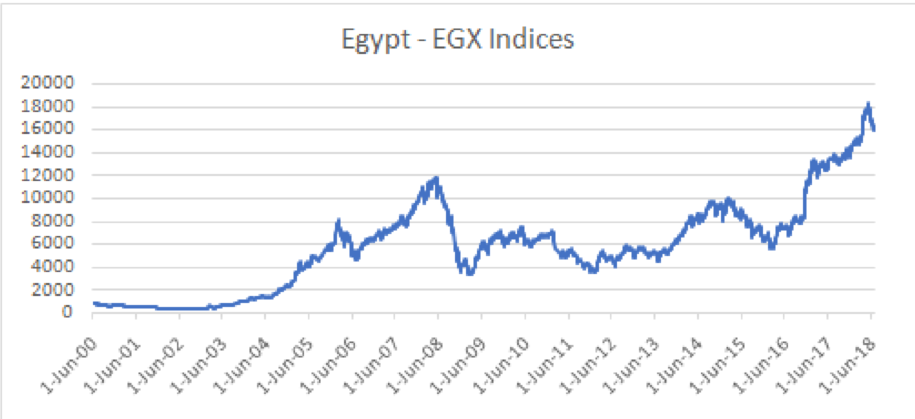
0.15
0.1
0.05
0
-0.05
-0.1
-0.15
-0.2
-0.25


Egypt - EGX Indices
20000
18000
16000
14000
12000
10000
8000
6000
4000
2000
0
1-Jun-00
1-Jun-01
1-Jun-02
1-Jun-03
1-Jun-04
1-Jun-05
1-Jun-06
1-Jun-07
1-Jun-08
1-Jun-09
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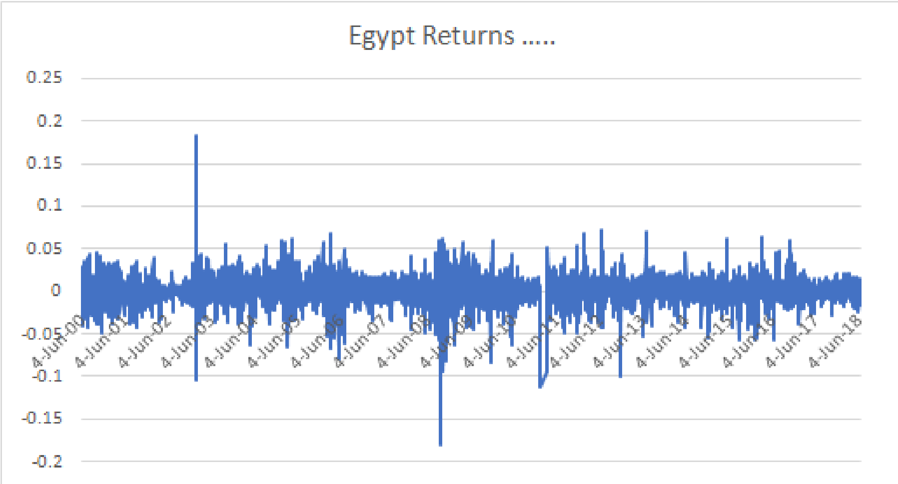
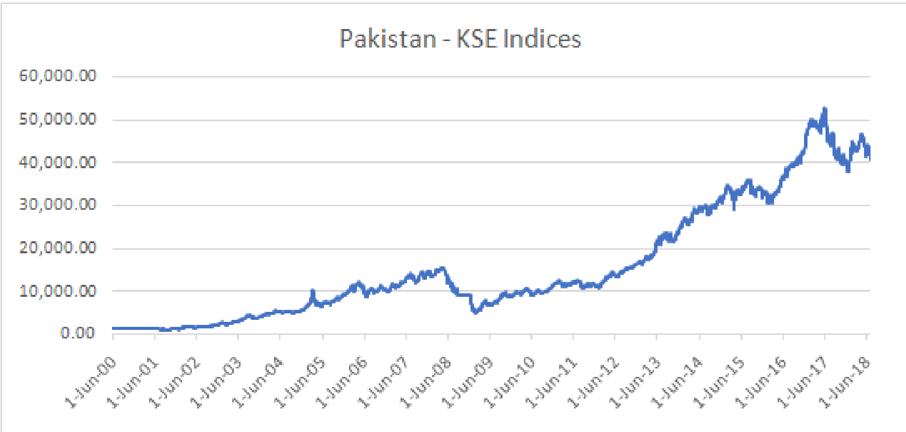
1-Jun-17
1-Jun-18


Egypt Returns .....
0.25
0.2
0.15
0.1
0.05
0
-0.05
-0.1
-0.15
-0.2


Pakistan - KSE Indices
60,000.00
50,000.00
40,000.00
30,000.00
20,000.00
10,000.00
0.00
1-Jun-00
1-Jun-01
1-Jun-02
1-Jun-03
1-Jun-04
1-Jun-05
1-Jun-06
1-Jun-07
1-Jun-08
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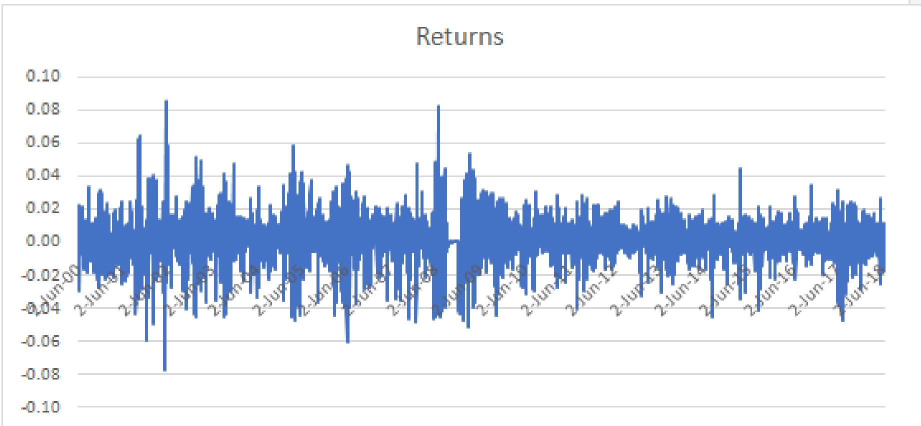
1-Jun-17
1-Jun-18


Returns
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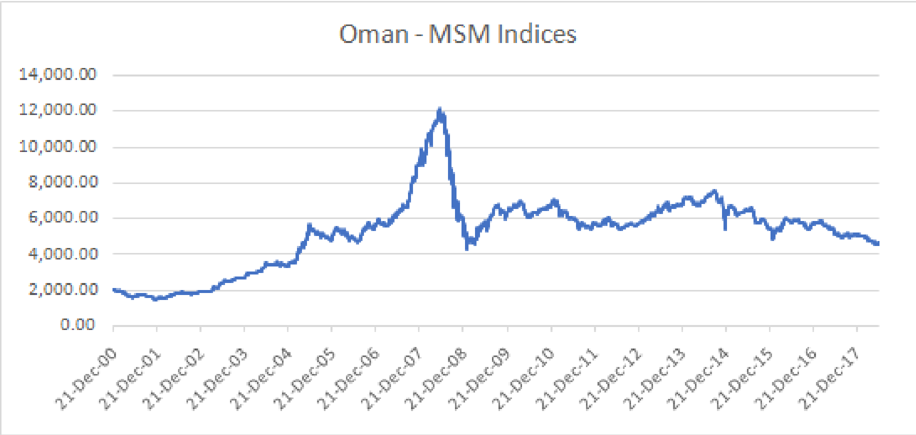
0.08
0.06
0.04
0.02
0.00
-0.02
-0.04
-0.06
-0.08
-0.10


Oman - MSM Indices
14,000.00
12,000.00
10,000.00
8,000.00
6,000.00
4,000.00
2,000.00
0.00
21-Dec-00
21-Dec-01
21-Dec-02
21-Dec-03
21-Dec-04
21-Dec-05
21-Dec-06
21-Dec-07
21-Dec-08
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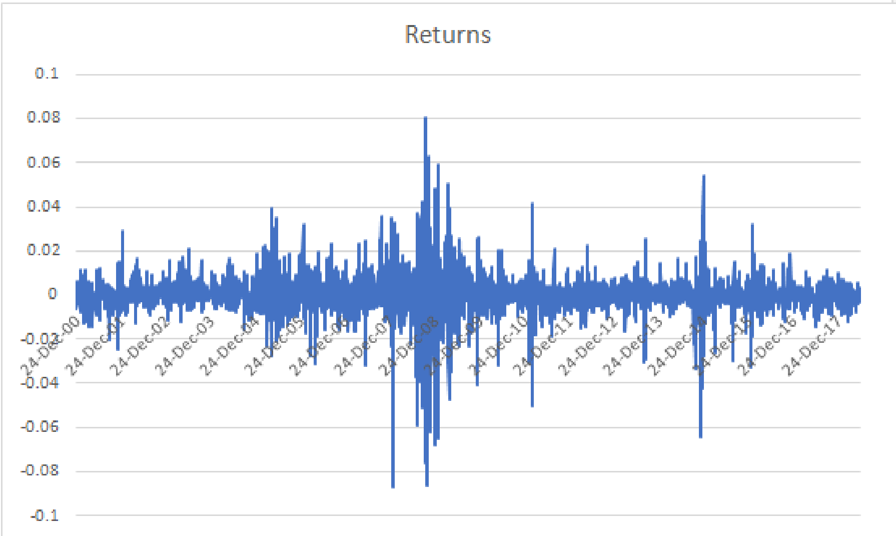
21-Dec-17


Returns
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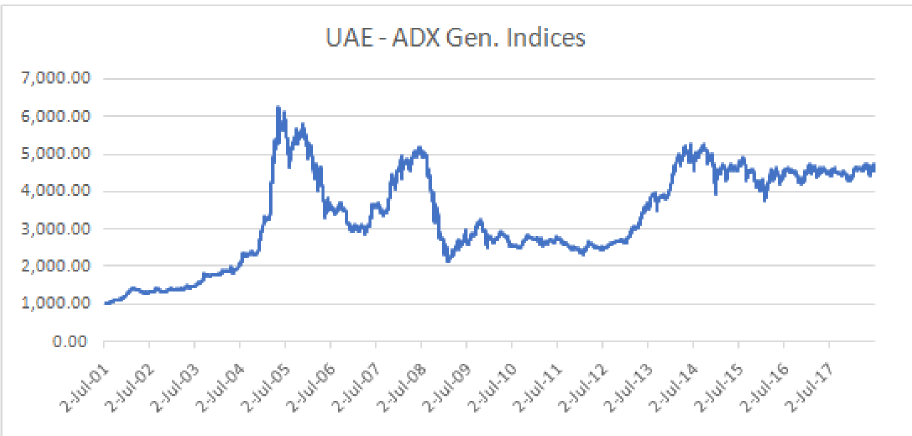
0.06
0.04
0.02
0
-0.02
-0.04
-0.06
-0.08
-0.1


UAE - ADX Gen. Indices
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6,000.00
5,000.00
4,000.00
3,000.00
2,000.00
1,000.00
0.00
2-Jul-01
2-Jul-02
2-Jul-03
2-Jul-04
2-Jul-05
2-Jul-06
2-Jul-07
2-Jul-08
2-Jul-09
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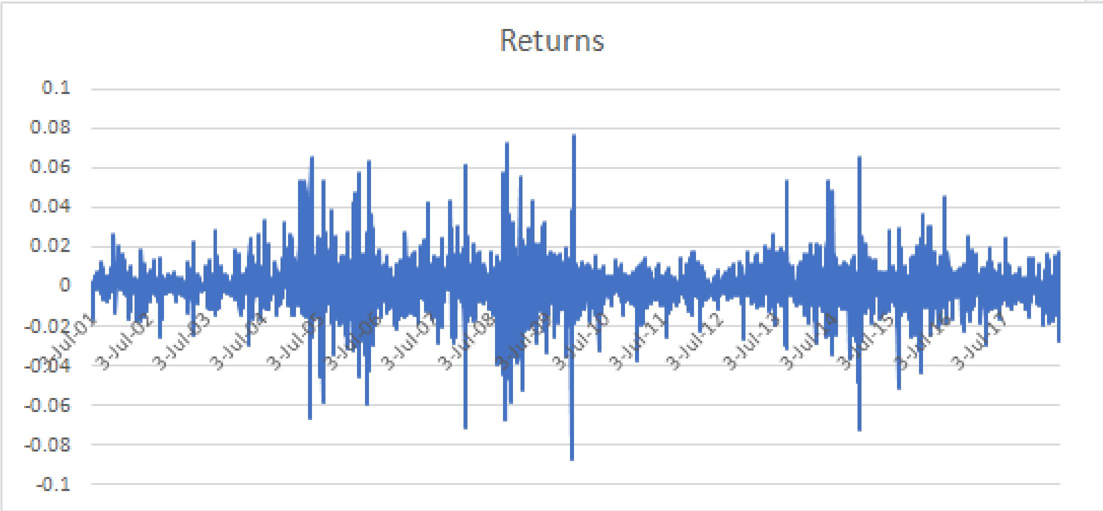
2-Jul-17


Returns
0.1
0.08
0.06
0.04
0.02
0
-0.02
-0.04
-0.06
-0.08
-0.1


Indonesia - JKSE Indices
8000
7000
6000
5000
4000
3000
2000
1000
0
2-Jun-00
2-Jun-01
2-Jun-02
2-Jun-03
2-Jun-04
2-Jun-05
2-Jun-06
2-Jun-07
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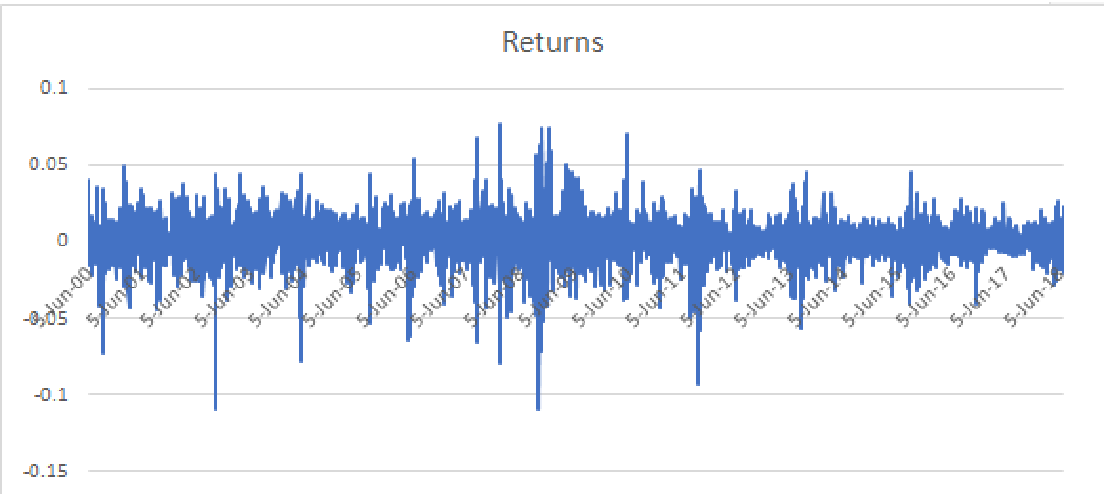
2-Jun-17
2-Jun-18


Returns
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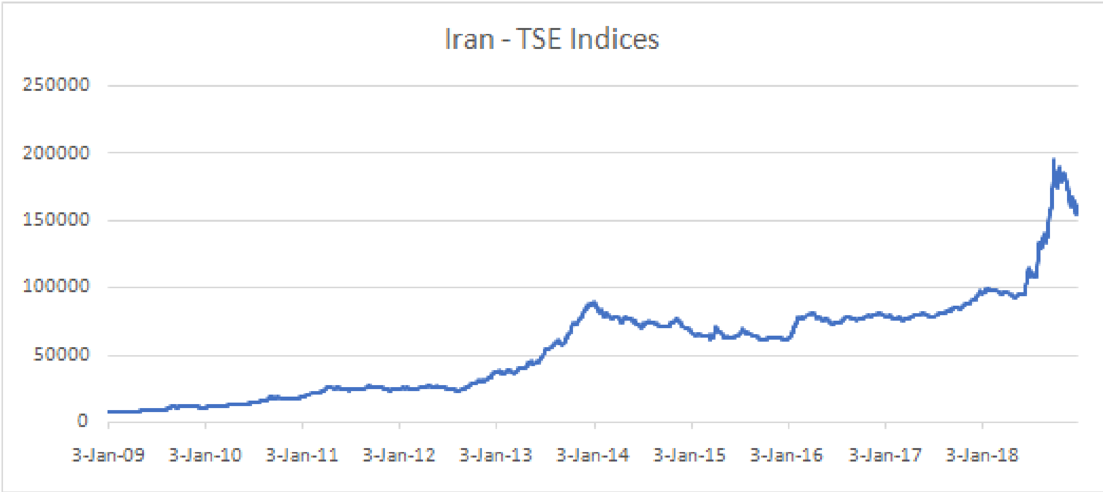
0.05
0
-0.05
-0.1
-0.15


Iran - TSE Indices
250000
200000
150000
100000
50000
0
3-Jan-09
3-Jan-10
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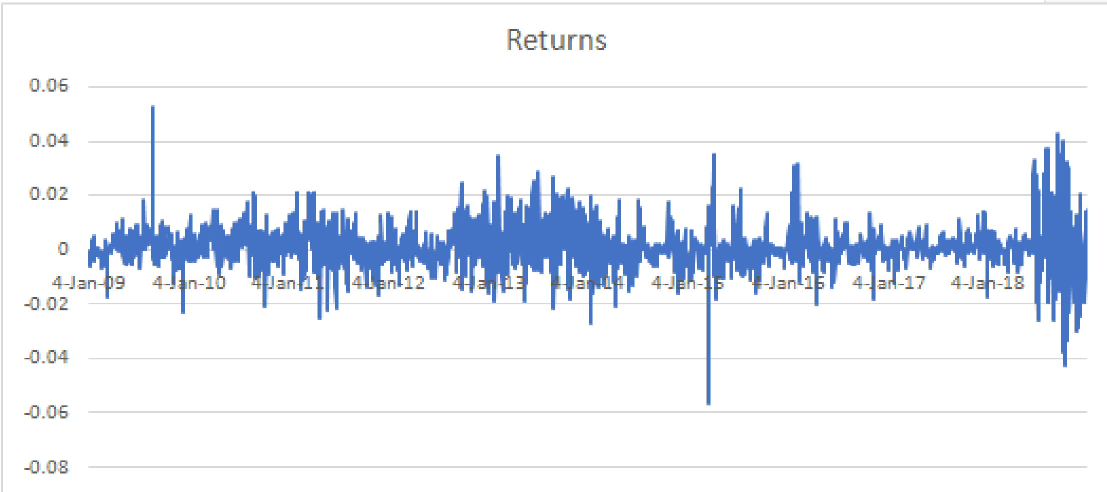
3-Jan-17
3-Jan-18


Returns
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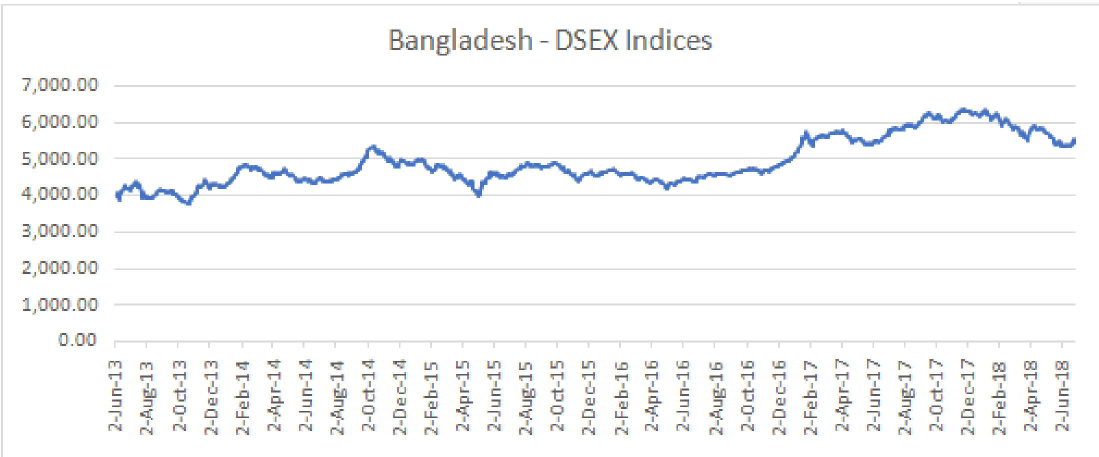
0.04
0.02
0
-0.02
-0.04
-0.06
-0.08
4-Jan-09
4-Jan-10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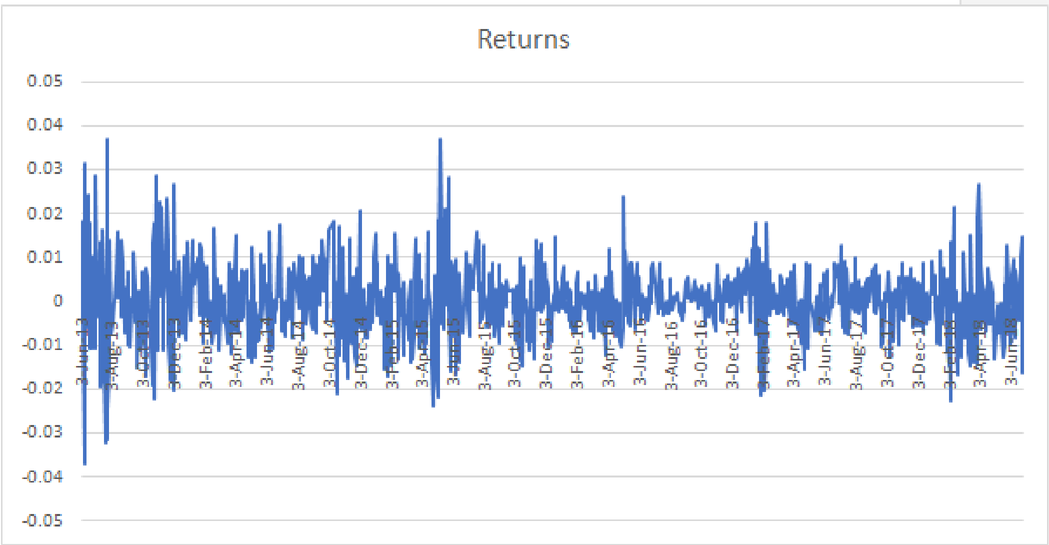
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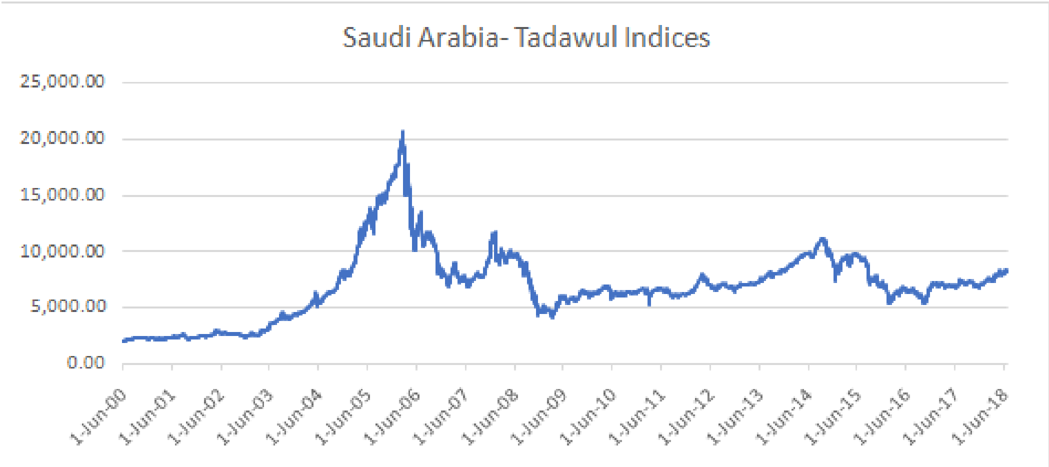
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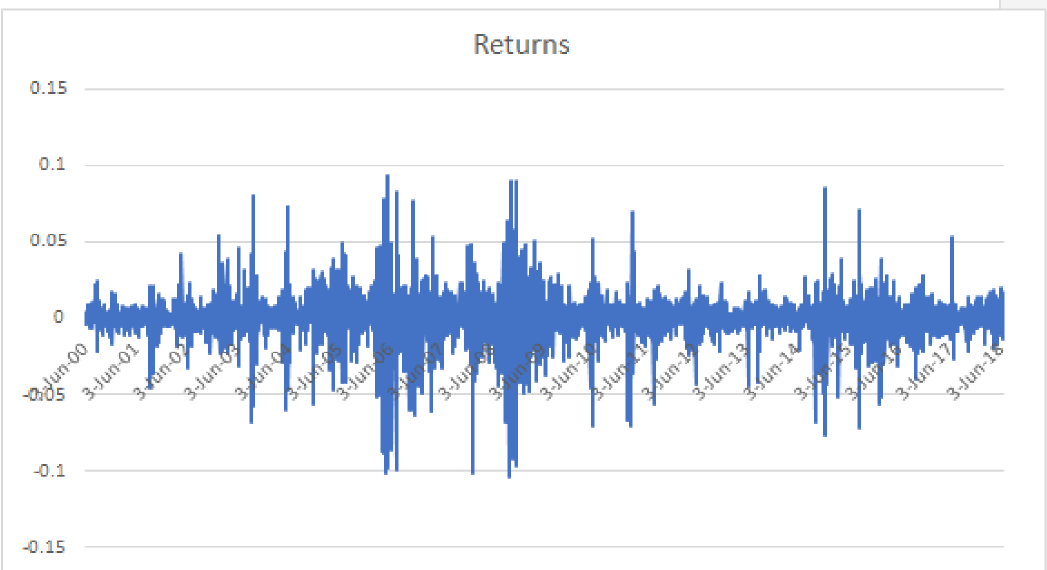
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0.05
0
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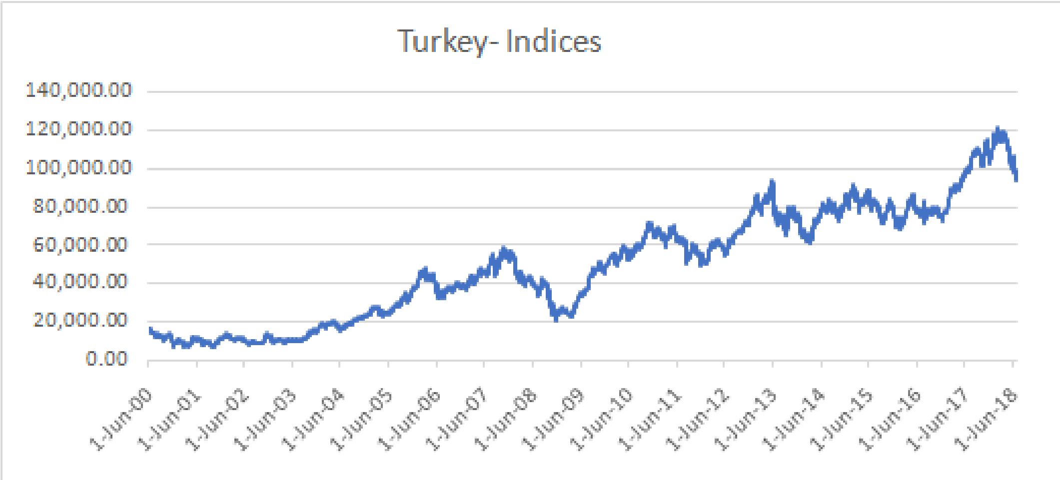

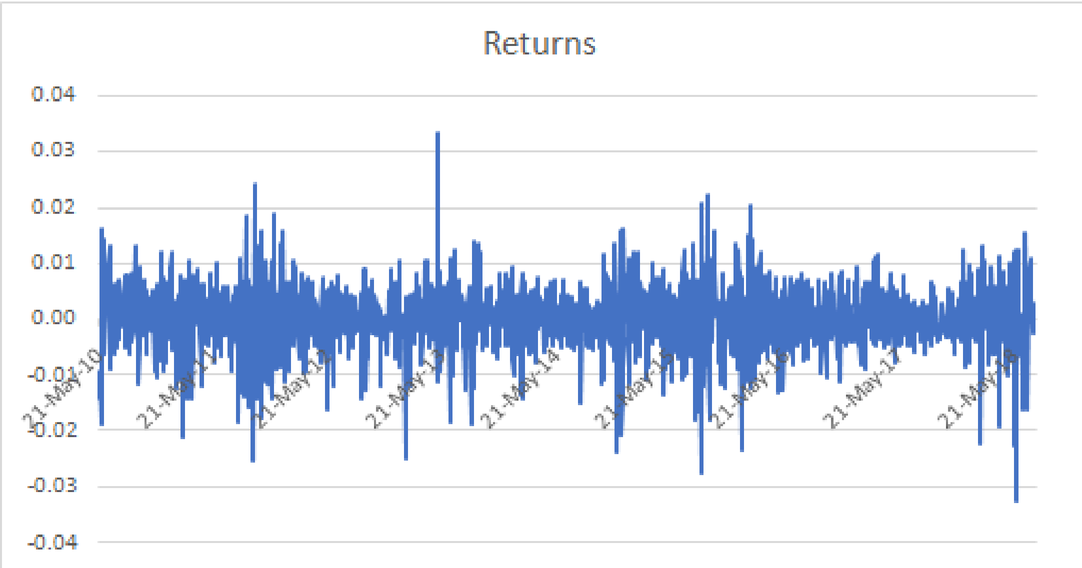

4.2 Descriptive Statistics

The descriptive statistics is used to summarize a given set of data by using brief descriptive coefficients that can represent the entire sample. Descriptive statistics are broken down into measures of variability and measures of central tendency. Measures of central tendency comprised of the mean, median, and mode, whereas measures of variability contain the standard deviation, variance, the minimum and maximum variables, the skewness and kurtosis. Sample period of this study is from 2000 to 2018 and is conducted on the daily stock returns of ten Islamic countries.

Table 4.1 indicates the descriptive statistics of daily stock returns of ten Islamic countries. Average mean returns measure the performance of the indices of these countries and for all countries mean is positive so it indicates that all countries have positive average returns. Maximum average return 0.0012 is exhibited by Iran and thus can be regarded as best return however minimum return 0.0001 is reported by Malaysia and Oman. Skewness can be defined as in the set of data it is the degree of distortion from the symmetrical bell curve or normal distribution. The skewness for Bangladesh and Iran is positive and indicates data is skewed at right side while Egypt, Indonesia, Malaysia, Oman, Pakistan, Saudi Arabia, Turkey and UAE are negatively skewed at left. Skewness greater than zero represents asymmetry of the data and it is provided that the stock of Indonesia is more asymmetric as its value is highest among all i.e. 0.67. Kurtosis is the measure of peakedness/flatness of the data. The kurtosis for all countries is > 3 that indicates the presence of the fat tail distribution of stock returns.

The leptokurtic return distribution is reported by Oman for maximum kurtosis value i.e. 22.879. The extreme fat tail of returns shows the non-normality of the data. A considerable positive approach is given by these tails for VaR Model Estimations. Stock market of Turkey reports the maximum risk of 0.0206 and is termed as more volatile and riskiest market while Malaysian market reveals the minimum risk of 0.0057 so it can be considered as least volatile market.

Table 4.1: Descriptive Statistics.

	Bangal	**Egypt**	**Indonesia**	**Iran**	**Malaysia**	**Oman**	**Pak**	**Saudia**	**Turkey**	**UAE**
Mean	0.0002	0.0006	0.0005	0.0012	0.0001	0.0001	0.0007	0.0002	0.0003	0.0003
Median	0.0001	0.0011	0.0011	0.0004	0.0002	0.0002	0.0010	0.0009	0.0007	0.0004
Maximum	0.0368	0.1836	0.0762	0.0526	0.0332	0.0803	0.0850	0.0939	0.1777	0.0762
Minimum	-0.0367	-0.1799	-0.1095	-0.0567	-0.0323	-0.0869	-0.0774	-0.1032	-0.1997	-0.0867
Std. Dev.	0.0076	0.0169	0.0133	0.0078	0.0057	0.0091	0.0129	0.0143	0.0206	0.0108
Skewness	0.1920	-0.3866	-0.6767	0.4373	-0.3885	-0.9894	-0.2925	-0.8873	-0.0895	-0.0893
Kurtosis	5.4450	12.028	10.077	8.6300	6.0138	22.879	6.5264	13.318	11.507	11.619

4.3 VaR Estimation Under Parametric, Non-Parametric Assumptions and Time Varying Volatility Models

Table 4.2 presents the results of VaR estimation under parametric, non-parametric and time varying volatility models at 95% confidence interval. VaR is used to express the expected potential loss suffered by any investment portfolio at a given confidence level.

TABLE 4.2: Value at Risk at 95% confidence interval.

	ND	HS	EWMA	GARCH
Pakistan	-0.0216	-0.0213	-0.0168	-0.0177
Saudi Arabia	-0.0215	-0.0235	-0.0138	-0.014
UAE	-0.0157	-0.0179	-0.0158	-0.0141
Oman	-0.0111	-0.0149	-0.0045	-0.0055
Turkey	-0.0314	-0.034	-0.0235	-0.0236
Iran	-0.0099	-0.0129	-0.0212	-0.0128
Bangladesh	-0.0119	-0.0125	-0.013	-0.0138
Malaysia	-0.0094	-0.0093	-0.0112	-0.0079
Indonesia	-0.0206	-0.022	-0.0198	-0.0236
Egypt	-0.0271	-0.0278	-0.0175	-0.0191

At 95% Confidence Interval, the normal distribution (ND), historical simulation (HS), generalized autoregressive conditional heteroscedasticity (GARCH) and the exponential weighted moving average (EWMA), all the four methods are reporting the highest risk for Turkey 3.14% in normal distribution, 3.4% in Historical simulation, 2.35% in EWMA and 2.36% in GARCH means that there are 95% chances that the loss will not exceed from 3.14%. So the highest risk is reported by the Normal distribution in case of Turkey.

Results represent that Malaysia bears the lowest risk 0.94% under normal distribution and 0.93% under Historical simulation and 0.79% in GARCH while Oman is the least risky stock reported by EWMA and GARCH so the potential loss for one day to the investor is lower in the stock of these two countries under time varying volatility models.

Table 4.3 presents the estimation of VaR at 99% confidence interval under normal distribution, Historical simulation, EWMA and GARCH. For estimation of VaR by increasing the confidence level. The study does not find major change in the pattern.

TABLE 4.3: Value at Risk at 99% confidence interval.

	ND	**HS**	**EWMA**	**GARCH**
Pakistan	-0.0411	-0.0301	-0.0238	-0.025
Saudi Arabia	-0.0504	-0.0333	-0.0195	-0.0198
UAE	-0.0336	-0.0253	-0.0223	-0.02
Oman	-0.03	-0.0211	-0.0064	-0.0078
Turkey	-0.0561	-0.0481	-0.0333	-0.0334
Iran	-0.0194	-0.0182	-0.0301	-0.0181
Bangladesh	-0.0199	-0.0177	-0.0184	-0.0195
Malaysia	-0.0169	-0.0132	-0.0159	-0.0112
Indonesia	-0.0389	-0.0311	-0.028	-0.0334
Egypt	-0.0472	-0.0393	-0.0248	-0.0271

At 99% confidence interval again all the four methods are presenting Turkey as the risky stock having risk 5.61% under normal distribution, 4.81% under Historical simulation, 3.33% under EWMA and 3.34% in GARCH. GARCH is reporting another country as a risky stock i.e. Indonesia having 3.34% risk.

Malaysia can be considered as less risky stock under normal distribution and historical simulation having risk of 1.6% and 1.3% respectively while EWMA and GARCH are representing Oman as the least risky stock. So the VaR with 99% indicates that under parametric, non-parametric and time varying volatility models, Malaysia is the country that contains minimum loss to invest and Turkey bears the highest risk for the investor.

4.4 Violation Ratio Under Parametric and Non-Parametric and Time Varying Volatility Methods

The VaR limit is considered as violated if on a particular day the financial loss exceeds the VaR forecast, so Violation ratio is a primary tool of back testing used to compare the observed frequency with expected number of violations. Violation ratio between 0.8 to 1.2 is considered good but to 1.5 is acceptable range and if violation ratio is less than 0.5 and greater than 1.5 the model is imprecise (Danialson 2011). Table 4.4 indicates the violation ratio at 95% confidence interval under parametric, non-parametric assumptions and time varying volatility models.

Table 4.4: Violation ratios at 95% confidence interval.

	ND	**HS**	**EWMA**	**GARCH**
Pakistan	1.0186	0.9732	1.0943	0.9732
Saudi Arabia	0.9528	1.069	1.0643	0.8691
UAE	0.9379	1.1788	0.9636	0.9123
Oman	0.8515	1.1526	0.9086	0.9397
Turkey	0.797	0.9059	0.9801	0.8564
Iran	0.7635	1.1506	0.8368	0.774
Bangladesh	0.8539	0.9641	1.1845	1.0468
Malaysia	0.9941	1.0333	1.0856	0.9025
Indonesia	0.87	0.9467	1.0133	0.9723
Egypt	0.9433	1.0351	1.0453	0.9892

This study reports that at 95% confidence interval, normal distribution is an example of perfect modeling as all the violation ratios for all the ten Islamic countries are greater than 0.8 and less than 1.2.

Under historical simulation same is the case as in normal distribution it is estimated that the violation ratios of Pakistan, Saudi Arabia, Turkey, Bangladesh, Malaysia, Indonesia and Egypt, UAE, Oman and Iran are perfectly modeled so there is no underestimation or overestimation of risk.

For time varying volatility models EWMA represents that results of all ten countries are within range and are perfectly modeled. GARCH shows the clear picture of accurate modeling as all the values are laying within range.

None of the countries is an example of overestimation and underestimation of the risk and while considering violation ratios to compare the expected frequencies with the observed frequencies here all the models are okay for all the countries for the risk estimation.

Table 4.5 presents the calculation of violation ratio at 99% confidence interval by using all the four assumptions and presenting a different scenario.

Table 4.5: Violation ratios at 99% confidence interval.

	ND	**HS**	**EWMA**	**GARCH**
Pakistan	2.4205	0.9329	2.2188	1.8406
Saudi Arabia	2.5563	1.2549	2.3007	2.1612
UAE	2.1783	1.2301	1.9477	1.6914
Oman	1.921	1.0124	2.0508	1.6095
Turkey	1.5346	0.891	1.6831	1.5594
Iran	1.8305	1.3598	1.4121	1.3598
Bangladesh	1.3774	0.6887	1.2396	1.1019
Malaysia	2.0928	1.2426	2.0928	1.7004
Indonesia	2.0982	0.8444	2.1494	1.8423
Egypt	1.9632	1.0453	2.0907	1.7338

Under 99% Confidence interval it is shown that in normal distribution method all the values of violation ratio for all ten countries are greater than 1.2 which means this method is not appropriate for risk forecasting at 99% confidence interval and similar is the case with EWMA and GARCH at 99% all the values are the clear sign of underestimation of the risk.

Only historical simulation relatively presents better estimates. so, at 99% confidence level this method is better modeled and can be used for the risk forecasting.

4.5 Volatility Under Parametric and Non-Parametric and Time Varying Volatility Assumptions

Table 4.6 reports the measurement of volatility at 95% confidence interval.

TABLE 4.6: Volatility at 95% confidence interval.

	ND	HS	EWMA	GARCH
Pakistan	0.005	0.008	0.008	0.008
Saudi Arabia	0.008	0.012	0.013	0.014
UAE	0.006	0.007	0.009	0.01
Oman	0.007	0.008	0.009	0.011
Turkey	0.009	0.008	0.01	0.01
Iran	0.002	0.002	0.006	0.007
Bangladesh	0.002	0.001	0.004	0.004
Malaysia	0.001	0.001	0.003	0.003
Indonesia	0.005	0.006	0.009	0.009
Egypt	0.004	0.006	0.011	0.012

Volatility is a statistical measure of the dispersion of returns for a given security or market index. It refers to market uncertainty and used to measure risk, model with lower volatility is considered reliable for VaR estimation.

At 95% confidence level, normal distribution is considered as less volatile model in case of Pakistan, Saudi Arabia, UAE, Oman, Indonesia and Egypt while in case of Iran and Malaysia the two models i.e. normal distribution and historical simulation both reports the same results with lowest volatility. At 95% Historical simulation performs the best with lowest volatility of 0.001 while considering Bangladesh. Saudi Arabia seems to be highly volatile market and Bangladesh and Malaysia are the lowest volatile markets in case of all the four approaches.

Normal distribution can be considered as the best model having least volatility in most of the countries at 95% confidence interval and generalized autoregressive conditional heteroscedasticity reports the highest volatility in case of all the countries so it will be considered as poor model in this case.

Table 4.7 deals with the calculation of volatility @99% confidence level So with the increase in confidence interval VaR volatility also increases.

TABLE 4.7: Volatility at 99% confidence interval.

	ND	**HS**	**EWMA**	**GARCH**
Pakistan	0.008	0.0085	0.0123	0.0123
Saudi Arabia	0.0126	0.0203	0.0191	0.0205
UAE	0.0086	0.0121	0.0129	0.0143
Oman	0.0103	0.0193	0.0138	0.0159
Turkey	0.0134	0.0145	0.0154	0.0152
Iran	0.0031	0.0028	0.0095	0.0102
Bangladesh	0.0026	0.0019	0.0041	0.0047
Malaysia	0.0015	0.002	0.0045	0.0043
Indonesia	0.0076	0.0111	0.0133	0.0131
Egypt	0.0063	0.0114	0.0159	0.0174

VaR Volatility at 99% confidence interval does not show a big difference in results as compare to 95% confidence interval as in case of Pakistan, Saudi Arabia, UAE, Turkey, Malaysia, Indonesia and Egypt, normal distribution method is to be considered as least volatile method and in case of Iran and Bangladesh historical simulation is the method with lowest volatility. GARCH and EWMA are considered to be more volatile and normal distribution can be considered as best fitted model as it is representing lowest volatility in most of the cases. At 99% it is also proved that Saudi Arab is highly volatile market and Bangladesh and Malaysia are the lowest volatile markets in case of all the four Approaches.

4.6 Back Testing Results (Kupeic POF and Christofersen Independence Test)

4.6.1 Kupeic POF Test

Table 4.8 presents the results of unconditional coverage test by Kupiec at 95% confidence interval and this test is used to compare the observed violations with the expected number of violations.

TABLE 4.8: Statistics of Kupeic test at 95% confidence interval.

	ND	HS	EWMA	GARCH	Critical Value
Pakistan	0.07	0.15	1.8	0.15	3.84
Saudi Arabia	0.51	1.05	0.92	4.04	3.84
UAE	0.8	6.23	0.27	1.62	3.84
Oman	4.66	4.24	0.31	0	3.84
Turkey	9.38	1.93	0.08	4.59	3.84
Iran	6.1	2.18	2.83	5.55	3.84
Bangladesh	0.85	0.04	1.23	0.08	3.84
Malaysia	0	0.08	0.57	0.78	3.84
Indonesia	3.62	0.59	0.03	0.15	3.84
Egypt	1.77	-0.49	-0.45	0.82	3.84

For a sample of n observations, the Kupiec test statistics takes the form of likelihood ratio and LR of POF are χ^2 distributed and if the LR value exceeds the critical. its value implies that the VaR model is inadequate.

At 95% confidence interval critical value is equals to 3.84 a simple check of the test statistic's non-rejection area, which basically determines whether or not the model has passed or failed. For Pakistan, Bangladesh, Malaysia, Indonesia and Egypt all the four methods are representing that likelihood ratios are within range and can be used for the risk assessment.

For Saudi Arabia the likelihood ratio is 4.04 under GARCH which is greater than 3.84 so this model cannot be used for the risk assessment but normal distribution, historical simulation and EWMA may be considered as their likelihood ratios are within range for this country. For UAE Historical simulation reports the higher value that is greater than critical value so it is rejected while normal distribution, EWMA and GARCH reports the results less than 3.84. In case of Oman the likelihood ratios of normal distribution (4.66) and Historical simulation (4.24) are greater than the critical value so these two methods are inadequate for risk assessment but EWMA and GARCH are showing their likelihood ratios within range.

For Turkey and Iran normal distribution and GARCH with the likelihood ratios of 9.38 and 4.59 respectively for Turkey and for Iran 6.10 in normal distribution and 5.5 in GARCH are rejected due to higher value than normal range while Historical simulation and EWMA reports the results which are less than critical value and can be considered for risk assessment. There is a mix trend that different methods report diverse results for different countries so only one method cannot be considered best for forecasting in this case. Table 4.9 reports the likelihood ratios at 99% confidence level which is presenting a different picture as compare to 95% confidence interval.

At this level the Critical value is 6.64 and the likelihood ratios less than this critical value would be considered for risk assessment. Historical simulation reports that likelihood ratios for all the countries are less than critical value hence are within range so this method can be used for further forecasting in case of all the countries while other three methods i.e. normal distribution, EWMA and GARCH disclosing that likelihood ratios for Bangladesh can be considered for risk assessment due to lower in value than 6.64. EWMA and GARCH with values 2.908 and 2.247 respectively may be considered suitable for Iran. GARCH representing the value the little bit lower than critical value in case of Malaysia. In Case of Pakistan, Saudi Arabia, UAE, Oman, Turkey, Indonesia and Egypt the likelihood ratios under normal distribution, EWMA and GARCH representing the greater values than 6.64 so cannot be considered for risk assessment and lie in the rejection region.

Table 4.9: LR statistics test at 95% confidence interval.

	ND	HS	EWMA	GARCH	Critical Value
Pakistan	57.86	0.184	44.18	22.68	6.64
Saudi Arabia	73.6	2.613	53.77	43.99	6.64
UAE	40.94	1.945	27.72	15.6	6.64
Oman	26.03	0.16	35.96	22.18	6.64
Turkey	10.02	0.502	15.8	10.91	6.64
Iran	10.69	2.247	2.908	2.247	6.64
Bangladesh	0.934	0.797	0.391	0.073	6.64
Malaysia	14.03	0.844	14.03	6.262	6.64
Indonesia	36.17	1.008	39.23	22.43	6.64
Egypt	27.19	0.042	34.05	16.48	6.64

Historical simulation is the best suited model at 99% confidence level because likelihood ratios for all the countries are less than 6.64 and representing a good range so it can be used for risk assessment.

4.6.2 Christoffersens Independence Test

Table 4.10 reports the likelihood ratios at 95% confidence level by using Christoffersens test which is basically used to measure clustering so Christofferson's test is applied to inspect whether the violations are spread evenly over time or they are occurring in clusters. The null hypothesis is the main consideration in this test and it assumes that there is no relationship among the categorical variables in the population so they are independent. Comparing the values of likelihood ratios to the critical value assess whether the observed frequencies are significantly different from the expected frequencies. If the value of likelihood ratio is greater than the critical value than null hypothesis is assumed to be rejected and the two attributes are related at a certain level but in case of smaller value of likelihood ratios than critical value it is assumed that the two attributes are not related so the degree of certainty is not met. If the value of likelihood ratio is equal to zero, the null hypothesis is true and the two attributes are totally unrelated.

TABLE 4.10: Statistics of Christofferson test at 95% confidence interval.

	ND	HS	EWMA	GARCH	Critical Value
Pakistan	114.3	97.81	28.13	4.835	3.84
Saudi Arabia	73.81	2066.9	20.13	4.27	3.84
UAE	77	71.93	20	7.113	3.84
Oman	89.16	107.9	74.38	44.86	3.84
Turkey	9.577	18.19	6.942	5.529	3.84
Iran	12.79	50.37	18.7	1.551	3.84
Bangladesh	6.96	14.96	2.319	0.118	3.84
Malaysia	6.33	9.753	0.815	0.151	3.84
Indonesia	30.08	34.37	12.78	6.407	3.84
Egypt	60.61	83.61	35.75	32.91	3.84

The results of above mentioned table reports that at 95% confidence interval, the values of likelihood ratios of Pakistan, Saudi Arabia, UAE, Oman, Turkey, Indonesia and Egypt are greater than 3.84 under all parametric, non-parametric and time varying volatility models which assumes that null hypothesis to be rejected and it is evidence of clustering availability. In case of Iran, GARCH supports the null Hypothesis and in Malaysia and Indonesia the likelihood ratios of both EWMA and GARCH are less than 3.84 showing no clustering trend and null hypothesis is accepted while Historical Simulation and normal distribution rejected the null hypothesis as the likelihood ratios are greater than 3.84 showing that probability of tomorrow's violation is depending upon today's violations.

Table 4.11 deals with the reporting of likelihood ratios of Christoffersen Independence test with the increased confidence interval which is representing different results as compare to previous confidence interval i.e. 95%.

Table 4.11: LR statistics of Christofferson test at 95% confidence interval.

	ND	HS	EWMA	GARCH	Critical Value
Pakistan	5.811	43.27	12.99	8.062	6.64
Saudi Arabia	54.77	359.2	15.47	0.692	6.64
UAE	40.94	48.5	8.347	2.294	6.64
Oman	29.11	43.19	492.5	41.26	6.64
Turkey	5.716	4.125	7.508	0.857	6.64
Iran	13	13.21	0.634	0.725	6.64
Bangladesh	2.052	4.43	2.398	3.021	6.64
Malaysia	8.389	1.424	0.162	0.548	6.64
Indonesia	20.46	4.627	6.5	3.713	6.64
Egypt	41.79	22.14	24.61	7.274	6.64

At 99% confidence level normal distribution reports that the likelihood ratios of Saudi Arabia, UAE, Oman, Iran, Malaysia, Indonesia and Egypt are greater than 6.64 which rejects the null hypothesis while this method supports the null hypothesis for Pakistan, Turkey and Bangladesh as their likelihood ratios are less than the critical value.

In case of Historical Simulation there is presence of violation clustering for Pakistan, Saudi Arabia, UAE, Oman, Iran and Egypt but for Turkey, Bangladesh, Malaysia and Indonesia there is no evidence of violation clustering so null hypothesis is assumed to be accepted here at 99% confidence level, EWMA reports that likelihood ratios for Pakistan, Saudi Arabia, UAE, Oman, Egypt and Turkey are greater than 6.64 and to be rejected while lie in the acceptance region for Iran, Bangladesh, Malaysia and Indonesia having likelihood ratios 0.634, 2.398, 0.162 and 6.50 respectively which are less than 6.64.

GARCH is representing that violation clustering is present in Pakistan, Oman and Egypt only while all other seven countries are having likelihood ratios which are less than the critical value, evidence no clustering and the probability of tomorrow's violation does not depend on today's violation give rise to the acceptance of null hypothesis.

4.7 Model Selection

On the basis of all the analysis and after all backtesting tests, the model which would be best for risk estimation has to be selected. To run the seasonality in regression equation the approved model is needed and in this study, normal distribution and historical simulation methods are providing better results at 95% and 99% confidence interval. Both normal distribution and historical simulation stand within acceptable range so, this study uses these two models to run the regression equation respectively for the factor of seasonality and to check its impact on VaR and VaR exceptions. EWMA and GARCH are reported as models having less precision for the risk estimation.

4.8 Seasonal Behavior in Value at Risk

Financial markets must be aware of seasonal fluctuations while estimating risk for their investment. Seasonal abnormalities are usually assigned to recurring environmental or cultural changes and events which happen for the whole year. Seasonality is the result of combined effects of many factors can be considered as an aggregate variable which serves as a surrogate measure of all these combined effects.Typically Seasonality may be considered as a dummy variable while presenting the market response to the decesion variables. Table 4.12 and 4.13 are presenting that either value at risk is effected by seasonal behavior on monthly basis or not.

4.8.1 Seasonal Behavior in Value at Risk on Monthly Basis at 95% Confidence Interval

While representing monthly effects on value at risk at both 95% confidence interval the value of coefficient is representing that either changes arise in predictor are associated with the changes in the response or not and the p value is to show the significance level.

Table 4.12: Seasonal behavior of monthly VaR at 95% confidence Interval by using normal distribution method.

	Pakistan	**Saudia**	**UAE**	**Oman**	**Turkey**	**Iran**	**Bangladesh**	**Malaysia**	**Indonesia**	**Egypt**
M1	-0.020	-0.023	-0.017	-0.014	-0.030	-0.011	-0.010	-0.009	-0.021	-0.027
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
M2	-0.020	-0.023	-0.017	-0.014	-0.029	-0.011	-0.010	-0.009	-0.021	-0.027
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
M3	-0.0205	-0.022	-0.017	-0.014	-0.029	-0.011	-0.010	-0.009	-0.021	-0.027
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
M4	-0.020	-0.022	-0.017	-0.013	-0.029	-0.011	-0.010	-0.009	-0.021	-0.027
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
M5	-0.0204	-0.022	-0.017	-0.013	-0.029	-0.011	-0.010	-0.009	-0.021	-0.027
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
M6	-0.0207	-0.022	-0.018	-0.014	-0.030	-0.011	-0.010	-0.009	-0.021	-0.027
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
M7	-0.0212	-0.023	-0.018	-0.014	-0.032	-0.011	-0.011	-0.009	-0.021	-0.028
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
M8	-0.0211	-0.023	-0.018	-0.013	-0.031	-0.011	-0.011	-0.009	-0.021	-0.027
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
M9	-0.0210	-0.022	-0.018	-0.014	-0.031	-0.011	-0.011	-0.009	-0.021	-0.027
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
M10	-0.0209	-0.022	-0.018	-0.014	-0.031	-0.012	-0.011	-0.009	-0.021	-0.027
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
M11	-0.0206	-0.023	-0.018	-0.014	-0.030	-0.012	-0.011	-0.009	-0.021	-0.026
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
M12	-0.0206	-0.022	-0.017	-0.014	-0.030	-0.012	-0.010	-0.009	-0.021	-0.027
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)

TABLE 4.13: Seasonal behavior of monthly VaR at 95% confidence interval by using historical simulation method.

	Pakistan	Saudia	UAE	Oman	Turkey	Iran	Bangladesh	Malaysia	Indonesia	Egypt
M1	-0.022	-0.022	-0.016	-0.012	-0.029	-0.009	-0.010	-0.009	-0.021	-0.026
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
M2	-0.022	-0.022 (0.00)	-0.016	-0.012	-0.028	-0.009	-0.010	-0.009	-0.021	-0.026
	(0.00)		(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
M3	-0.022	-0.022	-0.016	-0.012	-0.028	-0.009	-0.010	-0.009	-0.021	-0.026
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
M4	-0.022	-0.021	-0.016	-0.012	-0.028	-0.009	-0.010	-0.009	-0.021	-0.026
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
M5	-0.022	-0.022	-0.016	-0.012	-0.028	-0.009	-0.010	-0.009	-0.021	-0.026
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
M6	-0.022	-0.022	-0.016	-0.012	-0.029	-0.009	-0.010	-0.009	-0.021	-0.026
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
M7	-0.022	-0.023	-0.016	-0.012	-0.030	-0.009	-0.011	-0.009	-0.021	-0.027
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
M8	-0.022	-0.023	-0.016	-0.012	-0.030	-0.009	-0.011	-0.009	-0.021	-0.027
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
M9	-0.022	-0.022	-0.016	-0.012	-0.030	-0.009	-0.011	-0.009	-0.021	-0.026
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
M10	-0.022	-0.022	-0.016	-0.012	-0.030	-0.009	-0.011	-0.009	-0.021	-0.026
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
M11	-0.022	-0.023	-0.016	-0.012	-0.029	-0.009	-0.010	-0.009	-0.021	-0.026
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
M12	-0.022	-0.022	-0.016	-0.012	-0.029	-0.010	-0.010	-0.009	-0.021	-0.026
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)

Table 4.12 is presenting results for impact of seasonal behavior on VaR at 95% confidence interval by using normal distribution method and Table 4.13 is depicting the seasonal behavior on VaR at 95% confidence interval by using historical simulation method. The significance value for both Tables i.e. 4.12 and 4.13 is 0.00 for each month so it is significant for each and every month in the year clearly indicating that VaR can be effected by any month of the year i.e. onal variation may be the main reasons to effect the forecasting of the VaR.

All the coefficients are having negative sign conveying that after incorporating the effect of seasonality, the forecasted VaR is now showing the different results i.e. the probability of loss is now deviated from its original calculated value before. Turkey presents the highest impact while Malaysia is with the lowest one.

4.8.2 Seasonal Behavior in Value at Risk on Monthly Basis at 99% Confidence Interval

At 99% confidence interval by using normal distribution method in Table 4.14 and historical simulation in Table 4.15 the results are not so different as compare to the results on 95% confidence interval. Again the p-value is 0.00 for each month in both tables, showing the significant impact of seasonal behavior on VaR.

All the Coefficients are having negative sign conveying that after incorporating the effect of seasonality, the forecasted VaR is now showing the different results i.e. the probability of loss is now deviated from its original calculated value before. At 99% again Turkey is having the highest impact while Malaysia and Bangladesh is having lowest impact.

TABLE 4.14: Seasonal behavior of monthly VaR at 99% confidence Interval by using normal distribution method.

	Pakistan	Saudia	UAE	Oman	Turkey	Iran	Bangladesh	Malaysia	Indonesia	Egypt
M1	-0.029	-0.032	-0.024	-0.019	-0.042	-0.016	-0.015	-0.030	-0.038	-0.039
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
M2	-0.028	-0.032	-0.024	-0.019	-0.042	-0.016	-0.015	-0.030	-0.038	-0.039
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
M3	-0.029	-0.031	-0.024	-0.019	-0.042	-0.016	-0.015	-0.030	-0.038	-0.039
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
M4	-0.029	-0.031	-0.024	-0.019	-0.042	-0.016	-0.015	-0.030	-0.038	-0.038
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
M5	-0.028	-0.031	-0.024	-0.018	-0.041	-0.015	-0.015	-0.030	-0.039	-0.039
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
M6	-0.029	-0.032	-0.025	-0.019	-0.043	-0.016	-0.014	-0.030	-0.038	-0.039
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
M7	-0.030	-0.032	-0.024	-0.019	-0.045	-0.016	-0.016	-0.031	-0.039	-0.039
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
M8	-0.029	-0.033	-0.025	-0.019	-0.044	-0.016	-0.016	-0.031	-0.039	-0.039
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
M9	-0.029	-0.032	-0.024	-0.019	-0.044	-0.017	-0.016	-0.030	-0.038	-0.039
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
M10	-0.029	-0.032	-0.024	-0.020	-0.044	-0.017	-0.016	-0.031	-0.039	-0.039
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
M11	-0.029	-0.032	-0.025	-0.020	-0.043	-0.017	-0.015	-0.030	-0.039	-0.039
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
M12	-0.029	-0.032	-0.024	-0.019	-0.043	-0.017	-0.015	-0.030	-0.039	-0.039
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)

Table 4.15: Seasonal behavior of monthly VaR at 99% confidence interval by using historical simulation method.

	Pakistan	Saudia	UAE	Oman	Turkey	Iran	Bangladesh	Malaysia	Indonesia	Egypt
M1	-0.036	-0.022	-0.030	-0.027	-0.051	-0.017	-0.015	-0.015	-0.038	-0.048
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
M2	-0.036	-0.022	-0.030	-0.026	-0.049	-0.016	-0.016	-0.015	-0.038	-0.048
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
M3	-0.036	-0.022	-0.030	-0.026	-0.049	-0.016	-0.016	-0.015	-0.038	-0.048
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
M4	-0.036	-0.021	-0.030	-0.025	-0.049	-0.016	-0.016	-0.015	-0.038	-0.048
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
M5	-0.035	-0.022	-0.030	-0.025	-0.048	-0.017	-0.016	-0.015	-0.039	-0.048
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
M6	-0.036	-0.022	-0.030	-0.026	-0.051	-0.017	-0.017	-0.016	-0.038	-0.048
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
M7	-0.037	-0.023	-0.030	-0.026	-0.053	-0.017	-0.017	-0.016	-0.039	-0.049
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
M8	-0.037	-0.023	-0.031	-0.028	-0.052	-0.017	-0.017	-0.016	-0.039	-0.049
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
M9	-0.037	-0.022	-0.031	-0.026	-0.052	-0.017	-0.017	-0.016	-0.038	-0.049
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
M10	-0.037	-0.022	-0.032	-0029	-0.052	-0.018	-0.018	-0.016	-0.039	-0.049
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
M11	-0.036	-0.023	-0.032	-0.030	-0.051	-0.018	-0.018	-0.015	-0.039	-0.049
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
M12	-0.036	-0.022	-0.030	-0.028	-0.051	-0.018	-0.018	-0.016	-0.039	-0.049
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)

4.8.3 Seasonal Behavior in Value at Risk on Daily Basis at 95% Confidence Interval

Financial risk forecasting can be effected on the basis of daily seasonal anomalies as it is one of the most robust findings in the stock returns. Tables 4.16 and 4.17 are conferring about the results of these daily anomalies.

From the Tables 4.16 and 4.17 by using normal distribution and historical simulation method respectively on daily seasonality it can be interpret that as the p value is perfectly significant i.e. 0.00 in each case at both 95% confidence interval so it is the symbol for the presence of consequences of daily seasonal anomalies on the VaR so the VaR that is estimated today may show a different result tomorrow due to Monday effect, Friday effect or effect of any other day of the week.

Values of coefficient having negative sign represents that results of VaR will deviate from its forecasted value due to presence of the Day of the week effect in case of all the ten Islamic countries. In the case of daily anomalies at 95% confidence interval the coefficient value of -0.030 in normal distribution and -0.029 proved that that Turkey has the highest impact of daily seasonality whereas Malysia is with the lowest impact in both the cases having the value of coefficient as -0.009.

Table 4.16: Seasonality in daily VaR at 95% confidence interval by using normal distribution method.

	Pakistan	**Saudia**	**UAE**	**Oman**	**Turkey**	**Iran**	**Bangladesh**	**Malaysia**	**Indonesia**	**Egypt**
D1	-0.020	-0.023	-0.017	-0.014	-0.030	-0.009	-0.011	-0.009	-0.021	-0.027
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
D2	-0.020	-0.023	-0.017	-0.014	-0.030	-0.009	-0.011	-0.009	-0.021	-0.027
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
D3	-0.020	-0.023	-0.017	-0.014	-0.030	-0.009	-0.011	-0.009	-0.021	-0.027
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
D4	-0.020	-0.018	-0.017	-0.014	-0.030	-	-0.011	-0.009	-0.021	-0.027
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)		(0.00)	(0.00)	(0.00)	(0.00)
D5	-0.020	-	-	-	-0.030	-	-	-0.009	-0.021	-
	(0.00)				(0.00)			(0.00)	(0.00)	
D6	-	-0.025	-0.015	-0.014	-	-0.009	-0.011	-	-	-0.027
		(0.00)	(0.00)	(0.00)		(0.00)	(0.00)			(0.00)
D7	-	-0.023	-0.017	-0.014	-	-0.009	-0.011	-	-	-0.027
		(0.00)	(0.00)	(0.00)		(0.00)	(0.00)			(0.00)

Table 4.17: Seasonality in daily VaR at 95% confidence interval by using historical simulation method.

	Pakistan	**Saudia**	**UAE**	**Oman**	**Turkey**	**Iran**	**Bangladesh**	**Malaysia**	**Indonesia**	**Egypt**
D1	-0.022	-0.023	-0.016	-0.012	-0.029	-0.011	-0.010	-0.009	-0.021	-0.026
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
D2	-0.022	-0.022	-0.016	-0.012	-0.029	-0.011	-0.010	-0.009	-0.021	-0.026
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
D3	-0.022	-0.023	-0.016	-0.012	-0.029	-0.011	-0.010	-0.009	-0.021	-0.026
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
D4	-0.022	-0.016	-0.016	-0.012	-0.029	-	-0.010	-0.009	-0.021	-0.026
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)		(0.00)	(0.00)	(0.00)	(0.00)
D5	-0.022	-	-	-	-0.029	-	-	-0.009	-0.021	-
	(0.00)				(0.00)			(0.00)	(0.00)	
D6	-	-0.025	-0.012	-0.012	-	-0.011	-0.012	-	-	-0.023
		(0.00)	(0.00)	(0.00)		(0.00)	(0.00)			(0.00)
D7	-	-0.022	-0.016	-0.012	-	-0.011	-0.010	-	-	-0.026
		(0.00)	(0.00)	(0.00)		(0.00)	(0.00)			(0.00)

4.8.4 Seasonal Behavior on Value at Risk on Daily Basis at 99% Confidence Interval

Tables 4.18 and 4.19 by using normal distribution and historical simulation method respectively on daily seasonality it is proved that the p value is again significant i.e. 0.00 in each case at 99% confidence interval so it is again indicating the presence of consequences of daily seasonal anomalies on the VaR.

Values of coefficient having negative sign represents that results of VaR will deviate from its forecasted value due to presence of the daily seasonal anomalies for all the ten Islamic countries. Turkey and Egypt seems to have highest impact of seasonality while Malaysia is having the lowest impact of seasonality and is followed by Bngladesh by using both normal distribution and historical simulation method.

TABLE 4.18: Seasonality in daily VaR at 99% confidence interval by using normal distribution method.

	Pakistan	**Saudia**	**UAE**	**Oman**	**Turkey**	**Iran**	**Bangladesh**	**Malaysia**	**Indonesia**	**Egypt**
D1	-0.029	-0.032	-0.024	-0.019	-0.043	-0.016	-0.015	-0.013	-0.030	-0.049
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
D2	-0.029	-0.032	-0.024	-0.019	-0.043	-0.016	-0.015	-0.013	-0.030	-0.049
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
D3	-0.029	-0.032	-0.024	-0.019	-0.043	-0.016	-0.015	-0.013	-0.030	-0.049
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
D4	-0.029	-0.025	-0.025	-0.019	-0.043	-	-0.015	-0.013	-0.030	-0.049
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)		(0.00)	(0.00)	(0.00)	(0.00)
D5	-0.029	-	-	-	-0.043	-	-	-0.013	-0.030	-
	(0.00)				(0.00)			(0.00)	(0.00)	
D6	-	-0.035	-0.022	-0.019	-	-0.016	-0.015	-	-	-0.049
		(0.00)	(0.00)	(0.00)		(0.00)	(0.00)			(0.00)
D7	-	-0.032	-0.024	-0.019	-	-0.016	-0.015	-	-	-0.049
		(0.00)	(0.00)	(0.00)		(0.00)	(0.00)			(0.00)

TABLE 4.19: Seasonality in daily VaR at 99% confidence interval by using historical simulation method.

	Pakistan	**Saudia**	**UAE**	**Oman**	**Turkey**	**Iran**	**Bangladesh**	**Malaysia**	**Indonesia**	**Egypt**
D1	-0.036	-0.023	-0.031	-0.027	-0.051	-0.017	-0.016	-0.016	-0.039	-0.039
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
D2	-0.036	-0.022	-0.031	-0.027	-0.051	-0.017	-0.016	-0.016	-0.039	-0.039
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
D3	-0.036	-0.022	-0.031	-0.027	-0.051	-0.017	-0.016	-0.016	-0.039	-0.039
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
D4	-0.037	-0.017	-0.031	-0.027	-0.051	-	-0.016	-0.016	-0.039	-0.039
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)		(0.00)	(0.00)	(0.00)	(0.00)
D5	-0.036	-	-	-	-0.051	-	-	-0.016	-0.039	-
	(0.00)				(0.00)			(0.00)	(0.00)	
D6	-	-0.025	-0.025	-0.027	-	-0.017	-0.017	-	-	-0.039
		(0.00)	(0.00)	(0.00)		(0.00)	(0.00)			(0.00)
D7	-	-0.023	-0.031	-0.027	-	-0.017	-0.016	-	-	-0.039
		(0.00)	(0.00)	(0.00)		(0.00)	(0.00)			(0.00)

4.9 Seasonal Behavior in VaR Exceptions

After calculating VaR the challenge is how to evaluate the precision of the measure and consequently, the accuracy of the distribution of returns. To know about precision of the measure is worthwhile for financial institutions because they use the techniques of value at risk to estimate about to cover potential losses how much cash they need to reserve. The VaR model having imprecisions represents that the institution is not holding sufficient reserves which may lead to substantial losses, sometimes due to seasonal variations risk that is estimated before may show the different scenario the value of VaR is may be different from the figure forecasted before this is known as VaR exception.

4.9.1 Seasonal Behavior in VaR Exceptions on Monthly Basis at 95% Confidence Interval

Tables 4.20 and 4.21 are representing that which month of the year cause VaR exceptions in these ten Islamic countries at 95% confidence interval.

The results of Table 4.20 by using normal distribution method at 95% confidence interval indicate all the coefficient values are negative except Bangladesh where value of coefficient having no sign equals to zero and p value is equals to 1.00 representing that seasonal variations have no impact on VaR exceptions in the Months of July, August, November and December.

In Pakistan except November all the other eleven months of the year have equal chances to create VaR exceptions. In Saudi Arabia, UAE and Turkey all the significant values represent the presence of VaR anomalies. For Oman, July is the month that will not affect the VaR results.

In Iran except March, April, July, August and September, the values for other seven months show the significant results that indicates the presence of seasonality in VaR. For Bangladesh, January, February, March, April and October may have seasonal variations. Malaysian Stock returns has seasonality in January, February, May, June, August, September and December at 95% confidence interval by using normal distribution method. The results of 5% chance of risk may be different for Indonesia in 10 months of the year except February and December. Egypt market has VaR seasonality in all months of the year.

Table 4.21 is using historical simulation method at 95% confidence interval and results are not so different as compare to normal distribution method at the same confidence interval. Again all the values of coefficients are negative except Bangladesh where value of coefficient having no sign equals to zero and p value is equals to 1.00 representing that seasonal variations have no impact on VaR exceptions in the Months of July, November and December.

For Pakistan again there is an evidence that except November all the other eleven months of the year have equal chances to create VaR exceptions. In Saudi Arabia, UAE, Oman and Egypt, all the significant values represent the presence of VaR anomalies at this confidence interval. For Turkey, April is the month that will not affect the VaR results having p value of 0.09.

In Iran results are somewhat different by using historical simulation as compare to normal distribution at 95% confidence interval, here only July and September are presenting insignificant results. For Bangladesh, January, February, March, April and October may have seasonal variations and same as in the case of normal distribution. Malaysian Stock returns has seasonality in January, February, May, June, August, September and December at 95% confidence interval by using historical simulation method again proving the results of previous method. The results of 5% chance of risk may be different for Indonesia in 10 months of the year except February and December and again it is same as in the case of normal distribution.

TABLE 4.20: Seasonality in monthly VaR exceptions at 95% confidence interval by using normal distribution method.

	Pakistan	**Saudia**	**UAE**	**Oman**	**Turkey**	**Iran**	**Bangladesh**	**Malaysia**	**Indonesia**	**Egypt**
M1	-8.8e-4	-9.7e-4	-1.0e-3	-9.5e-4	-1.2e-3	-6.7e-4	-1.1e-3	-6.6e-4	-8.5e-4	-1.5e-3
	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
M2	-6.4e-4	-7.6-4	-4.5e-4	-2.1e-4	-1.1e-3	-2.8e-4	-0.8e-4	-6.4e-4	-1.6e-4	-1.6e-3
	0.00	0.00	0.04	0.21	0.00	0.13	0.00	0.00	0.51	0.00
M3	-1.3e-3	-1.2-3	-6.1e-4	-6.8e-4	-1.7e-3	-1.4e-4	-1.0e-3	-1.2e-4	-1.8e-4	-1.3e-3
	0.00	0.00	0.00	0.00	0.00	0.47	0.00	0.47	0.00	0.00
M4	-1.2e-3	-1.2-3	-6.2e-4	-3.5e-4	-6.3e-4	-4.3e-4	-5.1e-4	-2.6e-4	-7.6e-4	-8.6e-4
	0.00	0.00	0.03	0.00	0.04	0.00	0.04	0.12	0.00	0.00
M5	-1.4e-3	-1.3-3	-9.9e-4	-5.8e-3	-1.5e-3	-3.4e-4	-1.5e-4	-7.5e-4	-1.1e-3	-1.8e-3
	0.00	0.00	0.00	0.00	0.00	0.05	0.52	0.00	0.00	0.00
M6	-1.4e-3	-8.1e-4	-7.5e-4	-3.3e-4	-1.0e-3	-5.1e-4	-1.7e-5	-5.5e-4	-1.1e-3	-1.1e-3
	0.00	0.00	0.04	0.03	0.00	0.00	0.50	0.00	0.00	0.00
M7	-9.1e-4	-6.9e-4	-7.7e-4	-3.3e-4	-9.6e-4	-1.4e-4	0.00	-2.3e-4	-6.0e-4	-1.4e-3
	0.00	0.01	0.05	0.05	0.00	0.24	1.00	0.13	0.01	0.00
M8	-1.7e-3	-6.8e-4	-5.6e-4	-6.8e-4	-1.2e-3	-4.7e-4	0.00	-8.3e-4	-1.3e-3	1.0e-3
	0.00	0.01	0.00	0.00	0.00	0.42	1.00	0.00	0.00	0.00
M9	-6.3e-4	-8.6e-4	-7.8e-4	-5.8e-4	-9.4e-4	-3.0e-4	-3.1e-4	-4.0e-4	-1.4e-3	-6.1e-4
	0.00	0.00	0.00	0.00	0.00	0.10	0.22	0.02	0.00	0.05
M10	-9.2e-4	-1.6e-3	-7.1e-4	-8.8e-4	-1.1e-3	-6.9e-4	-6.5e-4	-2.0e-4	-1.4e-4	-1.3e-3
	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.23	0.00	0.00
M11	-5.0e-4	-1.6e-3	-9.8e-4	-6.0e-4	-1.6e-3	-1.1e-3	0.00	-2.4e-4	-9.4e-4	-1.6e-3
	0.06	0.00	0.00	0.00	0.00	0.00	1.00	0.15	0.00	0.00
M12	-1.1e-3	-1.0e-3	-1.3e-3	-7.3e-4	-1.3e-3	-4.0e-4	0.00	-3.9e-4	-3.5e-4	-6.7e-4
	0.00	0.00	0.00	0.00	0.00	0.02	1.00	0.02	0.15	0.01

Table 4.21: Seasonality in monthly VaR exceptions at 95% confidence interval by using historical simulation method.

	Pakistan	**Saudia**	**UAE**	**Oman**	**Turkey**	**Iran**	**Bangladesh**	**Malaysia**	**Indonesia**	**Egypt**
M1	8.0e-4	-8.8e-4	-1.1e-3	-1.0e-3	-1.1e-3	-7.0e-4	-1.1e-3	-6.4e-4	-9.9e-4	-1.7e-3
	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
M2	6.5e-4	-7.0e-4	-5.5e-4	-3.2e-4	-1.0e-3	-5.0e-4	-8.8e-4	-5.5e-4	-2.3e-4	-1.5e-3
	0.01	0.01	0.00	0.04	0.00	0.00	0.00	0.00	0.35	0.01
M3	1.4e-3	-1.2e-3	-7.0e-4	-7.8e-4	-1.7e-7	-3.4e-4	-8.9e-4	-1.6e-4	-7.6e-4	-1.3e-3
	0.00	0.00	0.00	0.00	0.00	0.05	0.00	0.31	0.00	0.00
M4	8.8e-4	-1.0e-3	-5.8e-4	-4.1e-4	-5.3e-4	-7.4e-4	-6.1e-4	-2.6e-4	-8.1e-4	-9.2e-4
	0.00	0.00	0.00	0.00	0.09	0.00	0.03	0.12	0.00	0.00
M5	1.5e-3	-1.2e-3	-1.0e-3	-5.1e-4	-1.4e-3	-4.4e-4	-3.0e-4	-8.1e-4	-1.0e-3	-1.8e-3
	0.00	0.00	0.00	0.00	0.00	0.00	0.21	0.00	0.00	0.00
M6	1.6e-3	-7.9e-4	-1.0e-3	-4.2e-4	-1.1e-3	-6.7e-4	-1.7e-4	-4.7e-4	-1.1e-3	-1.1e-3
	0.00	0.00	0.00	0.00	0.00	0.00	0.50	0.00	0.00	0.00
M7	7.9e-4	-8.0e-4	-5.6e-4	-3.7e-4	-8.4e-4	-1.9e-4	0.00	-2.3e-4	-5.3e-4	-1.4e-3
	0.00	0.01	0.00	0.02	0.00	0.24	1.00	0.12	0.02	0.00
M8	1.5e-3	-7.8e-4	-5.7e-4	-6.2e-4	-1.2e-3	-3.7e-4	0.00	-8.7e-4	-1.4e-3	-1.0e-3
	0.00	0.01	0.00	0.00	0.00	0.02	1.00	0.00	0.00	0.00
M9	6.8e-4	-1.0e-3	-7.1e-4	-6.5e-4	-8.5e-4	-3.1e-4	-2.9e-4	-4.4e-4	-1.2e-3	-7.0e-4
	0.01	0.00	0.00	0.00	0.00	0.06	0.26	0.01	0.00	0.02
M10	7.7e-4	-1.6e-3	-8.6e-4	-8.6e-4	-1.3e-3	-6.2e-4	-8.4e-4	-2.3e-4	-1.4e-4	-1.4e-3
	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.17	0.00	0.01
M11	3.3e-4	-1.5e-3	-1.1e-3	-6.8e-4	-1.4e-3	-9.6e-4	0.00	-2.7e-4	-1.0e-3	-1.7e-3
	0.21	0.00	0.00	0.00	0.00	0.00	1.00	0.10	0.00	0.00
M12	1.1e-3	-9.5e-4	-1.2e-3	-8.3e-4	-9.9e-4	-3.5e-4	0.00	-4.0e-4	-4.9e-4	-7.4e-4
	0.00	0.00	0.00	0.00	0.00	0.03	1.00	0.01	0.06	0.01

4.9.2 Seasonal Behavior in VaR Exceptions on Monthly Basis at 99% Confidence Interval

Table 4.22 is presenting the results of monthly seasonality on VaR exceptions at 99% confidence interval by using normal distribution method. In case of Pakistan here is the indication of seasonal effect on eight months of the year except February, October, November and December. For Saudi Arabia in February, August and December the insignificant values are indicating that there will be no impact of seasonal variations on these three months. United Arab Emirates is presenting that VaR exceptions are may be the results of anomalies exist in January, May, June, July, October, November and December. In Oman there is only one month i.e. June for the reason of these deviation from the results.

For Turkey, the months that have exceptions are January, March, May, June and August, October and November. Iran is having month of April, May, August, October and November that indicates the seasonal pattern. For Malysia, January, May, August, September and December and for Indonesia, January, May, June, July, August, September and October are the months having seasonal variations. For Egypt there is the impact of seasonal variations in the month of January, April May, June, August, September and October. In Bangladesh only January and February shows significant results, so this country seems to have least impact of monthly seasonal variations on its estimated risk of stock returns.

TABLE 4.22: Seasonality in monthly VaR exceptions at 99% confidence interval by using normal distribution method.

	Pakistan	**Saudia**	**UAE**	**Oman**	**Turkey**	**Iran**	**Bangladesh**	**Malaysia**	**Indonesia**	**Egypt**
M1	-8.9e-4	-9.9e-4	-6.8e-4	-7.3e-4	-6.0e-4	-3.5e-4	-4.1e-4	-3.2e-4	-5.8e-4	-5.8e-4
	0.00	0.00	0.00	0.25	0.02	0.06	0.03	0.03	0.01	0.00
M2	-1.8e-4	-3.7e-4	-4.0e-5	-1.3e-4	-2.3e-4	9.2e-5	-7.0e-4	-3.0e-4	-5.3e-4	-5.3e-5
	0.64	0.20	0.84	0.83	0.39	0.61	0.00	0.06	0.82	0.82
M3	-1.1e-3	-1.3e-3	-3.5e-4	-2.7e-4	-8.4e-4	-1.3e-4	6.3e-4	0.00	-3.5e-4	-3.5e-5
	0.00	0.01	0.07	0.66	0.00	0.48	1.00	1.00	0.12	0.12
M4	-5.0e-4	-9.2e-4	-2.0e-4	-1.8e-4	1.9e-4	-4.2e-4	2.4e-4	-1.7-4	-5.4e-4	-5.4e-4
	0.04	0.00	0.30	0.76	0.47	0.01	0.22	0.25	0.01	0.01
M5	-9.5e-4	-1.1e-3	-7.9e-4	-1.1e-4	-7.7e-4	-3.8e-4	0.00	-3.4e-4	-6.3e-4	-6.3e-4
	0.00	0.00	0.07	0.85	0.04	0.02	1.00	0.02	0.00	0.00
M6	-1.0e-3	-5.4e-4	-3.7e-4	-2.4e-3	-6.5e-4	-2.5e-4	-2.4e-4	-1.7e-4	6.7e-4	-6.7e-4
	0.00	0.04	0.01	0.00	0.01	0.16	0.10	0.21	0.00	0.00
M7	-4.9e-4	-6.2e-4	-4.7e-4	-1.3e-4	-5.1e-4	-2.0e-4	0.00	7.6e-5	3.6e-4	-3.6e-4
	0.05	0.02	0.05	0.84	0.06	0.23	1.00	0.58	0.11	0.11
M8	-1.0e-3	-4.3e-3	-3.7e-4	-4.6e-4	-1.0e-3	-3.7e-4	0.00	-7.6e-4	-1.5e-4	-1.5e-4
	0.00	0.12	0.00	0.47	0.00	0.03	1.00	0.00	0.00	0.00
M9	-6.9e-4	-7.4e-4	-7.3e-4	-5.1e-4	-4.7e-4	-9.4e-4	0.00	-3.4e-4	-6.5e-4	-6.5e-4
	0.01	0.01	0.00	0.44	0.09	0.59	1.00	0.02	0.00	0.00
M10	2.1e-4	-1.1e-3	-6.7e-4	-9.5e-4	-6.9e-4	-4.6e-4	0.00	- 8.7e-4	-1.3e-4	-3.4e-4
	0.25	0.00	0.00	0.15	0.01	0.00	1.00	0.56	0.00	0.00
M11	-2.8e-4	-9.4e-4	-8.1e-4	-2.9e-4	-7.6e-4	-6.2e-4	0.00	0.00	-3.3e-4	-3.3e-4
	0.27	0.00	0.00	0.67	0.00	0.00	1.00	1.00	0.15	0.15
M12	-1.1e-3	-5.2e-4	-6.9e-4	-6.8e-4	-4.6e-4	-2.0e-4	0.00	-7.6e-4	9.5e-5	-9.5e-5
	0.00	0.06	0.00	0.30	0.09	0.25	1.00	0.00	0.69	0.69

Table 4.23: Seasonality in monthly VaR exceptions at 99% confidence interval by using historical simulation method.

	Pakistan	**Saudia**	**UAE**	**Oman**	**Turkey**	**Iran**	**Bangladesh**	**Malaysia**	**Indonesia**	**Egypt**
M1	-6.0e-4	-5.0e-4	-4.7e-4	-1.1e-4	-4.0e-4	-0.00	-2.3e-4	-2.8e-4	-6.1e-4	-6.1e-4
	0.00	0.07	0.00	0.45	0.09	0.14	0.13	0.05	0.00	0.00
M2	-1.0e-4	-3.4e-4	-0.00	-1.0e-4	-1.4e-4	0.00	-7.4e-4	-1.0e-4	-9.6e-5	-9.6e-5
	0.43	0.23	1.00	0.51	0.56	1.00	0.00	0.50	0.61	0.61
M3	-1.5e-4	-6.7e-3	-3.1e-4	-1.5e-4	-7.7e-4	-0.00	0.00	0.00	-5.1e-5	-5.1e-5
	0.00	0.01	0.07	0.27	0.00	0.44	1.00	1.00	0.77	0.77
M4	-1.2e-4	-7.8e-4	-1.3e-4	-9.5e-5	0.00	-0.00	0.00	-8.8e-4	-2.1e-4	-2.1e-4
	0.48	0.00	0.45	0.51	1.00	0.01	1.00	0.54	0.25	0.25
M5	-3.2e-4	-7.0e-3	-4.4e-4	-9.7e-5	-4.8e-4	-0.00	0.00	-2.8e-4	-5.9e-4	-5.9e-4
	0.07	0.00	0.01	0.50	0.04	0.04	1.00	0.06	0.00	0.00
M6	-3.9e-4	-6.8e-4	-2.8e-4	-1.5e-4	-7.2e-4	-0.00	-2.6e-4	-2.0e-4	0.00	-0.00
	0.03	0.01	0.11	0.30	0.00	0.07	0.10	0.09	1.00	1.00
M7	-3.1e-4	-2.3e-4	-3.8e-4	-1.2e-5	-3.3e-4	-0.00	0.00	0.00	0.00	-0.00
	0.08	0.39	0.03	0.40	0.15	0.60	1.00	1.00	1.00	1.00
M8	-3.3e-4	-4.4e-4	-3.2e-4	-2.1e-5	-6.3e-4	-0.00	0.00	-7.3e-4	-8.4e-4	-8.4e-4
	0.07	0.11	0.06	0.16	0.00	0.01	1.00	0.00	0.00	0.00
M9	-3.5e-4	-4.5e-4	-3.0e-4	-3.6e-4	-4.3e-4	-0.00	0.00	-1.4e-4	-1.1e-4	-1.1e-4
	0.05	0.12	0.09	0.01	0.08	1.00	1.00	0.34	0.53	0.53
M10	0.00	-7.3e-4	-5.5e-4	-1.1e-3	-3.3e-4	-0.00	0.00	0.00	-9.3e-5	-9.1e-4
	1.00	0.01	0.00	0.00	0.17	0.00	1.00	1.00	0.00	0.00
M11	-1.3e-4	-6.3e-4	-4.7e-4	-5.6e-5	-5.0e-4	-0.00	0.00	0.00	-8.3e-4	-9.3e-4
	0.48	0.02	0.01	0.72	0.04	0.00	1.00	1.00	0.61	0.61
M12	-2.0e-4	-3.4e-4	-5.4e-4	-3.6e-4	-1.2e-4	-0.00	0.00	-3.6e-4	0.00	-0.00
	0.27	0.23	0.06	0.01	0.59	0.64	1.00	0.01	1.00	1.00

Table 4.23 is providing the results of monthly seasonality on VaR exceptions at 99% confidence interval by using historical simulation method. For Pakistan there is an indication of seasonal effect in January, March, June and September by Using historical simulation method. For Saudi Arabia, presence of seasonal anomalies is recorded in the months of March, April, May, June, September and October. United Arab Emirates is presenting that VaR exceptions are may be the results of anomalies exist in January, May, July, October, November and December. In Oman there are three months i.e. June for the reason of these deviation from the results.

For Turkey, the months that have exceptions are January, March, May, June and August, October and November. Iran is having month of April, May, August, October and November that indicates the seasonal pattern. For Malysia, January, May, August, September and December and for Indonesia, January, May, June, July, August, September and October are the months having seasonal variations. For Egypt there is the impact of seasonal variations in the month of January, May, August, and October. In Bangladesh only February shows significant results, so this country seems to have least impact of monthly seasonal variations on its estimated risk of stock returns as it is also proved by normal distribution method at 99% confidence interval.

4.9.3 Seasonal Behavior in VaR Exceptions on Daily Basis at 95% Confidence Interval

Table 4.24 is using normal distribution method and Table 4.25 is relying on historical simulation method and both are presenting the outcomes that may have seasonal variations on daily basis at 95 confidence level.

Table 4.24: Seasonality in daily VaR exceptions at 95% confidence interval by using normal distribution method.

	Pakistan	**Saudia**	**UAE**	**Oman**	**Turkey**	**Iran**	**Bangladesh**	**Malaysia**	**Indonesia**	**Egypt**
D1	-1.7e-3	-7.9e-3	-7.2e-4	-5.8e-4	-1.4e-3	-2.5e-4	-6.4e-5	-6.4e-4	-1.2e-3	-1.4e-3
	0.00	0.00	0.00	0.00	0.00	0.03	0.69	0.00	0.00	0.00
D2	-1.0e-3	-1.3e-3	-9.4e-4	-6.0e-4	-1.0e-3	-3.4e-4	-2.5e-5	-4.0e-4	-1.0e-3	-1.2e-3
	0.00	0.00	0.00	0.00	0.00	0.00	0.11	0.00	0.00	0.00
D3	-9.0e-4	-1.0e-3	-7.2e-4	-7.1e-4	-1.0e-3	-5.3e-4	-1.4e-4	-4.2e-4	-7.3e-4	-1.1e-4
	0.00	0.00	0.00	0.00	0.00	0.00	0.37	0.00	0.00	0.00
D4	-8.3e-4	-3.8e-4	-5.6e-4	-4.2e-4	-1.2e-3	-	-8.1e-4	-4.3e-4	-9.6e-4	-1.1e-3
	0.00	0.10	0.00	0.00	0.00		0.00	0.00	0.00	0.00
D5	-8.2e-4	-	-	-	-9.2e-4	-	-	-2.9e-4	-6.6e-4	-
	0.00				0.00			0.00	0.00	
D6	-	-1.8e-3	-1.0e-3	-	-	-3.6e-4	0.00	-	-	0.00
		0.00	0.00			0.00	1.00			1.00
D7	-	-1.0e-3	-1.0e-3	-5.4e-4	-	-8.2e-4	-8.0e-4	-	-	1.3e-4
		0.00	0.00	0.00		0.00	0.00			0.00

Table 4.25: Seasonality in dailly VaR exceptions at 95% confidence interval by using historical simulation method.

	Pakistan	Saudia	UAE	Oman	Turkey	Iran	Bangladesh	Malaysia	Indonesia	Egypt
D1	-1.7e-3	-8.1e-4	-7.2e-4	-6.7e-4	-1.5e-3	-3.4e-4	-1.1e-4	-6.5e-4	-1.2e-4	-1.3e-3
	0.00	0.00	0.00	0.00	0.00	0.00	0.47	0.00	0.00	0.00
D2	-1.0e-3	-1.2e-3	-1.0e-3	-7.0e-4	-1.1e-3	-3.9e-4	-3.2e-4	-4.0e-4	-9.7e-4	-1.2e-4
	0.00	0.00	0.00	0.00	0.00	0.00	0.06	0.00	0.00	0.00
D3	-7.9e-4	-9.4e-4	-7.7e-4	-7.8e-4	-1.1e-3	-4.7e-4	-1.9e-4	-4.0e-4	-8.0e-4	-1.1e-3
	0.00	0.00	0.00	0.00	0.00	0.00	0.23	0.00	0.00	0.00
D4	-7.3e-4	-4.2e-4	-6.0e-4	-4.3e-4	-1.1e-3	-	-8.7e-4	-4.9e-4	-8.7e-4	-1.2e-3
	0.00	0.08	0.00	0.00	0.00		0.00	0.00	0.00	0.00
D5	-8.4e-4	-	-	-	-8.8e-4	-	-	-2.7e-4	-9.8e-4	-
	0.00				0.00			0.01	0.00	
D6	-	-2.0e-3	-1.0e-3	-	-	-5.6e-4	0.00	-	-	0.00
		0.00	0.00			0.00	1.00			1.00
D7	-	-9.4e-4	-1.0e-3	-5.6e-4	-	-7.9e-4	-6.9e-4	-	-	-1.4e-4
		0.00	0.00	0.00		0.00	0.00			0.00

Sign(-) shows the public holiday of each country

Daily seasonal impact on VaR exceptions is estimated at 95% confidence in Table 4.24 by using normal distribution and in Table 4.25 by using historical simulation method and it is provided that this seasonal impact is present in almost each day except holidays of each country but for Bangladesh there is a different case where this impact is found only on Thursday and Sunday proved by both methods and for Egypt this impact is not present on Friday Only at 95% confidence interval.

4.9.4 Seasonal Behavior in Daily VaR Exceptions at 99% Confidence Interval

Normal distribution method is used in Table 4.26 and Table 4.27 use historical simulation method and both are conducted at 99% confidence interval to know the impact of daily seasonal variations on VaR exceptions. While considering Pakistan, Turkey, Malaysia and Indonesia, Saturday and Sunday are the Public Holidays so for other five days in Pakistan at 99% confidence level it is shown that all the five days of the week can affect the results of predicted VaR by using normal distribution and in historical simulation this effect is not present on Friday. By using normal distribution method in Turkey, Malaysia and Indonesia the seasonal behavior is followed by the outcomes shown in the Pakistan's scenario but by historical simulation method it is shown that Wednesday and Friday in Turkey, Tuesday, Thursday and Friday in Malaysia while Tuesday and Friday in Indonesia does not have seasonal anomalies and are the clear indication of not creating VaR exceptions.

Saudi Arabia, UAE and Egypt have weekend on Friday so by using normal distribution method, for other six working days it is estimated that at 99% confidence interval all the five days have VaR exceptions except Thursday in Saudi Arabia and Wednesday, Thursday by historical simulation method. While considering the outcomes for UAE it is stated that all the working days could be the cause of VaR exceptions except Saturday shown by normal distribution method and by using historical simulation method, Thursday and Saturday are indicating insignificant results. In Egypt by using both normal distribution and historical simulation method it is shown that in working days only Saturday may not cause any influence on the forecasted VaR results.

For Oman and Iran working days are from Saturday to Wednesday and the results for Oman by normal distribution it is shown that this seasonal behavior is not present only on Thursday but here historical simulation provides a quite different result where only Wednesday does not have seasonal behavior. For Iran, except Monday and Saturday other three working days having the seasonal variations result into deviation from the actual VaR forecasting by normal distribution and on Monday by historical simulation method.

Bangladesh is having a weekend on Friday and Saturday, results for this country at 99% confidence interval by using both normal distribution and historical simulation method just Sunday is to be considered as seasonal anomaly, so again from daily seasonality it appears that this country have the least impact of the seasonal variations.

Table 4.26: Seasonality in monthly VaR exceptions at 99% confidence interval by using normal distribution method.

	Pakistan	Saudia	UAE	Oman	Turkey	Iran	Bangladesh	Malaysia	Indonesia	Egypt
D1	-1.4e-3	-5.6e-4	-4.5e-4	-3.6e-4	-1.0e-3	-9.9e-5	-9.5e-4	-4.1e-4	-1.0e-4	-6.1e-4
	0.00	0.02	0.01	0.38	0.00	0.38	0.47	0.00	0.00	0.03
D2	-4.8e-4	-1.0e-3	-4.8e-4	-5.0e-4	-4.9e-4	-2.6e-4	-1.8e-4	-1.9e-4	-5.2e-4	-7.5e-4
	0.00	0.00	0.00	0.23	0.00	0.02	0.17	0.05	0.00	0.00
D3	-6.8e-4	-5.9e-4	-4.8e-4	-3.9e-4	-3.9e-4	-3.2e-4	-1.7e-4	-2.2e-4	-5.6e-4	-8.0e-5
	0.00	0.00	0.00	0.34	0.02	0.01	0.18	0.02	0.02	0.00
D4	-6.5e-4	-4.0e-4	-3.2e-4	-1.1e-3	-3.4e-4	-	-1.0e-4	-2.4e-4	-6.2e-4	-6.5e-4
	0.00	0.10	0.00	0.00	0.00		0.42	0.01	0.03	0.00
D5	-3.4e-4	-	-	-	-7.4e-4	-	-	-1.8e-4	-3.0e-4	-
	0.04				0.05			0.05	0.05	
D6	-	-1.7e-3	-3.3e-4	-	-	-3.2e-4	0.00	-	-	-0.00
		0.00	0.24			0.09	1.00			1.00
D7	-	-6.9e-4	-8.8e-4	-4.5e-4	-	-5.1e-4	-3.9e-4	-	-	-8.2e-4
		0.00	0.00	0.27		0.00	0.00			0.00

TABLE 4.27: Seasonality in daily VaR exceptions at 99% confidence interval by using historical simulation method.

	Pakistan	**Saudia**	**UAE**	**Oman**	**Turkey**	**Iran**	**Bangladesh**	**Malaysia**	**Indonesia**	**Egypt**
D1	-5.7e-4	-4.0e-4	-3.0e-4	-3.2e-4	-8.3e-4	-1.0e-4	-1.0e-4	-3.8e-4	-6.5e-4	-3.4e-4
	0.00	0.02	0.01	0.00	0.00	0.26	0.31	0.00	0.00	0.03
D2	-2.7e-4	-7.8e-4	-3.8e-4	-2.1e-4	-4.1e-4	-1.0e-4	0.00	-1.4e-4	-2.5e-4	-4.6e-4
	0.00	0.00	0.00	0.02	0.00	0.00	1.00	0.11	0.24	0.00
D3	-3.5e-4	-2.8e-4	-3.7e-4	-1.5e-4	-1.9e-4	-1.0e-4	0.00	-2.1e-4	-2.5e-4	-6.0e-4
	0.03	0.10	0.00	0.10	0.21	0.01	1.00	0.02	0.02	0.00
D4	-2.3e-4	-1.4e-4	-1.4e-4	-0.026	-4.0e-4	-	-1.1e-4	-1.4e-4	-2.4e-4	-3.6e-4
	0.04	0.56	0.22	0.00	0.00		0.28	0.13	0.03	0.02
D5	-1.5e-4	-	-	-	-2.0e-4	-	-	-4.6e-5	-2.1e-4	-
	0.21				0.19			0.62	0.08	
D6	-	-1.1e-3	-1.0e-4	-	-	-1.0e-4	0.00	-	-	-0.00
		0.00	0.68			0.00	1.00			1.00
D7	-	-4.9e-4	-5.2e-4	-0.025	-	-1.0e-4	-3.2e-4	-	-	-5.3e-4
		0.00	0.00	0.00		0.00	0.00			0.00

Chapter 5

Conclusion and Recommendations

5.1 Conclusion

Anomaly is a term relating an event where the forecasted or expected results differ from the actual results, so are the reason of violation from efficient market hypothesis (EMH). This seasonal behavior is vital to consider while forecasting the risk of the stock returns by using a technique namely Value at Risk which is a statistical technique used to quantity the amount of potential loss over a specified period of time that can arise in an investment portfolio. So, it provides the probability of losing more than expected amount in a given portfolio.

The objective of this study is finding out the element of seasonality in VaR and VaR exceptions and likewise in which specific day of the week or month of the year, VaR is increased or decreased. For this purpose, daily stock returns of ten Islamic countries i.e. Pakistan, Saudi Arabia, Iran, Oman, Turkey, UAE, Bangladesh, Egypt, Indonesia and Malaysia from January 2000 to June 2018 are used. For data analysis this study is divided into three stages i.e. VaR estimation, back testing of VaR and the third one is to find out the presence of seasonality in VaR and VaR exceptions.

In the first phase VaR has been estimated by using parametric assumption (normal distribution), non-parametric assumption (historical simulation) and time varying volatility models (EWMA and GARCH) at 95% and 99% confidence interval for all the ten countries. Turkey is declared as the highest risky stock under all the four assumptions at 95% and 99% confidence interval whereas Malaysia bears the lowest risk.

Second phase includes the selection of appropriate model for the risk estimation by using violation ratios, volatility, Kupeic-POF test, and Christoffersen's independence test. While considering violation ratio at 95% confidence level it is assumed that normal distribution method and time varying volatility models are better for the risk estimation however historical simulation is also in acceptable range at 95 and 99% confidence interval. By allowing volatility as a predictor of accurate model selection it is demonstrated that both at 95 and 99% confidence interval parametric and non-parametric assumptions are considered as least volatile and better to use for the risk estimation while time varying volatility models are considered as highly volatile so having market uncertainty.

To compare the observe violations with expected number of violations, the likelihood ratios of Kupeic test are used, at 95% confidence Interval For Pakistan, Bangladesh, Malaysia, Indonesia and Egypt all the four methods are representing that likelihood ratios are within range and can be used for the risk assessment. For other six countries there is a mix trend that different methods report diverse results for different countries so only one method cannot be considered best for forecasting in this case whereas at 99% confidence level historical simulation would be considered best for the risk estimation.

To measure volatility clustering, Christoffersen's independence test is used in this study and its results at 95% confidence interval are reporting that the values of likelihood ratios of Pakistan, Saudi Arabia, UAE, Oman, Turkey, Indonesia and Egypt are greater than 3.84 under all parametric, non-parametric and time varying volatility models which assumes that null hypothesis to be rejected so here is the evidence of clustering availability. At 99% confidence interval the results are quite different under all assumptions. Normal distribution reports that the likelihood ratios of Saudi Arabia, UAE, Oman, Iran, Malaysia, Indonesia and Egypt are greater than 6.64 which rejects the null hypothesis while this method supports the null hypothesis for Pakistan, Turkey and Bangladesh. Historical Simulation accounts for the presence of volatility clustering in Pakistan, Saudi Arabia, UAE, Oman, Iran and Egypt but for Turkey, Bangladesh, Malaysia and Indonesia there is no evidence of violation clustering. EWMA rejects the null hypothesis for Pakistan, Saudi Arabia, UAE, Oman, Egypt and Turkey and accepts it for Iran, Bangladesh, Malaysia and Indonesia. GARCH is representing that violation clustering is present in Pakistan, Oman and Egypt only.

The third and the central part of this study is to examine the impact of monthly and daily seasonal behavior on VaR and VaR exceptions for which regression equation is been run by using normal distribution and historical simulation method. Value of coefficient and level of significance is reported and it is observed that VaR and Seasonal behavior (daily and monthly) at both 95% and 99% confidence interval has negative significant relationship evidenced by both parametric and non-parametric assumptions. For each day of the week and for each month of the year there is a chance of seasonality in predicted VaR.

One of the most vital objective of this research was to examine that do VaR exceptions have seasonality. After generating VaR exceptions, Regression is run by using both normal distribution and historical simulation method and when there is 5% probability of loss there is a greater chance that seasonality affects the VaR and create VaR exceptions in almost all the days of the week except weekend of each country and have impact on at least ten or eleven months of the year for each country except VaR estimation of Malaysia where March, July, October, November and December are free from the seasonality impact and in Bangladesh there is chance of this effect during the starting 5 months of the year whereas there is no evidence of daily seasonality on VaR exceptions. By using both parametric and non-parametric assumptions it is provided that results are almost consistent and resembles with each other except in the case of Oman, where historical simulation method shows the different results as compare to normal distribution method for VaR exceptions.

Moreover, only with the 1% probability of loss it is concluded that there are chances of having seasonal behavior in VaR exceptions in two to three months for each country and in Bangladesh this seasonal behavior does not impact VaR exceptions on daily or monthly basis and Malaysia is not affected on daily basis but for other countries it is provided that daily seasonality is there in each country.

5.2 Recommendations

There are following three recommendations to be considered based on the current study.

1. Based on analysis and outcomes of this research it is recommended that at 95% and 99% confidence interval normal distribution and historical simulation both perform well and can be considered for risk estimation. Time varying volatility models may be considered as less reliable for VaR forecasting in case of stock returns of Islamic countries.

2. While forecasting VaR, the daily and monthly seasonality in stock markets is one of the most captivating problems in financial economics so this impact of seasonality must be considered as there is a clear indication of presence of daily and monthly seasonality on VaR. Likewise, VaR exceptions occur due to this seasonality impact not in consistent manner but in specific days and months for each country apart from Bangladesh and Malaysia where this impact is within acceptable range. So it raises a question mark for the accuracy of VaR models in those specific months and days of the week where these VaR exceptions occur.

3. VaR models are usually used with seasonal data, example of macroeconomics can be considered where most of the time series like unemployment and GDP of the countries are seasonal. Seasonality can be adjusted, either outside of the model i.e. before fitting a VAR model by seasonally adjusting the series or within the model by means of including seasonal dummy variables. Above all there are the evidences of VaR exceptions. So while considering

the seasonal behavior of the stock markets of Islamic countries it will be helpful to make investment decisions for both risk takers and the risk averse investors so they can adjust their profiles accordingly.

5.3 Limitations

This study focuses on value at risk (VaR) for risk estimation because of its huge practical relevance and now in financial risk management it is an industry standard because it used a simple concept and its computational or statistical implementation is straightforward relative to many other risk measures but VaR has some insufficiencies as the VaR does not encounter the loss in worst scenario i.e. at 99% it is ignoring 1% area which may be 3 to 4 trading days of the year. Furthermore, representativeness of VaR can be questioned as different methods of VaR may lead to different results accordingly different approaches can also lead to very different results with the same portfolio, that's why the uncertainty of VaR forecasts and their validation are important topics and this field still deserve more research in order to reach more conclusive results on the accuracy and performance of alternative procedures.

Extreme Value Theory can be used here and to cope up with the seasonality problem, Quasi-Vector autoregressive Models can be used (Blazsek; Escribano and Licht, 2018). This study deals with the seasonality impact on stock returns of Islamic countries only but it can be tested for other stock indices of the world as well as this impact can be tested on risk estimation of interest rates, exchange rates, different commodity prices and seasonal fluctuations can be brought into an account.

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