CAPITAL UNIVERSITY OF SCIENCE AND TECHNOLOGY, ISLAMABAD

Risk Forecasting in The Stock Markets of Islamic Countries

by

Zoha Khalid

A thesis submitted in partial fulfillment for the degree of Master of Science

in the

Faculty of Management & Social Sciences
Department of Management Sciences

2023

To My Beloved Parents and Teachers

CERTIFICATE OF APPROVAL

Risk Forecasting in The Stock Markets Of Islamic Countries

by

Zoha Khalid

(MMS203016)

THESIS EXAMINING COMMITTEE

S. No.	Examiner	Name	Organization
(a)	External Examiner	Dr. Sumayya Chughtai	IIU, Islamabad
(b)	Internal Examiner	Dr. Imran Riaz Malik	CUST, Islamabad
(c)	Supervisor	Dr. Arshad Hassan	CUST, Islamabad

Dr. Arshad Hassan
Thesis Supervisor
April, 2023

Dr. Lakhi Muhammad
Head
Dept. of Management Sciences
April, 2023

Dr. Arshad Hassan
Dean
Faculty of Management & Social Sci.
April, 2023

Author's Declaration

I, **Zoha Khalid** hereby state that my MS thesis titled "**Risk Forecasting in The Stock Markets of Islamic Countries**" is my own work and has not been submitted previously by me for taking any degree from Capital University of Science and Technology, Islamabad or anywhere else in the country/abroad.

At any time if my statement is found to be incorrect even after my graduation, the University has the right to withdraw my MS Degree.

(Zoha Khalid)

Registration No:MMS203016

Plagiarism Undertaking

I solemnly declare that research work presented in this thesis titled "**Risk Forecasting in The Stock Markets of Islamic Countries**" is solely my research work with no significant contribution from any other person. Small contribution/help wherever taken has been duly acknowledged and that complete thesis has been written by me.

I understand the zero tolerance policy of the HEC and Capital University of Science and Technology towards plagiarism. Therefore, I as an author of the above titled thesis declare that no portion of my thesis has been plagiarized and any material used as reference is properly referred/cited.

I undertake that if I am found guilty of any formal plagiarism in the above titled thesis even after award of MS Degree, the University reserves the right to withdraw/revoke my MS degree and that HEC and the University have the right to publish my name on the HEC/University website on which names of students are placed who submitted plagiarized work.

(Zoha Khalid)

Registration No:MMS203016

Acknowledgement

In the Name of Allah, The Most Gracious, The Most Merciful. . .
Praise be to God, the Cherisher and Sustainer of the worlds. All thanks to Almighty Allah, The Lord of all that exist, who bestowed me with His greatest blessing i.e. knowledge and Wisdom to accomplish my task successfully. Thousands of salutations and benedictions to the Holy Prophet Hazrat Muhammad PBUH the chosen-through by whom grace the sacred Quran was descended from the Highest. I would like to thank the following: Dr. Arshad Hassan, my supervisor, for his encouragement, patience and expert advice and finally thanks to my friends and family who have supported me throughout this project.

(Zoha Khalid)

Abstract

This study estimates the stock market volatility of ten Islamic countries from MENA region and South Asia and measures the market risk using Value at Risk using daily indices for the period January 1st, 2002 to 29th May 2022. Value at Risk (VaR) is estimated with the help of generalized autoregressive conditional heteroskedasticity (GARCH) models, which are used for volatility modelling. Both symmetrical and asymmetrical GARCH models (EGARCH, PGARCH, QGARCH and TGARCH) are used for estimating VaR. The analysis exhibits that the volatility shocks are quite persistent in all stock markets. The VaR violations, Christoffersen's tests, and Kupiec test are used for back testing as these tests assess the reliability and correctness of the volatility model employed. This research provides further evidence that asymmetric time-varying GARCH models are superior than symmetric GARCH models for accurately predicting stock market volatility. It demonstrates that adverse news has a greater impact on stock price volatility then the positive news of same quantum therefore, giving clear indication of the presence of the leverage effect in the return's series.

Keywords: Symmetrical GARCH models, Asymmetrical GARCH models, Value at Risk, Volatility, Leverage effect, Risk Forecasting, Back testing

Contents

List of Figures

List of Tables

Abbreviations

DFM	Dubai Financial Market
EGX 30	Egyptian Stock Exchange 30 Index
EGARCH	Exponential Generalized Autoregressive Conditional Heteroskedasticity
GARCH	Generalized Autoregressive Conditional Heteroskedasticity
JKSE	Jakarta Stock Exchange
KLCI	Kuala Lumpur Composite Index
KSE 100	Karachi Stock Exchange 100 Index
MASI	Moroccan All Shares Index
PGARCH	Power Generalized Autoregressive Conditional Heteroskedasticity
QGARCH	Quadratic Generalized Autoregressive Conditional Heteroskedasticity
TASI	Tadawul All Share
TGARCH	Threshold Generalized Autoregressive Conditional Heteroskedasticity

Chapter 1

Introduction

1.1 Background of the Study

In recent decades, there has been an exceptional boost in the activities of financial markets as a result of globalization. Investing entails risk, and in order to earn a profit, some level of risk must be accepted. The mitigation of this risk is always at the core of a successful investing plan. Get this correctly, and the rest will fall into place automatically.

The most important need of an investment strategy is that the risk being taken is truly understood; that the hazards are quantified and assessed before any choice is made. That's why risk is one of the foremost analyzed and studied concerns, largely as a consequence of the market's frequent crises. Capital Markets, financial institutions and companies have always been prone to financial risk. Nevertheless, it is not until the 1970s that the financial sector adopted a number of risk-mitigation strategies to overcome the dangers of the financial market.

Financial markets of Islamic world remain undeveloped even after a financial influence on Sovereign Wealth Funds (SWF). Unfortunately, Stock markets in Muslim countries are small in comparison to global standards (Rizvi et al., 2014). Researchers are concerned about the effectiveness and risk of the equity markets in Muslim countries. Some studies that previously focus on Capital Market of Islamic countries includes "Movements of Islamic Stock Indices in Selected OIC Countries" (Nurrachmi, 2018). Due to the increased demand for oil, the economy of Oman is expected to grow by 3.3%, and the Kingdom of Saudi Arabia's effort to become a tech hub is anticipating a growth of 7.4% in 2022.

Moreover, Qatar hosted FIFA World Cup 2022, and developmental and economic projects in UAE are aiming to accelerate their respective economic growths (Patton, 2022). Keeping in view these growth opportunities MENA countries are expecting FDIs which will ultimately have a role to play in the economic development in the region.

To have a strong, and sustainable stock market it is important to identify the magnitude of the risk and mitigate it. With the flow of money, there will be an increase in the number of trading financial assets in Islamic Countries, therefore, measuring market risk is expected to be a concern for regulators and internal risk managers.

Market risk is the risk that financial institutions or economies face losses as a result of adverse market movements. However, Volatility is essential to the functioning of financial markets. It is considered as a barometer of uncertainty surrounding investment in financial assets (Fakhfekh et al., 2021).

Variation in financial markets over time results in volatility. The greater the fluctuations in the returns of an investment, the greater the underlying market risk. This risk applies to the entire global financial market, including stock prices, option prices, capital market debentures, agricultural commodity prices, foreign currency quotations, government securities, money market assets, and credit market interest. Value-at-risk (VaR) is a standard for assessing market risk in academics and business as per the Basel II Accord. Currently, the most prevalent methodology for evaluating the market risk is Value-at-Risk (Gaio et al., 2018). It is developed in the 1990s by J. P. Morgan Bank and became a worldwide benchmark for risk estimation.

1.2 Theoretical Background

Concerns about financial risk have been growing on a global scale. Countries and Companies belonging to all sizes and sectors are attempting to establish sophisticated financial risk management frameworks that meet compliance requirements, contribute to better decision making, and improve performance in the environment.

The effects of terrorist events on September 11, 2001, the invasions of Iraq and Afghanistan, the Palestinian dilemma, financial crisis 2008, COVID- 19, & 2020 Stock Market crash (Black Monday & Black Thursday) have left Islamic Countries in an economic turmoil. The structural framework of equity markets of Islamic countries suffers largely from geopolitical risk, governance issues, transparency, lack of implementation of rules and regulations, weak economic and administrative policies and in some regions from war shocks too making them highly volatile. It is important for market participants such as portfolio managers and risk managers to respond in accordance with the changing times, as an attempt for adjusting to the new settings in which they find themselves currently. Stock indices of Islamic countries have to put up with complicated adjustments against the context of challenging and volatile market circumstances. So, it is important for their respective Capital Markets to compute financial risk in order to enforce adequate safeguards for staying protected from any economic downfall.

Hence, when it comes to estimating underlying loses, the value-at-risk (VaR) technique has been one of the most popular approaches since it allows for the ease of application of an assessment of maximum losses at a given level of confidence aiming to quantify market risks. According to McNeil and Frey (2000), it is a financial statistic that quantifies the volatility or risk associated to a financial institutions or asset portfolios.

The likelihood of losing more than a certain amount in a portfolio is expressed as Value at Risk. In general, the most prevalent ways for evaluating VaR in recent years has been to three; firstly, non-parametric historical volatility with quantiles, secondly parametric variance-covariance method and finally, Extreme value theory-based model.

Recently, academia and market participants have put greater emphasis on Value at Risk (VaR) when examining market risk. According to the International Monetary Fund (IMF), the 2008 financial crisis cost the world's top financial institutions a total of $3.4 trillion (Dattels, 2009). Since the 1930s, there has been a massive economic deterioration. In the event of Black Monday, the global stock market fell in a matter of minutes which shows that it is very important to keep a plan ready to mitigate risk. Being the primary quantitative indicator of market risk, VaR aims to quantify the risk of unanticipated changes in prices or the log-return rate over a certain time period.

It is a relatively straightforward and widely used method of calculating market volatility. The value at risk (VaR) is a measurement of the level of risk that an organisation is subjected to within the context of the financial market. As such, one of the benefits of VaR is that it is a concretely comprehensible statistic. Although the expression "Value at Risk" did not enter the lexicon of financial language until the early 1990s, its roots stretch back far further in time. In point of fact, one may argue that the word originates from the need for US businesses to ensure the security of their capital around the turn of the twentieth century, beginning with the application of the informal capital test.

Markowitz's theory of portfolio is where value at risk (VaR) got its start. To be more specific, the approach that underpins the VaR is the product of the integration of contemporary portfolio theory and statistical analysis, both of which investigate various risk variables. VaR has become a crucial component of any professional corporate risk management due to the fact that it provides a number that summarizes a company's and also a stock index's total market risk. It serves as a critical step in apprehending adequate volatility over time, however estimating variance can also be difficult due to the sensitivity of volatility to dynamic economic structures.

Badaye and Narsoo (2020) explains that VaR and Expected shortfall models constructed for a portfolio of financial assets are focused on capturing the fluctuations of the underlying assets and also model the dependence structure between them, which can prove to be a major challenge for researchers.

Volatility affecting returns is often quantified employing conditional variance models. To analyze a series' conditional mean and variance independently at the same time, Engle (1982)proposed the ARCH model. Because of the challenge in projecting the error term in the model and the need for numerous parameters in ARCH models, Bollerslev (1986) proposed a variety of more sophisticated GARCH techniques for modeling the conditional variance. These advanced models attempt to better capture the empirically observed stylized facts of the conditional variance process. Due to their autocorrelated structure and the fact that ARCH and GARCH models respond symmetrically to shocks on volatility as well as the broad distributional characteristic of financial data, reliable outcomes could no longer be acquired from research based on these models.

To address these issues, academics have created a variety of variance models. Since the EGARCH model, proposed by Nelson (1991), is more sensitive to big news, it has a distinct influence on volatility whether there is good or negative news. In addition there are more variants of GARCH model which capture the effects of both positive and negative shocks on volatility such as The Quadratic GARCH (QGARCH) model by Sentana (1995), the NGARCH model (Higgins and Bera, 1992) and the TGARCH model (Zakoian, 1994). More generalized parameterizations, like the APARCH model (Ding et al., 1993) and the HGARCH model (Hentschel, 1995), nest a variety of simpler GARCH models.

Ederington and Guan (2005) found that GARCH(1,1) generally yields better forecasts than the historical standard deviation and exponentially weighted moving average models, though between GARCH and EGARCH there is no clear favorite. In the studies of Bali et al. (2008), EGARCH outperform GARCH and TGARCH in providing most accurate forecasts of the future realized volatility.

1.3 Gap Analysis

There are crucial policy and financial ramifications for understanding risk forecasting in the equity markets of Islamic Countries. However, there is a research gap in the area of risk forecasting in on Islamic Countries. While there is a wealth of literature on forecasting the volatility of stock markets across the world, less attention has been paid to the special considerations that may affect volatility in Muslim countries. Equity investment risk and return are affected by Shariah-compliant investing procedures which includes prohibition of riba hence minimizing the dependence of these equity markets on leverage. As a result, further study is required to comprehend the dynamics of risk forecasting in the equity markets of Muslim Countries and to create efficient risk management solutions for investors in these markets. This study examines market behavior and extreme variations which explain risk measures hence computing the tail of conditional distribution of the heteroscedastic financial series.

1.4 Problem Statement

Islamic countries have always struggled with their political and economic conditions resulting in having riskier economies which ultimately impact their stock markets. Nevertheless, MENA region is also one that has witnessed a significant financial development and the countries are welcoming foreign direct investment. So, it is important to study the market risk to which these stock indices are exposed to with a focus on mitigating these risks beforehand. In this case VAR is computed using parametric approach to find out which one works best for each index.

Furthermore, unpredictability in VaR forecasting and their confirmation are key fields that still need considerable analysis in order to provide further solid conclusions on the behavior of different approaches.

1.5 Research Questions

This research will answer the following questions:

Research Question 1

Which GARCH model is most appropriate for forecasting the Stock Market volatility of Islamic Countries?

Research Question 2

Are GARCH models good risk measures in the times of international financial crisis?

Research Question 3

What is the predictive capacity of various GARCH model for forecasting risk in Stock Markets of Islamic Countries?

1.6 Objectives of the Study

Objectives of the study are as follows:

Research objective 1

To forecast risk for Stock markets of Islamic Countries using GARCH Model.

Research objective 2

To evaluate various GARCH models for forecasting market risk in Islamic Countries.

Research objective 3

To prepare appropriate model for forecasting market risk in Islamic Countries.

1.7 Hypothesis of the Study

Ho : *GARCH models are not appropriate for risk forecasting in equity markets of Islamic Countries.*

H1: *GARCH models are appropriate for risk forecasting in equity markets of Islamic Countries.*

1.8 Significance of the Study

The Basel III accord is a collection of international banking regulations guidelines designed to increase the sustainability of the world banking system. While the Basel III agreement is primarily concerned with regulating banks and other financial institutions, there has been an increasing demand for the equity markets to be subject to comparable rules.

The fact that equity markets have systemic risks to the financial system is one of the key justifications for implementing Basel III restrictions on these markets. For instance, market players that use too much leverage and take on too much risk may experience market collapses and economic instability. To reduce systemic risks in stock markets, this might entail establishing minimum capital levels, leverage ratios, and other prudential restrictions. Similarly, stock markets of Islamic

Countries face risk which can be evaluated Using the GARCH models which can further lead to imposing minimum capital requirements based on their respective risk exposure in order to support these markets in times of financial and economic crisis.

GRACH models can forecast future economic patterns more precisely and aid in spotting economic risks and exposures. Moreover, GRACH models can assist analysts and policymakers in determining the elements that contribute to economic growth and in evaluating the possible effects of external shocks or changes in policy.

Two of the most important goals of risk management are as follows:

i. To keep improving the economy's overall financial performance

ii. To make certain that the economies do not face losses that are too high.

Therefore, this study aims to examine risk in the stock indices of Islamic countries and to suggest the model that works best for these markets.

Moreover, since precise volatility modeling is critical for risk management, the study also focuses on the ability of models to accurately predict VaR at different levels of confidence.

1.9 Plan of the Study

There are five major sections to this research. Each of the first three chapters discuss the theoretical context of the current topic at hand, the latter two chapters investigate the factual aspects of the study.

Chapter 1:

It lays forth the study's basic idea. The background information, explanation of the issue, gap analysis, research questions, objectives, and importance of this study are all presented in this section.

Chapter 2:

It presents a comprehensive analysis of the subject, including both theoretical and empirical reasons based on previous studies.

Chapter 3:

This chapter goes over the different methods used for the computation of Value at Risk.

Chapter 4:

It discusses the results of the empirical research and provide further details on the findings. Findings are vetted using back-testing methods based on the aims of the thesis.

Chapter 5:

In this chapter, the findings of the study are reviewed and provide recommendations for various risk forecasting models depending on the state of the markets.

Chapter 2

Literature Review

2.1 Literature Review

Understanding market volatility has become even more crucial in the aftermath of the turmoil such 2007–2008 financial crisis & COVID-19 Pandemic. Volatility models, specifically volatility forecasting, have become increasingly important as asset classes, and markets have become more uncertain. In the valuation of any asset where the magnitude and riskiness of future returns are of concern, for example, in option pricing, investment strategy, portfolio management, hedging and risk management and policymaking, volatility has attracted considerable attention from investors, researchers, regulators, portfolio managers and other stakeholders. It is very important for portfolio and risk managers to forecast risk in order to construct and implement a risk management process for securing investments. The current risks are analysed for identifying potential risks to perform a risk assessment and evaluation for building an effective risk management strategy. Risk forecasting helps them in spreading risk awareness amongst investors so that they can invest based on their risk preferences. Portfolio and risk managers respond to financial market fluctuations in a timely manner keeping in view the forecasts. With the assistance of volatility models, risk managers can create risk maps for all investment risk exposures based on forecasted frequency and severity so that they can seize the opportunity of maximizing profits by mitigating those risks.
According to Markowitz (1952) portfolio, the framework of return dependency

among financial assets has played a key role in the development of investment strategies, the domain of finance theory, which is very important in the context of diversification and risk minimization. Furthermore. Mandelbrot (1963) studies that significant changes in asset values are followed by huge changes, whereas tiny movements are followed by those little movements.

For the mitigation and computation of risk, Value at risk (VaR) is considered to be a basic risk indicator which calculates the maximum loss that might incur with respect to times over the next 'k' trading days given a certain confidence level. As a percentile rank of the profit/loss distribution, potential losses are represented by VAR, although they may also be regarded to as positive numbers (Danielsson, 2011). As mentioned in Market Risk Analysis, Quantitative Methods in Finance by Alexander (2008).

The variance-covariance, historical simulation, and Monte Carlo methods, all of which are centered mostly on construction of a weighted sum of an investment portfolio and the peripheral allocation of each of the investments which construct it, are some of the approaches for estimating VaR.

Najand (2002) conducted his study on Forecasting Stock Index Futures Price Volatility. The results show that the autoregressive model is shown to be the strongest linear model of stock index futures volatility depending on the RMSE and MAPE criteria. GARCH-M, EGARCH, and ESTAR are applied on the data set comprising of daily closing prices of S&P 500 futures index from January 1983 to December 1996. EGARCH seems to be the best model for forecasting stock index futures price volatility, as contrasted to linear models employing RMSE and MAPE error statistics.

Franses and Van Dijk (1996) look at how well the GARCH model and its two extensions are predicting the weekly volatility of the stock market. The QGARCH model and the GJR- GARCH have been proposed to explain things like the negative skewness that is often seen in stock market returns. It is found that the QGARCH model performs better when the forecasting sample doesn't include extreme events like the 1987 stock market crash. Awartani and Corradi (2005) examine the out-of-sample predictive power of several GARCH models, with a focus on the asymmetric component's predictive content. As per their results, the

GARCH model works much better when the market stands consistent, whereas EGARCH and TGARCH work better at explaining volatility whenever the market is volatile and information is asymmetric.

Estimation of Value at Risk (VaR) is the subject of a research conducted by So and Philip (2006), which examines seven GARCH models, namely Risk Metrics and two long memory GARCH models. There is consideration given to both long and short positions of investment. In order to evaluate the accuracy of each of the seven models in calculating VaR at a variety of confidence levels, the models are applied to a total of 12 market indexes and four different exchange rates.

According to the findings, both stationary and fractionally integrated GARCH models perform better than Risk Metrics when it comes to calculating the 1% value at risk. It is more crucial to consider a model with fat-tailed error when calculating VaR, despite the fact that the majority of return series exhibit a fat-tailed distribution and are consistent with the long memory feature. Asymmetric behaviour is also identified in the stock market data, which shows that t-error models produce better 1% VaR estimates than normal-error models. This difference is only shown in the long position. The statistics on the exchange rate do not reveal any disparity of this kind.

Girard and Biswas (2007) indicated that asymmetric GARCH models perform better in the estimation of stock market volatility. The study used both TARCH and exponential GARCH (EGARCH) to study volume-volatility relationship present in data set of 49 equity markets (22 developed and 27 emerging markets) from January 1, 1985 to June 30, 2005).

In another study by Alberg et al. (2008) various GARCH models are used to conduct an extensive exploratory examination of the mean return and conditional variance of Tel Aviv Stock Exchange (TASE). These conditional shifting variance models are compared to contemporary asymmetric GJR and APARCH models in terms of their ability to forecast.

To better estimate conditional variance, the study used an asymmetric GRC model with fat-tailed density distributions. Student-t distribution EGARCH strategy is ideal for TASE index forecasting, according to this study. Daily stock price fluctuations at the Khartoum Stock Exchange (KSE) are investigated by Ahmed and

Suliman (2011). The research used both symmetric and asymmetric GARCH models, with the latter providing much more accurate volatility estimates. The findings confirm the positive correlation hypothesis between volatility and predicted stock returns, and they also reveal that the conditional variance process is very persistent (explosive).

In addition, it is concluded that that the asymmetric models better explain the data than the symmetric ones do, providing more evidence of the existence of the leverage effect. These findings provide a comprehensive rationale for the significant volatility of index return series seen in the Sudanese stock market over the time of analysis and KSE stock returns are quite volatile.

Harrison and Moore (2011) conducted a study on forecasting Stock Market Volatility in Central and Eastern European Countries. The study examined the stock market volatility forecasting abilities of many well-known model variations. The findings of this study confirm that GARCH type models outperform alternative popular forecasting techniques. CEE markets have been shown to be more volatile than other developed markets, therefore if volatility can be foreseen, it may be able to predict return behavior. It is evident that integration of asymmetry into long-term volatility models significantly enhances their forecasting abilities.

Using the daily closing prices of the S&P CNX Nifty Index from 2003 to 2012, Banumathy and Azhagaiah (2015) also model the volatility of the Indian stock market. Analysis of volatility based on GARCH variants show that the GARCH (1,1) and TGARCH (1,1) models are among the most appropriate ones to use when attempting to forecast symmetrical as well as asymmetrical stock volatility.

Gupta and Guidi (2012) predict the volatility of the stock markets of the ASEAN-5 countries, which are the five original members of the Association of South-East Asian Nations. The analysis uses Asymmetric-PARCH (APARCH) models under two different statistical distributions (Student-t and GED) to determine if an asymmetric effect captures the relation between stock return and volatility in the ASEAN-5 markets and, if so, under which distribution these models perform best. We use a number of different measures of forecast error to demonstrate that t-distributed APARCH models are superior in most cases. All stock markets examined in this study are found to have asymmetric effects, with the largest leverage effects occurring in the more liquid stock markets. Finally, volatility asymmetry measure demonstrated that, on average, the Indonesian stock market has the largest reaction of volatility to a negative shock, outperforming the other ASEAN-5 stock markets by a wide margin.

Ezzat (2012) examine the volatility of daily returns mostly on Egyptian Exchange throughout the sociopolitical crisis that began in 2011. Both the GARCH and EGARCH models are used in the study. The investigation used daily close prices of four indices from the Egyptian stock market: the EGX 30, EGX70, EGX100, and EGX20 caps. The period include index inceptions through June 30, 2012.

The sample period includes both before and after the Egyptian revolution, when stock prices saw wild swings. To look into the long memory and leverage effect with in high volatility of the two time periods, the EGARCH model has been an appropriate model to forecast volatility. The results show that the standard deviations of daily returns are higher mostly during revolution period across all indices, with the EGX 70 showing the highest volatility.

Within the context of the Egyptian Stock Exchange, Ezzat (2013), conducted another study to investigate sector-specific volatility to learn how various industries react to volatility shocks. Firms are categorized into 12 subsectors for the purposes of the Egyptian Exchange indexes.

GARCH, EGARCH, and TGARCH are used to investigate the temporal volatility dynamics of various sectors. For each industry, the researchers look at stylized facts like the clustering of volatility, the long memory, and the leverage impact. Based on the results, TGARCH can be considered the best option because it successfully specifies all sector indices for high volatility time periods.

Both the Khartoum Stock Exchange (KSE) in Sudan and Cairo and Alexandria Stock Exchange, CASE in Egypt have been studied and assessed by Ahmed and Suliman (2011) for stock market volatility. Daily closing prices on the general indexes in both markets from January 2nd, 2006 to November 30th, 2010, are used for the study. The GARCH model, both symmetric and asymmetric (GARCH-M (1,1), EGARCH (1,1), TGARCH (1,1) and PGARCH (1,1)) is used in this study. For the KSE index returns series, conditional variance (volatility) is an intense phenomenon, whereas for the CASE index returns series, it is relatively persistent. Based on the data it is concluded that the volatility of the CASE index returns series is very stable over time, whereas the volatility of the KSE index returns series is an explosive process.

In addition, the findings corroborate the presence of a positive risk premium in both markets, lending credence to the idea that volatility is positively correlated with predicted stock returns. There is also evidence that the stock returns in the two markets are asymmetric, indicating that there is a strong influence of leverage in the return's series.

Furthermore, Degiannakis et al. (2013) analyze the returns of twenty of the most prominent stock market indexes and discovers evidence that a longer memory may not always lead to an increase in VaR projections. This is the case despite the fact that there is evidence of persistence in the volatility process.

Using daily data of indices from January 1999 to May 2010, Tripathy and Garg (2013) applies ARCH, GARCH, GARCH-M, EGARCH, and TGARCH models to predict the volatility of stock markets in six developing nations. The data demonstrates that volatility shocks are widely replicated across stock markets worldwide. Corroboration of asymmetry in stock returns is discovered by the asymmetric GARCH models for all six stock markets. The results of this investigation corroborate the existence of a leveraging effect in the returns series and show that negative news has a greater influence on the volatility of stock prices. The findings show that negative shocks in stock returns are associated with a greater rise in volatility. Using data from the Malaysian stock market, Lim and Sek (2013) conducted a study to predict its volatility. The volatility is studied using GARCH type models (symmetric and asymmetric GARCH). Data from January 1990 to the end of 2010 is used to conduct the study. As per findings, for the normal period (pre- and post-crisis), symmetric GARCH model (ARCH & GARCH) perform better than the asymmetric GARCH (EGARCH, TGARCH, PGARCH) but for fluctuation period (crisis period), asymmetric GARCH model is preferred. The study show that the Malaysian stock market's volatility is majorly influenced by exchange rate and crude oil prices. AbdElaal (2011) also studies how well five models can predict the volatile returns of the Egyptian stock market. As our in-sample time frame, we select the time span beginning on January 1, 1998 and ending on December 31, 2009. EWMA, ARCH, GARCH, GJR, and EGARCH are some of the competing models. To further verify the efficacy of the GARCH family in predicting market index volatility, we also look at the ARCH effect. The empirical findings confirm that, when compared to the other models we considered, EGARCH performs the best. For both the EGX30 and CIBC100 indices, the results reject the null hypothesis of a homoscedastic normal process.

An article by Okpara (2015) , calculate the VaR of the model variations by applying conventional GARCH, EGARCH, and TARCH models using the day of the week return series data from the Nigerian Stock market, which include a total of 246 days of data. To estimate the models, normal, student t is used, and generalised error distributions.

This allowed the researcher to take into account an asymmetric return distribution as well as the fat-tail phenomena that occurs in financial time series.As per the findings of the research that made use of the Akaike Information Criterion, it would appear that the EGARCH model that employs student t innovation distribution can be capable of generating a more accurate estimate of VaR than any of the other models. In light of this, the likelihood ratio tests of proportional failure rates is used to the VaR produced from the EGARCH model in order to estimate the short and long positions' performances regarding the VaR.

Bentes (2015) and Elenjical et al. (2016) provide fresh explanations for taking into consideration long memory qualities when modelling the unpredictability of financial market conditions. The first method uses a variety of GARCH models to anticipate the volatility of the gold return, and the results show that the extended memory FIGARCH performs much better than its rivals. As a consequence of this, the development of extended memory models could be able to improve empirical applications such as VaR even after the financial crisis.

The research work, by Ogege (2016), uses monthly stock indices from January 2003 through December 2014 to analyse the characteristics of stock returns on the Nigerian Stock Exchange (NSE). Compelling evidence for volatility clusters in the NSE return series and volatility persistent for the Nigeria stock returns data is found in the study that employed the GARCH (1,1) model to examine stock returns.

Nieto and Ruiz (2016) examine the predictive capacity of a VaR computed using different variants of GARCH Model. Surprisingly, the research reveale that predicting outcomes is impacted not only by the quantity of out-of-sample data but also by the time range that is investigated as a whole. They came to the conclusion that there is no one model that is superior to the others in any given scenario. In fact, the asymmetric EGARCH-based model is the only model that is able to pass the various tests that are performed on models.

During the time period of 2001-2015, Tamilselvan and Vali (2016) project the volatility of the stock market by employing four (4) indices derived from the Muscat security market. The GARCH, EGARCH, and TGARCH models are used in the research, and the findings indicated that there is a positive correlation between risk and return. In particular, the data showed that GARCH models indicate significant proof of an asymmetrical relationship between return shocks and variance changes across all four indices.

Using implied volatility forecasts for stock index return volatility, Kambouroudis et al. (2016) examine the input data using several autoregressive models. The study investigates whether forecasts of implied volatility are able to provide additional information about future volatility. S&P Composite 500 (S&P500), Dow Jones Industrial Average (DJIA), and Nasdaq100 closing prices, as well as their implied volatility indices (VXD and VXN), make up the vast majority of the data. There is a significant link between implied volatility and index returns, as shown by the results of this study.

In summary it can be concluded that an asymmetric GARCH Model combined with implied and realized volatility by (asymmetric) ARMA model is a better model for volatility forecasting. An article by Vasudevan and Vetrivel (2016) utilizes daily data starting on July 1, 1997, and ending on December 31, 2015, in an effort to model and predict the volatility of the BSE-SENSEX Index returns of the Indian stock market.

Both the symmetric GARCH (1,1) model and asymmetrical GARCH models (Exponential GARCH (1,1) and Threshold GARCH (1,1) models) are considered in this analysis. Out-of-sample predictions and most evaluation metrics reveal that the asymmetric GARCH models outperform the symmetric GARCH model in predicting the conditional distribution of the BSE-SENSEX returns, hence establishing the existence of the leverage effect. As per findings asymmetric GARCH models are superior than the parsimonious symmetric GARCH models in predicting the conditional variance of Indian stock market returns.

Dana (2016) studies Amman Stock Exchange and the purpose of research is to investigate the volatility features on Jordan's capital market, which include clustered volatility, leptokurtosis, and the leverage impact. The research is based on picking symmetric and asymmetric models from the GARCH family of models. It employs ARCH, GARCH, and EGARCH to explore the behaviour of stock return volatility for the Amman Stock Exchange (ASE) from January 1, 2005 to December 31, 2014. The major findings indicate that symmetric ARCH/GARCH models may capture ASE features and give better evidence for both volatility clustering and leptokurtic, however EGARCH output provides little support for the presence of leverage impact in Amman Stock Exchange stock returns.

Using daily data starting on September 17, 2007, and ending on December 30, 2016, Susruth (2017) predict and estimate the volatility of returns on the S&P BSE 500 Index of the Indian stock market. The volatility of stock returns in the Indian stock market is analysed using the GARCH, EGARCH, and GARCH-M models. Clustering volatility, the leverage impact, and the risk premium are just some of the aspects of stock market volatility that this research hopes to shed light on. This paper demonstrates that volatility clustering occurs on the Indian stock market, and that GARCH-type models are superior to more basic measures of volatility such as historical averages, moving averages, and so on for predicting market volatility. Using GARCH family models, this research projects volatility over a 200-day horizon.

The research finds that the Indian stock market display characteristics such as volatility clustering, indications of asymmetric as well as leverage effect on volatility, and the absence of a risk premium. Lin (2018) uses GARCH type models to undertake an analysis of the Shanghai Stock Exchange Composite Index volatility, figuring out the index's properties from an econometric viewpoint. The analysis reveals that the SSE Composite Index has considerable time-varying and clustering properties from the standpoint of time series.

A leptokurtosis with considerable ARCH and GARCH effects can be seen in the series distribution of this data set. It can be claimed that EGARCH (1, 1) outperforms GARCH (1, 1) (symmetric) as well as TARCH (1, 1) (asymmetric) when it comes to fitting and forecasting performance. The study recommends that China's financial markets must also reinforce its system architecture, limit unnecessary government intrusion, and encourage rational investing attitude.

Mutaju and Pastory (2019) using daily closing stock price indices from the Dar es Salaam Stock Exchange (DSE) between January 2, 2012 and November 22, 2018, conducted a study to replicate the volatility of stock returns.All symmetrical and asymmetrical Generalised auto regressive Heteroskedastic model (GARCH) techniques are used in the modelling, including GARCH (1,1), E-GARCH (1,1), and P-GARCH (1,1). . The findings show that each of the three models has a high predictive potential for forecasting the stock's volatile returns on the DSE.

Furthermore, GARCH (1,1) and P-GARCH (1,1) reveal that when there is good news, the strength of shocks in volatility is larger than when there is negative news. These are demonstrated to be the fact. The EGARCH model (1,1) showed evidence of a leverage effect related to stock returns. This impact may be detrimental to trading companies' capital structures. P-GARCH (1,1) is discovered to be more precise than when seemed to anticipate stock return volatility.

Sobreira and Louro (2020) studies data from multiple Euronext Lisbon stock exchange-traded equities to conduct a forecasting competition between several approaches for estimating Value-at-Risk (VaR) and Expected Shortfall (ES). As per the results, VaR and ES forecasting are superior for the asymmetric GARCH class with Extreme Value Theory, particularly for more conservative coverage levels. The GJR-GARCH is still favored over models without asymmetric effects, but by a lesser margin, the data demonstrate that the EGARCH accumulates the majority of preferences. A research by Shaik and Syed (2019) analyze the Tadawul All Share Index in order to investigate the patterns of intraday volatility that are seen in Saudi Arabia's stock market (TASI). Beginning on the 25th of October 2017 and continuing until the 9th of May 2018, the study collect return data from the SASEIDX at a frequency of 5 minutes. When we investigate the volatility of the stock market by using a variety of symmetric and asymmetric GARCH models, and make the following observation: the symmetric GARCH models reveals a substantial positive connection between risk and return. In a similar vein, the results of the asymmetric GARCH models demonstrate that the estimates are substantial, but the leverage estimate is negative and significant.

This suggests that there is no leverage impact in the return series. In addition, the asymmetric findings imply that negative shocks do not lead to future volatility that is greater than that caused by positive shocks. Because of this, the symmetric and asymmetric GARCH models both work well to represent the volatility of the Saudi stock market using the intraday data.

Bonga (2019) the volatility of the Zimbabwean stock market by utilising monthly return series that have 109 data spanning from January 2010 to January 2019. The GARCH family of models is used, as proven by the ARCH effects test. GARCH(1,1), GARCH-M(1,1), IGARCH(1,1), and EGARCH are some of the symmetric and asymmetric models that are employed in this study (1,1). In order to validate each model's usefulness for policymaking, post-estimation tests looking for additional ARCH impacts are carried out. It is discovered that EGARCH(1,1) is the optimal model to use when using the AIC and SIC criteria; it is also discovered that the existence of asymmetry is important.

According to the findings of the research, both positive and negative shocks have varying degrees of an impact on the stock market return series. Both positive and negative news will have a proportional impact on the degree to which returns on the stock market are volatile. This just indicates that investors on the Zimbabwean stock market respond differently to information based on whether or not it is favorable or negative in nature while making investment choices.

Another study examines the daily volatility in market returns of Total Nigeria Plc calculated using nine distinct versions of the GARCH model Emenogu et al. (2020).These models are: SGARCH, GIJGARCH, EGARCH, IGARCH, AGARCH, TGARCH, NGARCH, NAGARCH, and AVGARCH. Value at risk estimation and backtesting are also included in this investigation. The study uses daily data for Total Nigeria Plc returns from January 2, 2001 to May 8, 2017, and come to the conclusion that EGARCH and SGARCH are better at predicting volatility for normal innovations, while NGARCH outperforms other models for student t innovations. This is based on period from January 2, 2001 to May 8, 2017. As most existing studies of the Nigerian stock market don't place a strong emphasis on the use of backtesting as a key technique of analysis, this study of said variance, VaR, and backtesting of the daily stock price of Total Nigeria Plc is significant.

The findings of the estimates lead us to conclude that the persistence of the GARCH models is reliable, with the exception of a few instances in which IGARCH and EGARCH exhibit unstable behavior. The mean number of days before a return reverses itself differs between the SGARCH and GIRGARCH models as implemented to student-t innovation. This study recommends that shareholders and investors in Total Nigeria Plc continue doing business with the company based on the findings of a Var model and its backtesting. In addition, a 99% confidence level indicated that risk is represented by large up and down fluctuation in the stock price. This finding lends credence to the idea that high risk results in high return.

The QGARCH model is used in this work to carry out an analysis of the insurance stock in Nigeria in a study conducted by ARUNA and ADENOMON (2021). The research uses daily insurance stocks that are gathered from the Nigeria Stock Exchange for the period of time 1961–2019. There is a total of four different QGARCH models that are taken into consideration, including QGARCH (1,1), QGARCH (1,2), QGARCH (2,1) and QGARCH (2,2) using a student t's distribution. Nevertheless, in order to carry out the investigation, the model uses the relevant characteristics, including half-life and persistence. The Akaike information served as the selection criteria for the models to be used (AIC).

Despite the fact that none of the models are satisfactory since their individual values of persistence are greater than one. With all of the parameters being important, the QGARCH (1,1) model performs much better than the others in terms of performance for the distributions. In order to get the best possible outcome while modelling financial time series of insurance stocks, it is essential to use QGARCH models. This is because doing so enables one to reach the best possible result. A research conducted by Gzel and Acar (2021)) investigates how the volatility of financial markets is affected when pandemics like as H1N1, MERS, and EBOLA are present. The observations in this data collection are on a daily frequency, and the time range covered by it is from January 1, 2009 to August 11, 2020. In the research, the first step consisted of determining the proper volatility model for the BIST 100 Index, which is the primary market index that is tracked by main market of Borsa Istanbul. In order to estimate the best volatility model, the ARCH, GARCH, T-GARCH, and E-GARCH models are all put through their paces.

The results suggest that the E-GARCH (1,1) model is the one that works best when attempting to simulate the BIST 100 Index's volatility. It is discovered that the H1N1 pandemic is the source of an increase in the volatility of the BIST 100 Index, as well as bad news. In addition to this, an analysis is done to determine how the COVID-19 pandemic may affect BIST 100 in the present climate. When opposed to earlier time periods, the pandemic era exhibits notable characteristics, the most notable of which are the excessive rise in volatility and the negative trend in the return series.

Naimian (2021) conduct a study on S&P 500. The data consisted on the daily closing prices from 2013-2019. This study evaluates the forecasting output of the four GARCH-based volatility models (GARCH, TGARCH, GJRGARCH, and IGARCH) and makes recommendations based on real - time VaR modelling. Predictions of VaR are backtested so that the suggested GARCH models and other distributions may be compared for their respective innovations and degrees of confidence in VaR. This is because the predictive performance of Value-at-Risk (VaR) models is essential to study and recommend which model works best.

Chapter 3

Data Description & Methodology

3.1 Sample of Study

Leverage, which is the use of borrowed money to improve the possible return on an investment, is not oftenly used in the financial markets of Islamic countries. This suggests that compared to conventional financial markets, financial markets in Muslims countries may have lower levels of leverage.

Researchers that are looking into how leverage affects financial stability, risk, and performance are interested in this feature of financial markets in Muslim Countries. This study aims to examine how financial markets function with minimal leverage and how this impacts their risk volatility.

The research consists on stock markets from each of the Islamic Country opted for study. The time period for analysis is from 2002 – 2022.

Frequency of the data is daily and closing stock indices are studied. From daily data log returns are calculated for the purpose of running all the test.

$$logreturn = ln\frac{p_t}{p_{t-1}}$$

Where, p_t = price of the index at time t and p_{t-1} =price of the index at previous day $t-1$

TABLE 3.1: Sample of The Study

Country		Index	Time Period
Pakistan	Karachi Stock Exchange 100	KSE 100	1st Jan 2002 – 27th May 2022
Malaysia	Kuala Lumpur Composite Index	KLCI	1st Jan 2002 – 27th May 2022
Egypt	Egyptian Exchange 30	EGX 30	2nd Jan 2002 – 29th May 2022
Tunisia	Tunindex	Tunindex	2nd Jan 2002 – 29th May 2022
Saudi Arabia	Tadawull All Share Index	TASI	1st Jan 2002 – 27th May 2022
Qatar	QE General Index	QSI	2nd Jan 2002 – 29th May 2022
United Arab Emirates	Dubai Financial Market	DFM	8th Mar 2007 – 27th May 2022
Indonesia	Jakrata Composite Index	JKSE	2nd Jan 2002 – 27th May 2022
Turkey	Bursa-Istanbul 100 Index	BIST 100	2nd Jan 2002 – 27th May 2022
Morocco	Moroccan All Shares Index	MASI	3rd Jan 2002 – 27th May 2022

3.2 Research Methodology

The parametric model implies the data follows a normal distribution. It is possible that this will not always be the case in the financial market due to the fact that market conditions might change and data can have fat tails as a result of the increased risk associated with financial markets. The constraints of the model structure are employed using parametric procedures in order to estimate the values of the VaR and CVaR calculations' parameters.

3.2.1 GARCH

In the context of variance, Bollerslev (1986) introduced the GARCH model. This model captures the characteristics of volatility and provides estimates of VaR and CVaR. VBecause of the fluctuation in prices on the market, this scenario has an inconsistent level of volatility. The GARCH model, which was established in 1982 by Robert F. Engle, is developed to assess the volatility of the market.
This model is favoured over others since it offers accurate forecasts of time-varying prices and interest rates for financial instruments. The GARCH model has seen widespread use in the modelling of volatility in historical time series. This model suggests that both positive and negative news have an equal impact on prospective volatility, and that this contribution is dependant on the past performance of stock. The GARCH model specification is comprised of two primary components: the conditional mean component, which formulates the evolution of returns volatility over time as a function of previous errors, and the conditional variance component, which captures the dynamics of the return series as a function of past returns. Both of these components may be found in the GARCH model.
It is reasonable to suppose that the conditional mean of the daily return series is governed by an autoregressive process of the first order,

$$r_t = \phi_0 + \phi_1 r_{t\ 1} + \epsilon_t$$

Where,

$r_{t\ 1}$ = lagged term

ϕ_0 and ϕ_1 = constants to be determined

ϵ_t = innovations term

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

$$\sigma_t^2 = \omega + \sum_{i=1}^{q} \alpha_i \epsilon_{t\ 1}^2 + \sum_{j\ \ 1}^{p} + \beta_j \sigma_{t\ j}^2$$

Where $\omega > 0, \alpha_i > 0, \beta_j > 0$ are positive parameters with the required restrictions to guarantee limited conditional variance as well as covariance stationary.

Positive and negative affect conditional variance equally in the GARCH model. Therefore, the GARCH model cannot represent the Leverage Effect. The GARCH model implies that the variability of financial returns varies in a manner that tends to depend on previous data. The squared residuals, or the difference between actual and predicted returns, are used as a historical predictor of future volatility.

3.2.2 EGARCH

Nelson's (1991) EGARCH (Exponential GARCH) model is a refinement of the earlier GARCH model. The author demonstrated that the EGARCH model may mitigate the major drawbacks of GARCH models. In financial markets, where news and events may have a substantial impact on market perception and volatility, the EGARCH model can be a helpful technique for modelling the asymmetrical consequences of shocks on volatility.

The equation of conditional variance of Exponential GARCH model is written as:

$$log(\sigma_t^2) = \omega + \sum_{i=1}^{q} [\alpha_i Z_{t\ 1} + \gamma_i (jZ_{t\ 1}j \quad \sqrt{\frac{2}{\pi}})] + \sum_{j\ \ i}^{p} \beta_j log(\sigma_{t\ j}^2)$$

The coefficients quantify and signal the effect magnitude.

Given that the logarithm is positive, positivity constraints are unnecessary for the EGARCH model. The coefficient determines asymmetric behaviour. The time-varying variance's asymmetrical response to shocks is discovered and demonstrated using this model. If the logarithm is larger than the mean, and the error term would also be larger than the mean, then this indicates that the influence of bad news has a higher impact than the effect of good news. in Shocks, both negative and positive, are represented by $\gamma_i$the EGARCH model, which represents the relationship between leverage or parameter. Uncertainty is usually greater after a negative shock than after a good one. A negative shock, indicating poor news in the financial market, might lead to an uncertain future. For high-risk investments, shareholders anticipate larger profits.

3.2.3 QGARCH

QGARCH is one type of asymmetric GARCH models that allows an asymmetric relationship between past returns and current volatility (Sentana, 1995). It addresses asymmetrical impact of shocks, both positive and negative. The QGARCH (1,1) is basically similar to the GARCH(1,1) with an additional parameter to capture the relationship of volatility-return which can capture the codified facts seen in data on financial returns.

$$\sigma_t^2 = \omega + \alpha_i r_{t\ \ i}^2 \beta_j \sigma_{t\ \ j}^2 + \gamma r_{t\ \ i}$$

It reduces to the commonly employed GARCH(1,1) model when $\alpha_i = 0$, but captures "the leverage effect" for $\alpha_i < 0$. It can better capture the stylized facts included in financial return data than the GARCH(1,1) model, suggesting that it should have superior forecasting ability. If $\gamma > 0$, then the current variance will increase more than would be expected from the past negative return. When γ is negative, the current volatility increases more than the prior positive return, which is the opposite of what happens when is positive. The term "leverage effect" describes this behavior.

3.2.4 TGARCH

The conditional variance is defined as a linear expectations in Threshold GARCH (TGARCH) model suggested by Zakoian (1994). As for TGARCH(1,1).

$$\sigma_t^2 = \omega_{st \ 1} + \alpha_{st \ 1} r_{t \ 1}^2 + \beta_{st \ 1} \sigma_{t \ 1}^2$$

Where, r_t = the series of returns, σ_t = conditional variance of returns given time t information.

Finally, we undertake that the sequence of innovations ϵ_t follow independent and identical distribution with mean 0 and variance 1: $\epsilon_t \tilde{i} idD(0,1)$. Because of this, we may simplify the theoretical derivation by assuming that the threshold variable is unrelated to σ_t.

3.2.5 PGARCH

Power GARCH (1,1), a technique suggested by Bollerslev and Chysels, is outlined below (1993). In order to define the group of P-GARCH processes, we may say the following:

$$\sigma_t^\delta = \omega_{st} + \sum_{i=1}^p \alpha_i (j\epsilon_{t \ i} j \quad \gamma_i \epsilon_{t \ i})^\delta + \beta_j \sigma_{t \ j}^\delta)$$

POWER PARAMETER, λ ¿ 0. The power term is the means by which the data are transformed. The power term captures volatility clustering by changing the influence of the outliers.

3.3 Value at Risk

Value-at-Risk (VaR) is a mathematical method that is used to assess the greatest probable loss in value of a portfolio of assets over a certain period of time for a particular likelihood.

Likelihood for this study is the confidence interval of 95% and 99%. This may be done by dividing the total value of the portfolio by the chance that it would suffer that loss.

To be more specific, the formulation of VaR calls for a quantile estimate of the distribution of unconditional returns' most extreme left tail. VaR is computed using following formula:

$$VaR = \quad \sigma_t Z$$

Where, σ_t is the standard deviation at time 't',

$Zscore(95\%CI) = 1.645$

$Zscore(99\%CI) = 2.33$

Because the involvement of positions over the observed time in the portfolio is constant, the value at risk metric gives a chance to evaluate the possibility for loss if the structure of the portfolio remains unchanged. About the estimated loss, it is possible to speak only as of the potential because it is a value that is calculated with a certain level of confidence; it cannot be said that this number indicates the maximum extent of feasible and safe loss because it cannot be said that this is a number that indicates the maximum extent of feasible and safe loss.

Therefore, Value at Risk does not reflect the possibility of losses in times of significant market volatility. For instance, if the degree of confidence is 95%, the computed indicator will declare that it should not make loss more than the specified amount in 95% of the situations; nevertheless, it will not tell you what may occur in the other 5% of circumstances.

3.4 Backtesting

It is a statistical method for contrasting and improving different risk models by pinpointing specific flaws and explaining their underlying causes. The goal of back-testing is to determine whether or not VaR values are reliable indicators of risk.VaR models may underestimate risk since they don't account for rare but highly consequential occurrences, often known as tail risk.

Furthermore, mistakes in VaR modelling might be caused by improper parameter estimation and low-quality data. Both under- and overestimation of risk are prevented. The VaR and CVaR models employed in this research are verified through back-testing. Backtesting uses VaR violations with 95% and 99% confidence, following Basel Committee criteria. As CVar models necessitate estimations of the tail expectation to the CVaR forecast, backtesting these models is challenging.

3.4.1 Violation Ratio

In the world of back testing, the violation ratio is a common tool. Here, we examine the gap between the observed and expected numbers of Var infractions. The formula is as:

$$VR = \frac{ObservedNumberofViolations}{ExpectedNumberofViolations}$$

Backtesting is the standard procedure for determining whether or not a given forecasting model has a high degree of accuracy. If the risk indicated by the model is the absolute minimum, but the violation ratio indicates that the risk is actually higher then the model may therefore not be used for future predictions. When the ratio of violations is equal to 1, it means that there are exactly as many violations as are anticipated. However, in the realm of finance data, it is not always easy to touch 1.

Even though it is impossible to attain an exact 1 in the financial business every time, a violation ratio of 0.8 to 1.2 is deemed reasonable in these researches. Since there are outliers to the pattern, we may infer that the model is either underestimating or overestimating the risk.

In terms of comprehension, $VR < 0.5$ or $VR > 1.5$ indicates that the corresponding model is weak in risk forecasting. In most cases, it is possible to make conclusions based on the violation ratio, which is well recognized as a robust method of forecasting.

A backtesting strategy is to assess the volatility in any model estimates. The standard deviation of VaR is the metric used to assess volatility. If the violation ratio for VaR estimation using two distinct models yields the same findings, then VaR volatility aids in determining which model is superior.

This strategy suggests going with whichever model has the smallest standard deviation. Backtesting techniques are used to evaluate VaR models. In the two-stage

Backtesting procedure, the best performing model is put through the Kupiec and Christoffersen test.

3.4.2 Kupiec (POF) Test

VaR estimations may be evaluated statistically using the Kupiec POF (Probability of Failure) test. The premise of the test is that VaR estimates are reliable if the binomial distribution holds for the number of outliers relative to the VaR bound. One degree of freedom of the chi-square distribution is used to make comparisons in the Kupiec test. If exceeds likelihood ratio only then the hypothesis is accepted. This chi-square value varies depending on the confidence interval.

The model is deduced incorrect when LR exceeds the chi-square value, and the null hypothesis is rejected and the observed number of violations exceeds the predicted number of violations, indicating that the model is unsuitable for VaR estimation, and vice versa.

The null hypothesis is going to be ruled out with 95% and 99% CI if the likelihood ratio is greater than $LR > 3.84$,that "the observed failure rate is the same as the failure rate that is suggested by the confidence interval" is what the null hypothesis is claiming.". The formula for Likelihood Ratio is:

$$LR_{POF} = \quad 2log\frac{(1 \quad p)^(N \quad x)p^x}{(1 \quad \frac{x}{N})^(N \quad x)(\frac{x}{N})^x}$$

Where $x = "numberofobservations,"$

$N = "numberoftimesamodelfailed,"$

$p = "VaRlevel(confidencelevel)p = "VaRlevel(confidencelevel)"$

In conclusion, the null hypothesis is valid, suggesting that the model is sufficient for risk forecasting, assuming the outcome does not exceed a threshold.

In this formula, the numerator represents the maximum likelihood of the observed result under the null hypothesis, while the denominator represents the highest probability of the observed result under the alternative hypothesis. This ratio's numerical value becomes the deciding factor. The bigger the LR-statistic, the lower the ratio. The null hypothesis is rejected if and only if the value is greater than the critical value of the x^2 distribution and the model is declared to be inaccurate.

3.4.3 Christoffersen's Test

Christoffersen (1998) formulates a test for conditional coverage. Backtesting results for stockmarket risk models are analysed using the Christoffersen test, a statistical test. For the purpose of determining whether or not the model can reliably anticipate the volatility of the capital asset under study, this method is employed. One type conditional coverage test is the Christoffersen test. It is the difference between the observed and expected number of occurrences, in this case the observed instances that the financial asset's volatility has exceeded the model's forecast volatility. The null hypothesis is that the $LR > x^2$ model is shown to be inaccurate. Under the assumption of the null hypothesis, the frequency of violations should remain constant over the course of time.

$$LR = \quad 2log(\frac{(1 \quad \pi)^T 00 + T10 + T01 + T11}{(1 \quad \pi 01)^T 00 \pi 01^T 01(1 \quad \pi 11)^T 10 \pi 11^T 11})$$

Where,

$$\pi = \frac{T01 + T11}{T00 + T01 + T10 + T11}$$

T00 = a time period with no failure, followed by time period with no failure

T10 = a time period with failure, followed by time period with no failure.

T01 = a time period with no failure, followed by time period with failure.

T11 = a time period with failure, followed by time period with failure.

$\pi 1$ = the probability of failure on period t, given that a failure occurred on period $(t \quad 1) = T11/(T10 + T11)$

$\pi 0$ = the probability of failure on period t, given that a failure occurred on period $(t \quad 1) = T01/(T10 + T11)$

π = Probability of having a failed instance at period $t = (T01 + T11)/(T00 + T01 + T10 + T11)$

The null hypothesis asserts no clustering, which indicates that a day with violation is not dependent on the prior day's violation. In such case, we would reject the null hypothesis and look for clusters of violations that have been recorded throughout the same time period.

Chapter 4

Data Analysis and Discussions

4.1 Descriptive Statistics

The behavior of the data for this research is analyzed using descriptive statistics shown in table 4.1. The data is evaluated using mean, median, and standard deviation. In addition, the distribution of data is studied using skewness, kurtosis and Jarque-Bera. Likewise, the spread of data is also examined using Maximum & Minimum return. The average return of the sample market indices may be calculated using the mean and median, which are indicators of central tendency. According to the findings, KSE-100 (Pakistan) shows highest mean return of 0.0704% per day whereas Dubai financial market shows mean return in negative value i.e. -0.00154%. Rest of the indices show mean return ranging from 0.016% to 0.058%. As far as standard deviations is concluded, DFM (Dubai) exhibites highest SD of 2.98% which is justified by its negative mean return. Riskier indices show greater standard deviation. We can see the highest and lowest daily earnings for each Index by looking at the maximum and minimum data.

As per the table, Tadawull All Share (TASI) shows the highest value of maximum return earned per day i.e. 32.6% whereas Tunindex shows the highest value of minimum return earned per day which is actually the loss of 26.6%. The distribution of data of BIST 100, EGX 30, JKSE, KSE 100, KLCI, MASI, QSI, & Tunindex can be seen negatively skewed which means that data has left-skewed distributions.

Table 4.1: Descriptive Statistics

	Mean	Maximum	Minimum	Std. Dev.	Skewness	Kurtosis	Jarque-Bera
BIST 100	0.000557	0.121281	-0.133359	0.017647	-0.305307	7.935566	5277.332
DFM	-1.54E-05	0.139762	-0.137312	0.02986	0.553688	7.975497	4120.288
EGX 30	0.000603	0.183692	-0.179916	0.01611	-0.469584	13.49465	23096.72
JKSE	0.000582	0.11576	-0.139227	0.01349	-0.778581	13.47589	23176.92
KSE 100	0.000704	0.085071	-0.077414	0.012773	-0.387572	6.717086	3021.084
KLCI	0.000159	0.066263	-0.068114	0.007577	-0.266892	11.95583	16913.35
MASI	0.00024	0.053054	-0.092317	0.007636	-0.885527	15.485	33690.62
QSI	0.000396	0.09422	-0.102077	0.012748	-0.451942	11.96595	17327.19
TASI	0.000325	0.326072	-0.103285	0.015181	1.149229	52.55705	520027.7
Tunindex	0.000349	0.265408	-0.266943	0.007419	-0.445886	660.1282	90861774

BIST 100: Turkey, **DFM:** UAE, **EGX 30:** Egypt, **JKSE:** Indonesia, **KSE 100:** Pakistan, **KLCI:** Malaysia, **MASI:** Morocoo, **QSI:** Qatar, **TASI:** Saudi Arabia, **TUNINDEX:** Tunisia

However, DFM and TASI show positive skewness and have values greater than zero which means that the data has fatter tail on the right side. Overall data is asymmetrically distributed. JARQUE BERA also tells about the distribution of data and since all markets show significant values of Jarque-Bera then it explains that the data is not normally distributed.

4.2 Pattren of The Return in The Past

According to graphs of each index, common volatility clustering can be observed in 2007-08 and 2019-20 because these are the times of recessions caused by Global Financial Crisis and COVID-19, respectively. Moreover, JKSE, EGX 30, BIST 100, KSE 100 & MASI show volatility spikes around the time of 2002 and 2003 which can be reasoned to the Dotcom Crash in which most of the stock markets plummeted due to effects coming from Nasdaq Composite Stock Market Index. EGX 30 and Tunindex show downward spike from 2011 to 2012 because Egypt, Yemen, Tunisia and Syria went through a revolution which adversely effected their stock markets.

Numerous political events, including protests, sit-ins, riots, strikes, and more, took place in Egypt between the start of the revolution on January 25 and the announcement of the results of the parliamentary elections on November 30 of the same year.

It's no secret that the production, employment, income, and investment choices in either physical or monetary assets on the Egyptian stock market are all damaged by these events. Whereas, 2016-2018 is commonly a calm time for all indices hence mostly indices show moderate movements across the graph.

4.3 Volatility Estimation using GARCH Models

The study reports the volatility forecasting by using volatility models.

4.3.1 Estimating Volatility by using GARCH

The GARCH model provides a statistical tool for assessing the volatility of a wide range of financial variables. The value at risk (VaR) and the conditional value at risk (CVaR) are analysed in the Pakistani stock market to reveal how price movements in the past affect the volatility of the present.

Estimation of Volatility by GARCH Model on each of the country shows that whether or not their respective future returns and volatility are derived from past behaviors.

Table 4.2 shows that log return(-1) of BIST 100(Turkey) & DFM(Dubai, UAE) is insignificant showing that today's result is not indicative of future returns for these two markets. Whereas rest of the markets including EGX 30, JKSE, KSE 100, KLCI, MASI, QSI, TASI, & Tunindex show significant effects of historical returns on the prediction of future returns. However in table 4.3, RESID(-1)2 and

TABLE 4.2: Mean Equation using GARCH Model

	Coefficient	**Std. Error**	**z-Statistic**	**Prob.**
BIST 100	0.013667	0.015042	0.908602	0.3636
DFM	0.002365	0.017702	0.133614	0.8937
EGX 30	0.1903	0.015252	12.47695	0
JKSE	0.065026	0.014897	4.364952	0
KSE 100	0.123852	0.014872	8.327811	0
KLCI	0.090525	0.014717	6.151197	0
MASI	0.182711	0.015055	12.1365	0
QSI	0.228048	0.01387	16.44192	0
TASI	0.055561	0.016203	3.429135	0.0006
Tunindex	0.276076	0.020122	13.72016	0

BIST 100: Turkey, **DFM:** UAE, **EGX 30:** Egypt, **JKSE:** Indonesia, **KSE 100:** Pakistan, **KLCI:** Malaysia, **MASI:** Morocoo, **QSI:** Qatar, **TASI:** Saudi Arabia, **TUNINDEX:** Tunisia

GARCH(-1) of all markets are positive and statistically significant. RESID (1)^2 indicate that previous price behavior of these indices can be used to predict future volatility.

In addition, Prolonged market volatility is indicated by high GARCH(-1) ratings. It can be said that there will be Long-term volatility in all of these stock markets which will be transferred into the next period as the sum of the RESID(-1)2 and GARCH(-1) coefficients is near to 1.

Table 4.3: Variance Equation using GARCH Model

	RESID(-1)^2				GARCH (-1)			
	Coefficient	**Std. Error**	**z-Statistic**	**Prob.**	**Coefficient**	**Std. Error**	**z-Statistic**	**Prob.**
BIST 100	0.089348	0.004895	18.2514	0	0.88557	0.005555	159.4073	0
DFM	0.16513	0.007519	21.96048	0	0.822883	0.005094	161.5491	0
EGX 30	0.188166	0.00992	18.96757	0	0.781823	0.010329	75.69145	0
JKSE	0.158132	0.007682	20.58377	0	0.823644	0.007637	107.8518	0
KSE 100	0.164784	0.0092	17.91136	0	0.795758	0.008951	88.90646	0
KLCI	0.111459	0.005492	20.29649	0	0.87668	0.005963	147.0285	0
MASI	0.218655	0.007944	27.52296	0	0.714468	0.008584	83.23481	0
QSI	0.267974	0.011354	23.6009	0	0.72434	0.009918	73.03083	0
TASI	0.443943	0.010681	41.56376	0	0.668486	0.006175	108.2491	0
Tunindex	0.232399	0.020693	11.23106	0	0.105696	0.031487	3.356822	0.0008

BIST 100: Turkey, **DFM:** UAE, **EGX 30:** Egypt, **JKSE:** Indonesia, **KSE 100:** Pakistan, **KLCI:** Malaysia, **MASI:** Morocoo, **QSI:** Qatar, **TASI:** Saudi Arabia, **TUNINDEX:** Tunisia
RESID(-1)2 ARCH TERM (Reaction Of Volatility Towards Return) **GARCH(-1)** Volatility Persistence

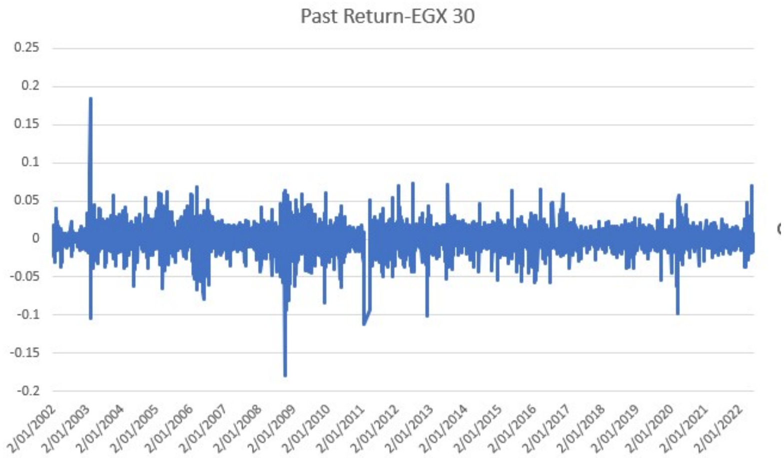

FIGURE 4.1: Past Return EGX 30

4.3.2 Estimating Volatility by using EGARCH

Exponential GARCH (EGARCH) model, proposed by Nelson (1991), overcomes the weakness in GARCH handling of financial time series.Specifically, it accounts for the unequal impact of past asset performance on expected future returns. The leverage effect is exponential due to the logarithm of conditional volatility in order to account for asymmetries in the shocks. The results in table 4.4 show that BIST 100 and Dubai Financial Market have insignificant effects of past return on future prices. In contrast, future return of rest of the markets are significantly affected by past returns. In the entire sample, according to EGARCH model, past returns in Tunindex show the highest potential to predict future returns by 25.55% accuracy.

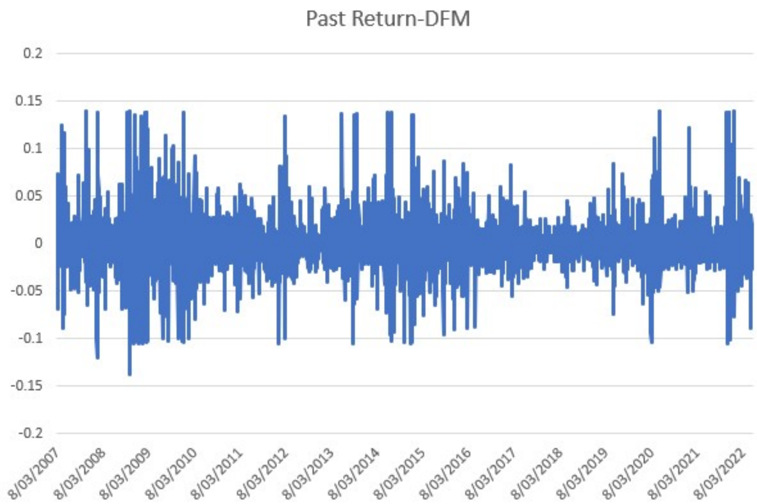

FIGURE 4.2: Past Return DFM

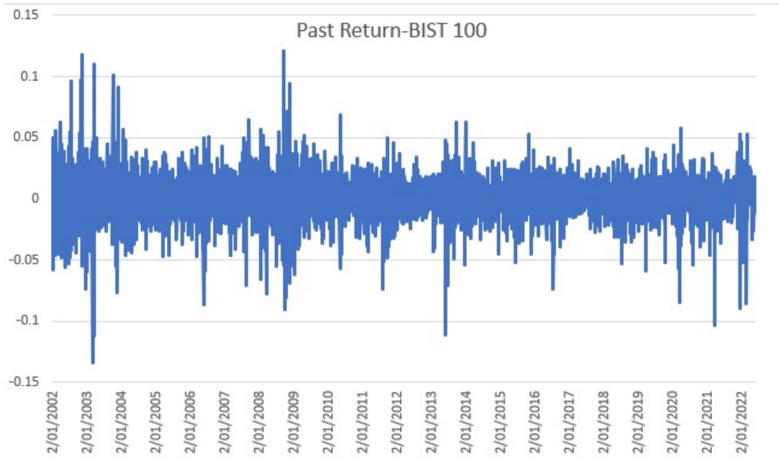

Figure 4.3: Past Return BIST 100

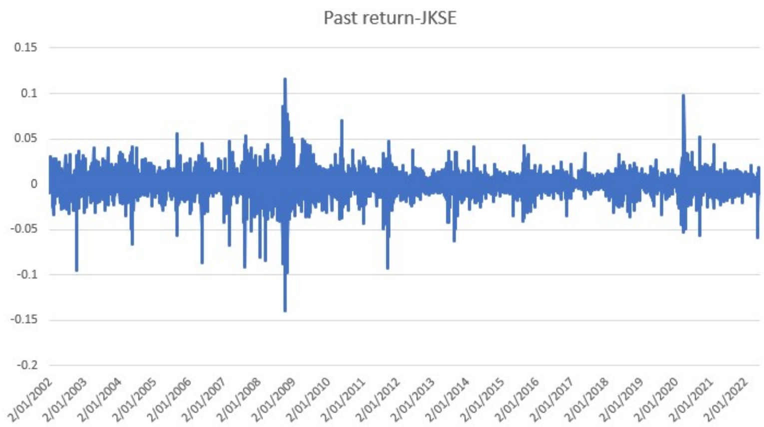

Figure 4.4: Past Return JKSE

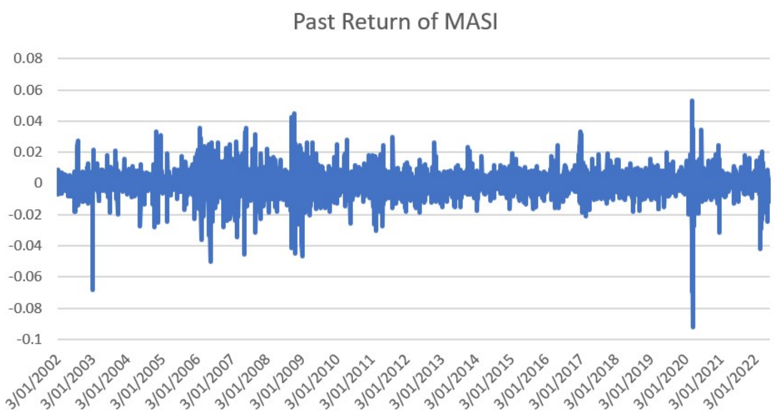

Figure 4.5: Past Return of MASI

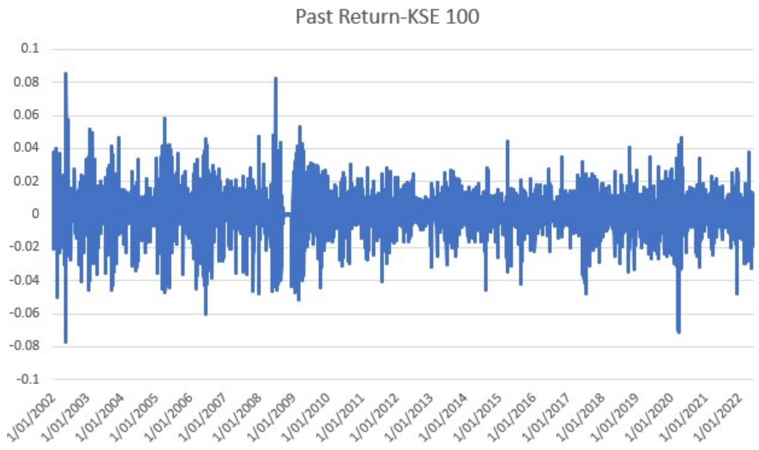

FIGURE 4.6: Past Return KSE 100

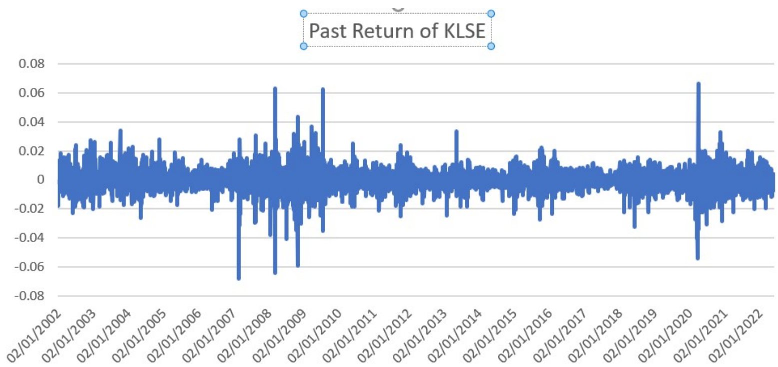

FIGURE 4.7: Past Return of KLSE

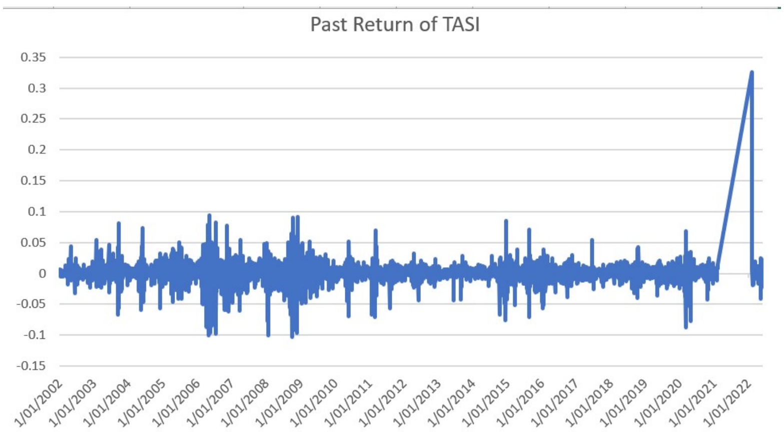

FIGURE 4.8: Past Return of TASI

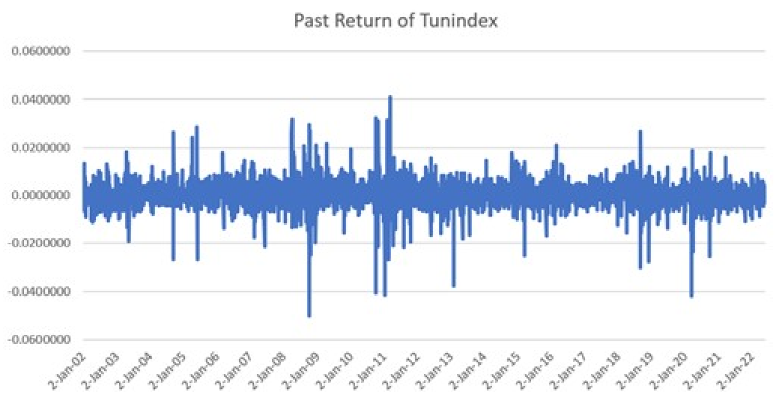

FIGURE 4.9: Past Return of Tunindex

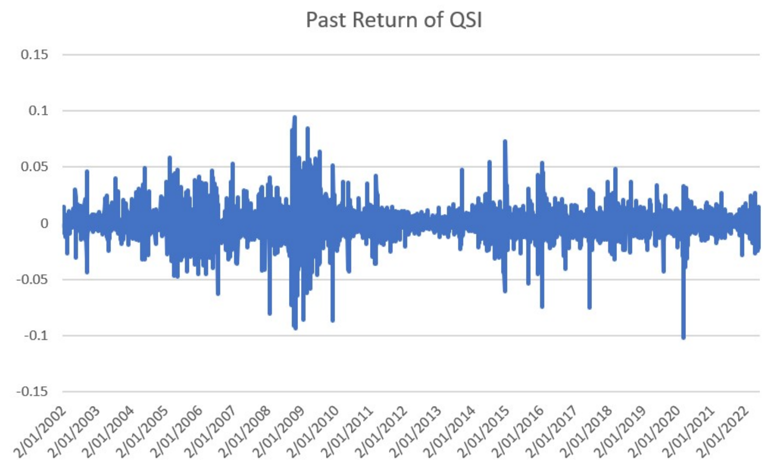

FIGURE 4.10: Past Return of QSI

TABLE 4.4: Mean Equation using EGARCH Model

	Coefficient	**Std. Error**	**Z-Statistic**	**Prob.**
BIST 100	0.007798	0.01429	0.545677	0.5853
DFM	-0.01597	0.016598	-0.96232	0.3359
EGX 30	0.192769	0.013863	13.90515	0
JKSE	0.072959	0.013356	5.462654	0
KSE 100	0.130853	0.014039	9.320497	0
KLCI	0.091635	0.014309	6.403914	0
MASI	0.187587	0.014232	13.18082	0
QSI	0.228231	0.013717	16.63839	0
TASI	0.053564	0.01543	3.471351	0.0005
Tunindex	0.255505	0.018771	13.61144	0

BIST 100: Turkey, **DFM:** UAE, **EGX 30:** Egypt, **JKSE:** Indonesia, **KSE 100:** Pakistan, **KLCI:** Malaysia, **MASI:** Morocoo, **QSI:** Qatar, **TASI:** Saudi Arabia, **TUNINDEX:** Tunisia

Table 4.5: Variance Equation using EGARCH Model

	C(4)			**C(5)**			C(6)		
	Coefficient	**Z-Statistic**	**Prob**	**Coefficient**	**Z-Statistic**	**Prob.**	**Coefficient**	**Z-Statistic**	**Prob.**
BIST 100	0.19187	23.0917	0	-0.05041	-10.8653	0	0.965465	337.0204	0
DFM	0.324321	0.01110	0	-0.02719	0.0073	0.0002	0.954924	0.003163	0
EGX 30	0.307218	27.9170	0	0.083116	10.0963	0	0.960585	242.2035	0
JKSE	0.260661	21.2247	0	-0.0819	-12.2465	0	0.96195	291.1256	0
KSE 100	0.309837	20.7250	0	-0.11712	-12.5703	0	0.920398	181.2671	0
KLCI	0.217678	25.4545	0	-0.05182	-9.53162	0	0.973555	360.8559	0
MASI	0.358135	33.1328	0	-0.02713	-4.03018	0.0001	0.9241	192.9582	0
QSI	0.413378	33.8092	0	-0.06133	-8.49335	0	0.935875	245.6139	0
TASI	0.440929	38.9199	0	-0.09181	-10.1862	0	0.935243	299.2103	0
Tunindex	0.50672	24.2459	0	-0.25377	-15.3306	0	0.309449	15.71454	0

BIST 100: Turkey, **DFM:** UAE, **EGX 30:** Egypt, **JKSE:** Indonesia, **KSE 100:** Pakistan, **KLCI:** Malaysia, **MASI:** Morocoo, **QSI:** Qatar, **TASI:** Saudi Arabia, **TUNINDEX:** Tunisia

Table 4.5 demonstrate variance equation using EGARCH model for entire sample. It addresses the effects of the coefficient, size, sign and persistence of volatility in the data. C(4) demonstrates the size impact; its positive and statistically significant value indicates that larger shocks increase volatility while smaller ones have lesser impacts.

C(5) demonstrates the sign effect; a negative and statistically significant value indicates that negative news generates greater market volatility than positive news; whereas, a positive and statistically significant value for EGX 30 explains that this market seems to be more sensitive to positive news.

Lastly, C(6) is positive and statistically significant, it indicates that volatility is persistent in the market and can be traced into the following year. This volatility is also likely to be of a long-term, structural type.

4.3.3 Estimating Volatility by using PGARCH

The study also investigates the general relevance of the PGARCH dynamics to capture the structure of volatility in future returns of ten stock markets belonging to Islamic Countries. The power term is the means by which the data are transformed. It explains volatility clustering by changing the influence of the outliers. While studying, its mean equation in Table 4.6 for each of the sample, it is noticed that, except for BIST 100 and DFM, future returns of all the indices are positively & significantly impacted by preceding trend of returns.

In Tadawull All Share Index, past returns effect future returns whereas that of EGX 30 future returns are influenced from previous market behavior. Now variance model in table 4.7 for PGARCH tells us about the size impact, sign impact and persistence of volatility. As per the results of 10 stock markets mentioned below, C(4), the size impact, for all indices is positive and significant hence suggesting that bigger shocks will have impacts of bigger magnitude.

Secondly, C(5) explains that impact of sign and since 9 out of 10 indices show positive and significant effects. It means that the negative news will be effecting the market more than the positive news of same magnitude.

TABLE 4.6: Mean Equation using PGARCH Model

	Coefficient	**Std. Error**	**z-Statistic**	**Prob.**
BIST 100	0.017402	0.015127	1.150375	0.25
DFM	0.004822	0.01816	0.26553	0.7906
EGX 30	0.194356	0.014415	13.48282	0
JKSE	0.074911	0.01396	5.366227	0
KSE 100	0.139131	0.014356	9.691453	0
KLCI	0.091986	0.014696	6.259442	0
MASI	0.18191	0.014936	12.17961	0
QSI	0.225436	0.01364	16.52793	0
TASI	0.054444	0.005535	9.835763	0
Tunindex	0.054444	0.005535	9.835763	0

BIST 100: Turkey, **DFM:** UAE, **EGX 30:** Egypt, **JKSE:** Indonesia, **KSE 100:** Pakistan, **KLCI:** Malaysia, **MASI:** Morocoo, **QSI:** Qatar, **TASI:** Saudi Arabia, **TUNINDEX:** Tunisia

Finally, C(6) demonstrates the persistence of volatility in the markets and according to results all markets will have to face persistence of volatility in their respective indices in upcoming years.

4.3.4 Estimating Volatility by using QGARCH

The Quadratic GARCH (QGARCH) model by Sentana (1995) is used to model asymmetric effects of both positive and negative shocks. It is easy to implement in multivariate models to apprehend dynamic asymmetries that GARCH rules out.

It reduces to the conventionally used GARCH (1,1) model, but captures 'the leverage effect' for ¡ 0. Again in table 4.8 it can be seen that BIST 100 and Dubai Financial Market show insignificant results because their p-value is greater than 0.05 and z-statistics is lesser than 2 hence implying that their respective market returns are not derived by past trends.

TABLE 4.7: Variance Equation using PGARCH Model

	C(4)			C(5)			C(6)			C(7)		
	Coeff	**z-Stat**	**Prob.**	**Coeff**	**z-Stat**	**Prob.**	**Coeff**	**z-Stat**	**Prob.**	**Coeff**	**z-Stat**	**Prob.**
BIST 100	0.099	17.611	0.000	0.216	9.644	0.000	0.878	152.294	0.000	1.660	15.728	0.000
DFM	0.160	19.511	0.000	0.099	5.459	0.000	0.820	104.282	0.000	2.203	14.221	0.000
EGX 30	0.171	24.783	0.000	-0.294	-12.923	0.000	0.836	108.497	0.000	1.259	15.285	0.000
JKSE	0.151	19.312	0.000	0.293	8.679	0.000	0.845	109.526	0.000	1.257	13.872	0.000
KSE 100	0.175	19.089	0.000	0.368	11.691	0.000	0.793	85.182	0.000	1.245	14.708	0.000
KLCI	0.116	22.829	0.000	0.212	7.365	0.000	0.887	162.784	0.000	1.343	14.798	0.000
MASI	0.215	26.973	0.000	0.062	3.343	0.001	0.744	70.610	0.000	1.596	14.119	0.000
QSI	0.247	26.193	0.000	0.170	8.940	0.000	0.759	86.547	0.000	1.191	17.125	0.000
TASI	0.198	24.354	0.000	0.310	14.588	0.000	0.809	143.664	0.000	0.457	14.395	0.000
Tunindex	0.405	21.820	0.000	0.708	43.288	0.000	0.226	13.341	0.000	0.582	17.175	0.000

BIST 100: Turkey, **DFM:** UAE, **EGX 30:** Egypt, **JKSE:** Indonesia, **KSE 100:** Pakistan, **KLCI:** Malaysia, **MASI:** Morocoo, **QSI:** Qatar, **TASI:** Saudi Arabia, **TUNINDEX:** Tunisia

However, QE General QSI returns are 23.08% affected by antecedent returns. Likewise, all the other markets including including EGX 30, JKSE, KSE 100, KLCI, MASI, TASI, & Tunindex show positive and significant results.

Table 4.10 variance equations computed from QGARCH model are presented in the following table. As per computations, RESID 1^2 is positive and statistically significant,it suggests that market volatility may be predicted from prior price behaviour.

Volatility remains evident for all markets from the high value of GARCH(-1). The RESID(-1)2 and GARCH(-1) The ARCH TERM (Reaction of volatility towards return) and Volatility Presistence coefficients are fairly close to 1 demonstrating that volatility is persistent throughout the time and is carried over into the following year.

Since GARCHRESIDORD(-1) has a negative and significant value for all markets, except for MASI, which indicate nonlinearity exists and a volatile returns will lead to a volatile market for the future.

4.3.5 Estimating Volatility by using TGARCH

A more accurate representation of the "leverage effect" in financial markets is provided by the TGARCH model, which is developed by Zakoian (1994), Glosten et al. (1993), and Zakoian (1994). Market news, for instance, can have an effect on the price of a stock.
Like rest of the models, mean equation BIST 100 and DFM using TGARCH show that there are insignificant impacts of part prices on future and present returns are totally independent of any past market behavior.

Yet again EGX 30, JKSE, KSE 100, KLCI, MASI, QSI, TASI, & Tunindex show significant and positive coefficients.
The Model incorporates a multiplicative dummy variable into the variance equation to determine whether there is a statistically significant difference when shocks

TABLE 4.8: Mean Equation using QGARCH Model

	Coefficient	Std. Error	z-Statistic	Prob.
BIST 100	0.013817	0.015486	0.892196	0.3723
DFM	0.003407	0.017871	0.190662	0.8488
EGX 30	0.189799	0.015015	12.64022	0
JKSE	0.066073	0.015168	4.35618	0
KSE 100	0.125352	0.014745	8.501178	0
KLCI	0.091285	0.014919	6.118913	0
MASI	0.183331	0.0151	12.14112	0
QSI	0.230886	0.014111	16.36269	0
TASI	0.051491	0.016725	3.078748	0.0021
Tunindex	0.253481	0.018529	13.68039	0

BIST 100: Turkey, **DFM:** UAE, **EGX 30:** Egypt, **JKSE:** Indonesia, **KSE 100:** Pakistan, **KLCI:** Malaysia, **MASI:** Morocoo, **QSI:** Qatar, **TASI:** Saudi Arabia, **TUNINDEX:** Tunisia

are negative. Since RESID 1^2 has a positive value and is statistically significant, this suggests that one can make use of historical price behaviour to make predictions regarding future volatility in the market.

The high value of the GARCH(-1) index continues to indicate that volatility will be present across all markets. The model computes positive and significant values of RESID 1^2 (RESID(-1)¡0 for all indices depicting that asymmetric effect is present and negative shocks will have bigger impacts in the respective markets.

However, an exception is observed in which EGX 30 is negatively impacted therefore implying the opposite of aforesaid statement.

Table 4.9: Mean Equation using TGARCH Model

	Coefficient	Std. Error	z-Statistic	Prob.
BIST 100	0.019536	0.015358	1.272037	0.2034
DFM	0.003081	0.018036	0.17085	0.8643
EGX 30	0.194087	0.014585	13.30775	0
JKSE	0.078179	0.015011	5.208041	0
KSE 100	0.144691	0.015035	9.623311	0
KLCI	0.097449	0.014957	6.515124	0
MASI	0.183609	0.015016	12.22718	0
QSI	0.232002	0.014296	16.22799	0
TASI	0.053575	0.016852	3.179212	0.0015
Tunindex	0.259576	0.021134	12.28251	0

BIST 100: Turkey, **DFM:** UAE, **EGX 30:** Egypt, **JKSE:** Indonesia, **KSE 100:** Pakistan, **KLCI:** Malaysia, **MASI:** Morocoo, **QSI:** Qatar, **TASI:** Saudi Arabia, **TUNINDEX:** Tunisia

4.4 Value at Risk Estimation

Results are shown in Table 4.12, along with a 95% confidence interval, KLCI has the maximum value among all countries of VaR suggesting that there are 95% chances that loss will not exceed from 4.3% on average using any of five models. Whereas, MASI shows the lowest potential for loss which will not exceed 1.05% using all studied GARCH models. However, rest of the markets follow a range of -1.1% to -2.89% for computing Value at risk. Yet again at 99% confidence interval, KLCI shows the maximum value among all countries of VaR suggesting that there are 99% chances that loss will not exceed from 6.2% on average using any of five models.

In addition, MASI shows the lowest potential for loss which will not exceed 1.5% using all studied GARCH models. While rest of the markets follow a range of -1.3% to -4.00% for estimating Value at risk.

4.5 Violation Ratio

Each model's violation ratio is presented in table 4.12 by comparing the expected number of model violations to the number of actual model violations discovered through back testing. In a perfect world, the actual total number of violations committed should be the same as the projected total number of violations, and in practise, this ratio ends up being 1.
Table 4.13 presents the determined violation ratios for the 95% and 99% confidence intervals. These ratios are derived by applying the assumptions that are associated with the traditional methods of VaR estimation.

Analyzing GARCH and its variants at 95% confidence interval, it can be seen that except for Tunindex (Tunisia) rest of the 9 countries show a violation ratio within the acceptable range (0.5 to 1.5), hence it can be deduced that GARCH, EGARCH, PGARCH, QGARCH and TGARCH are good models to estimate VaR in Stock markets of Islamic Countries.

At 99% Confidence Interval, KLCI, QE General QSI, JKSE, and MASI show VR greater than 1.5 for all models hence suggesting that none of these models are going to appropriately compute VaR for their respective markets. However, for EGX 30, Tunindex, TASI, BIST 100 and DFM all GARCH models will be accurate for estimating VaR because their VR fall under the range of 0.5 to 1.5. Lastly, VaR for KSE 100 index can only be appropriately estimated using EGARCH and QGARCH at 99% Confidence Interval.

TABLE 4.10: Variance Equation using QGARCH Model

	RESID(-1)^2			**GARCH(-1)**			**GARCHRESIDORD(-1)**		
	Coefficient	**z-Statistic**	**Prob.**	**Coefficient**	**z-Statistic**	**Prob.**	**Coefficient**	**z-Statistic**	**Prob.**
BIST 100	0.096884	18.45707	0	0.867978	144.689	0	-0.00111	-11.6943	0
DFM	0.163782	21.90183	0	0.823627	159.2276	0	-0.00075	-3.53125	0.0004
EGX 30	0.165744	20.60205	0	0.806742	93.81742	0	0.001403	8.69905	0
JKSE	0.153049	18.31114	0	0.824043	98.45081	0	-0.00088	-10.0047	0
KSE 100	0.178046	16.77937	0	0.772123	73.89531	0	-0.00129	-11.8249	0
KLCI	0.111797	21.38226	0	0.87521	149.7651	0	-0.0003	-7.00891	0
MASI	0.21729	25.72311	0	0.716017	81.27588	0	-9.88E-05	-1.64955	0.099
QSI	0.267878	23.55126	0	0.721919	72.82904	0	-0.00063	-6.97914	0
TASI	0.454175	34.5627	0	0.671128	100.1442	0	-0.00073	-4.40335	0
Tunindex	0.580288	18.92946	0	0.129817	10.10993	0	-0.00468	-29.3497	0

BIST 100: Turkey, **DFM:** UAE, **EGX 30:** Egypt, **JKSE:** Indonesia, **KSE 100:** Pakistan, **KLCI:** Malaysia, **MASI:** Morocoo, **QSI:** Qatar, **TASI:** Saudi Arabia, **TUNINDEX:** Tunisia

Table 4.11: Variance Equation using TGARCH Model

	RESID(-1)^2			**RESID(-1)^2*(RESID(-1)<0)**			**GARCH(-1)**		
	Coefficient	**z-Statistic**	**Prob.**	**Coefficient**	**z-Statistic**	**Prob.**	**Coefficient**	**z-Statistic**	**Prob.**
BIST 100	0.061178	12.03613	0	0.07049	8.625396	0	0.870436	146.733	0
DFM	0.134073	17.22325	0	0.063996	4.993611	0	0.824916	159.5108	0
EGX 30	0.271974	15.70134	0	-0.1842	-10.2714	0	0.806483	91.93358	0
JKSE	0.089417	9.259203	0	0.113961	9.973704	0	0.83066	105.4684	0
KSE 100	0.082628	9.471587	0	0.178623	10.47459	0	0.779814	77.82436	0
KLCI	0.076277	14.18738	0	0.066166	7.329246	0	0.877207	149.5387	0
MASI	0.193487	15.51245	0	0.046484	3.303592	0.001	0.716413	79.91423	0
QSI	0.19462	16.2071	0	0.145729	8.657202	0	0.723019	72.3165	0
TASI	0.41262	33.30557	0	0.061649	2.219386	0.0265	0.670522	97.68825	0
Tunindex	0.092511	5.966664	0	0.318037	6.689284	0	0.162427	6.376441	0

BIST 100: Turkey, **DFM:** UAE, **EGX 30:** Egypt, **JKSE:** Indonesia, **KSE 100:** Pakistan, **KLCI:** Malaysia, **MASI:** Morocoo, **QSI:** Qatar, **TASI:** Saudi Arabia, **TUNINDEX:** Tunisia

Table 4.12: Value at Risk

	95%					99%				
	GARCH	**EGARCH**	**PGARCH**	**QGARCH**	**TGARCH**	**GARCH**	**EGARCH**	**PGARCH**	**QGARCH**	TGARCH
KSE 100	-2.896%	-2.658%	-2.776%	-2.736%	-2.876%	-4.058%	-3.733%	-3.899%	-3.846%	-4.039%
KLCI	-4.422%	-4.325%	-4.385%	-4.392%	-4.379%	-6.275%	-6.152%	-6.236%	-6.242%	-6.220%
EGX 30	-2.186%	-2.180%	-2.178%	-2.196%	-2.184%	-3.057%	-3.034%	-3.028%	-3.052%	-3.038%
Tunindex	-2.078%	-2.008%	-2.025%	-2.039%	-2.050%	-2.910%	-2.825%	-2.847%	-2.867%	-2.899%
TASI	-2.044%	-2.009%	-1.999%	-2.002%	-2.010%	-2.844%	-2.798%	-2.795%	-2.879%	-2.798%
QSI	-1.174%	-1.149%	-1.155%	-1.161%	-1.161%	-1.655%	-1.624%	-1.632%	-1.642%	-1.641%
DFM	-1.136%	-1.114%	-1.125%	-1.133%	-1.130%	-1.597%	-1.571%	-1.584%	-1.594%	-1.591%
JKSE	-1.871%	-1.803%	-1.818%	-1.843%	-1.839%	-2.623%	-2.537%	-2.558%	-2.594%	-2.600%
BIST 100	-2.402%	-2.388%	-2.269%	-2.402%	-2.403%	-3.377%	-3.355%	-3.186%	-3.333%	-3.383%
MASI	-1.061%	-1.120%	-1.087%	-1.051%	-1.055%	-1.342%	-1.479%	-1.505%	-1.476%	-1.455%

BIST 100: Turkey, **DFM:** UAE, **EGX 30:** Egypt, **JKSE:** Indonesia, **KSE 100:** Pakistan, **KLCI:** Malaysia, **MASI:** Morocoo, **QSI:** Qatar, **TASI:** Saudi Arabia, **TUNINDEX:** Tunisia

Table 4.13: Violation Ratio

	95%					99%				
	GARCH	**EGARCH**	**PGARCH**	**QGARCH**	**TGARCH**	**GARCH**	**EGARCH**	**PGARCH**	**QGARCH**	**TGARCH**
KSE 100	0.82737	0.81146	0.81941	0.81162	0.79157	0.31026	1.45187	1.55131	1.51184	1.57120
KLCI	0.92027	0.92027	0.93217	0.94029	0.92424	1.66601	1.58667	1.60651	1.64650	1.66601
EGX 30	0.77047	0.74238	0.73435	0.72647	0.73836	1.24398	1.24398	1.20385	1.18403	1.16372
Tunindex	0.34858	0.25352	0.24955	0.28520	0.30501	0.69321	0.49515	0.45554	0.45554	0.55457
TASI	0.75345	0.71795	0.74556	0.75360	0.74951	1.45957	1.53846	1.45819	1.42040	1.42012
QSI	0.87333	0.86939	0.88120	0.89693	0.88120	1.75059	1.77026	1.75059	1.75059	1.71125
DFM	0.91004	0.92573	0.91004	0.92597	0.91527	1.20293	1.20293	1.15063	1.12477	1.15063
JKSE	0.85518	0.88745	0.90359	0.89570	0.89149	1.87576	1.85559	1.85559	1.83579	1.83542
BIST 100	0.78217	0.82127	0.81345	0.84099	0.82127	1.36879	1.46656	1.38835	1.48641	1.44701
MASI	0.85759	0.86153	0.86546	0.85776	0.86939	1.61290	1.65224	1.67191	1.63289	1.63257

BIST 100: Turkey, **DFM:** UAE, **EGX 30:** Egypt, **JKSE:** Indonesia, **KSE 100:** Pakistan, **KLCI:** Malaysia, **MASI:** Morocoo, **QSI:** Qatar, **TASI:** Saudi Arabia, **TUNINDEX:** Tunisia

4.6 Backtesting

The study represents the results of back tests used to examine the strength of volatility models in estimating Value at Risk.

4.6.1 Kupiec (POF) Test

In back testing, actual returns and losses are contrasted to VaR projections to see how close the two are to one another. The Kupiec Probability of Failure Test is the global standard for back-testing. The secondary data is being used to test the null hypothesis of the POF, which states that the observed failure rate p is equal to the failure rate predicted by the confidence interval. The test findings demonstrate that the null hypothesis is rejected with 95% and 99% confidence, indicating that the model is inaccurate and misleading.

The critical value is 3.84 and 6.635 for 95% and 99% CI, respectively. An acceptable or potentially accurate risk prediction model has an LR of less than 3.84 at the 95% confidence level and less than 6.635 at the 99% confidence level.

Based on the computations at 95% confidence interval, KSE 100, EGX 30, Tunindex, TASI, BIST 100 & MASI have their respective Likelihood ratio greater than 3.84 hence rejecting null hypothesis and deducing that all the GARCH models used for the research are unacceptable for risk forecasting of these markets.

In contrast, DFM & KLCI have their LR lesser than 3.84 for all models from which it is indicated that all five GARCH models are perfect for risk forecasting. However, for JKSE only asymmetric GARCH models are accurate for forecasting and for QE General QSI, PGARCH, QGARCH and TGARCH are acceptable forecasting models.

Table 4.14: Kupiec Probability of Failure Test

	95%					99%				
	GARCH	**EGARCH**	**PGARCH**	**QGARCH**	**TGARCH**	**GARCH**	**EGARCH**	**PGARCH**	**QGARCH**	TGARCH
KSE 100	8.3581	10.0273	9.1725	10.0076	12.3440	170.4475	9.1003	13.2145	11.4986	14.1168
KLCI	1.6158	1.6158	1.1501	0.8844	1.4516	19.0081	15.0449	15.9983	17.9803	19.0081
EGX 30	14.9563	19.0436	20.3116	21.5964	19.6720	2.7812	2.7812	1.9641	1.6096	1.2820
Tunindex	14.75783	20.69332	20.97624	18.54005	17.28725	5.2487	15.7516	18.7320	18.7320	11.8770
TASI	16.5977	22.2174	17.7689	16.5977	17.1778	9.8690	13.2145	14.1168	8.3594	8.3594
QSI	4.3880	4.6729	3.8463	2.8629	3.8463	24.2304	25.3852	24.2304	24.2458	21.9889
DFM	1.6772	1.1372	1.6772	1.1294	1.4852	1.4938	1.4938	0.8358	0.5779	0.8358
JKSE	5.7427	3.4299	2.5031	2.9367	3.1840	30.5415	29.2767	29.2767	28.0510	28.0340
BIST 100	13.7612	9.1317	9.9766	7.1756	9.1317	6.3003	9.8308	6.9500	10.6294	9.0691
MASI	4.8811	4.5869	4.3022	4.8811	4.0270	16.9769	19.0081	20.0602	17.9803	17.9803

BIST 100: Turkey, **DFM:** UAE, **EGX 30:** Egypt, **JKSE:** Indonesia, **KSE 100:** Pakistan, **KLCI:** Malaysia, **MASI:** Morocoo, **QSI:** Qatar, **TASI:** Saudi Arabia, **TUNINDEX:** Tunisia

Now keeping in view the outcomes at 99% CI, none of the GARCH model used is accurate for risk forecasting in KSE100, KLCI, TASI, QE General QSI, JKSE, & MASI because their LR is greater than 6.635. Whereas, GARCH model is appropriate for risk forecasting of EGX30, BIST 100 and Tunindex.

4.6.2 Christoffersen's Independence Test

The null hypothesis asserts no clustering, which indicates that a day with violation is not dependent on the prior day's violation. The null hypothesis is rejected when the $LR > x^2$ model. In such case, we would reject the null hypothesis and look for clusters of violations that have been recorded throughout the same time period.

Results of Christoffersen's test for each index are in table 4.15. Starting with 95% Confidence interval, after evaluating all models, Tunindex, QE General QSI, DFM and MASI have LR ¿ X^2 due to which null hypothesis is rejected and it can be said that any violation today will have effects on future volatility. GARCH, QGARCH and TGARCH outperform EGARCH and PGARCH for predicting volatility in KSE 100. Volatility in BIST 100 can be effectively predicted using asymmetrical GARCH Models whereas volatility in JKSE can only be predicted using symmetrical GARCH Model.
Moreover, for TASI, PGARCH can be used to forecast risk. In addition, KLCI shows volatility clustering when GARCH and QGARCH are used. Lastly, for EGX 30 all models can be used to forecast volatility.
Now moving towards discussing results at 99% CI, KSE100, KLCI, TASI, EGX 30, BIST 100, DFM & JKSE exhibits no clustering across any model, we cannot infer future volatility from past volatility.
MASI rejects null hypothesis only by EGARCH and shows volatility clustering whereas appropriate models to anticipate risk is QSI are PGARCH, QGARCH and TGARCH. Tunindex can be efficiently predict volatility using asymmetrical GRACH Model.

Table 4.15: Christo ersen's Independence Test

	95%					99%				
	GARCH	**EGARCH**	**PGARCH**	**QGARCH**	**TGARCH**	**GARCH**	**EGARCH**	**PGARCH**	**QGARCH**	**TGARCH**
KSE 100	3.6844	4.4045	5.4534	1.8903	0.5153	-0.0397	-0.0600	-0.0397	-0.0469	-0.0211
KLCI	5.7645	3.1447	3.8093	4.6950	1.8281	0.1313	1.6674	1.5760	0.1652	0.1313
EGX 30	-0.9739	1.0554	1.2886	-0.7894	-0.4636	0.0237	0.02812	0.0616	0.0833	0.1071
Tunindex	49.9972	27.7357	14.4649	11.6287	26.0182	15.3728	2.4711	2.7740	2.6190	6.7105
TASI	-1.2665	-1.0698	4.2730	-1.0321	-1.0381	-0.0572	-0.0397	1.7616	-0.0614	-0.0614
QE General QSI	9.7322	13.5510	12.6777	9.1682	4.7100	7.3729	10.0856	4.7598	4.7584	0.0362
DFM	9.8825	14.5637	8.1391	9.0026	9.5885	0.2301	0.2301	0.3135	0.3595	0.3135
JKSE	2.7353	17.3427	17.9770	14.5699	11.4012	0.6302	2.2418	2.2418	2.2933	2.3528
BIST 100	4.0810	0.3882	-0.2107	0.0272	-0.4029	2.8158	4.6511	5.3351	4.4883	2.3482
MASI	18.3705	28.7802	21.8248	20.4404	17.3634	6.0276	11.7333	5.4761	5.8401	5.8401

BIST 100: Turkey, **DFM:** UAE, **EGX 30:** Egypt, **JKSE:** Indonesia, **KSE 100:** Pakistan, **KLCI:** Malaysia, **MASI:** Morocoo, **QSI:** Qatar, **TASI:** Saudi Arabia, **TUNINDEX:** Tunisia

FIGURE 4.11: Summary of Back Testing

Name of Stock Markets		GARCH	EGARCH	PGARCH	QGARCH	TGARCH	GARCH	EGARCH	PGARCH	QGARCH	TGARCH
KSE 100	VOILATION RATIO	0.83	0.81	0.82	0.81	0.79	0.31	1.45	1.55	1.51	1.57
	Kupiec (POF) Test	8.3581	10.0273	9.1725	10.0076	12.3440	170.4475	9.1003	13.2145	11.4986	14.1168
	Christoffersen's Test	3.6844	4.4045	5.4534	1.8903	0.5153	-0.0397	-0.0600	-0.0397	-0.0469	-0.0211
KLCI (KLSE)	VOILATION RATIO	0.92	0.92	0.93	0.94	0.92	1.67	1.59	1.61	1.65	1.67
	Kupiec (POF) Test	1.6158	1.6158	1.1501	0.8844	1.4516	19.0081	15.0449	15.9983	17.9803	19.0081
	Christoffersen's Test	5.7645	3.1447	3.8093	4.6950	1.8281	0.1313	1.6674	1.5760	0.1652	0.1313
EGX 30	VOILATION RATIO	0.77	0.74	0.73	0.73	0.74	1.24	1.24	1.20	1.18	1.16
	Kupiec (POF) Test	14.96	19.04	20.31	21.60	19.67	2.78	2.78	1.96	1.61	1.28
	Christoffersen's Test	-0.9739	1.0554	1.2886	-0.7894	-0.4636	0.0237	0.02812	0.0616	0.0833	0.1071
Tunindex	VOILATION RATIO	0.35	0.25	0.25	0.29	0.31	0.69	0.50	0.46	0.46	0.55
	Kupiec (POF) Test	14.75783	20.69332	20.97624	18.54005	17.28725	5.2487	15.7516	18.7320	18.7320	11.8770
	Christoffersen's Test	49.9972	27.7357	14.4649	11.6287	26.0182	15.3728	2.4711	2.7740	2.6190	6.7105
Tadawull All Share (TASI)	VOILATION RATIO	0.75	0.72	0.75	0.75	0.75	1.46	1.54	1.56	1.42	1.42
	Kupiec (POF) Test	16.5977	22.2174	17.7689	16.5977	17.1778	9.8690	13.2145	14.1168	8.3594	8.3594
	Christoffersen's Test	9.7322	13.5510	12.6777	9.1682	4.7100	7.3729	10.0856	4.7598	4.7584	0.0362
QE General QSI	VOILATION RATIO	0.87	0.87	0.88	0.90	0.88	1.75	1.77	1.75	1.75	1.71
	Kupiec (POF) Test	4.3880	4.6729	3.8463	2.8629	3.8463	24.2304	25.3852	24.2304	24.2458	21.9889
	Christoffersen's Test	9.73	13.55	12.68	9.17	4.71	7.37	10.09	4.76	4.76	0.04
Dubai Financial Market (PJSC)	VOILATION RATIO	0.91	0.93	0.91	0.93	0.92	1.20	1.20	1.15	1.12	1.15
	Kupiec (POF) Test	1.6772	1.1372	1.6772	1.1294	1.4852	1.4938	1.4938	0.8358	0.5779	0.8358
	Christoffersen's Test	9.8825	14.5637	8.1391	9.0026	9.5885	0.2301	0.2301	0.3135	0.3595	0.3135
JKSE	VOILATION RATIO	0.86	0.89	0.90	0.90	0.89	1.88	1.86	1.86	1.84	1.84
	Kupiec (POF) Test	5.7427	3.4299	2.5031	2.9367	3.1840	30.5415	29.2767	29.2767	28.0510	28.0340
	Christoffersen's Test	2.7353	17.3427	17.9770	14.5699	11.4012	0.6302	2.2418	2.2418	2.2933	2.3528
BIST 100	VOILATION RATIO	0.78	0.82	0.81	0.84	0.82	1.37	1.47	1.39	1.49	1.45
	Kupiec (POF) Test	13.7612	9.1317	9.9766	7.1756	9.1317	6.3003	9.8308	6.9500	10.6294	9.0691
	Christoffersen's Test	4.0810	0.3882	-0.2107	0.0272	-0.4029	2.8158	4.6511	5.3351	4.4883	2.3482
Moroccan All Shares (MASI)	VOILATION RATIO	0.86	0.86	0.87	0.86	0.87	1.61	1.65	1.67	1.63	1.63
	Kupiec (POF) Test	4.8811	4.5869	4.3022	4.8811	4.0270	16.9769	19.0081	20.0602	17.9803	17.9803
	Christoffersen's Test	18.3705	28.7802	21.8248	20.4404	17.3634	6.0276	11.7333	5.4761	5.8401	5.8401

Chapter 5

Discussion and Conclusion

5.1 Conclusion

The research sets out to evaluate the risk forecasting in ten Islamic stock markets by means of the models from GARCH class (GARCH, EGARCH, P-GARCH, Q-GARCH, and T-GARCH). There are two sections to this research. Value at risk is initially examined using parametric models in the first section of the research. While second section is comprised on ensuring that our models are accurate so we apply the Backtesting method and use Kupiec POF and Christoffersen's Independence test to verify our hypotheses. In calculating the value at risk, a threshold is considered, and losses that are far more than this trigger the alarm. . VaR is computed employing GARCH models, hence this study compares losses between the upper and lower VaR threshold using the confidence interval at 95% and 99%.Results for VaR estimate at 95% and 99% indicate that KLCI has the highest potential for loss, whereas MASI is the safest index with a loss probability of as low as just 1.05%. Now discussing the Violation Ratio, at 95% CI VaR of 90% indices can be efficiently estimated using all five GARCH models. However, at 99% Confidence Interval, all GARCH models can accurately estimate VaR for EGX 30, Tunindex, TASI, BIST 100 and DFM only. As results suggest, VaR for KSE 100 index can computed using EGARCH and QGARCH which also efficiently assists in capturing the leverage effect in the market. The parametric GARCH models employed in the study are suitable for risk forecasting for DFM

& KLCI, as determined by the calculation by Kupiec POF Test with 95% Confidence interval. Whereas, asymmetrical GARCH models outperform symmetrical GRACH model in predicting volatility in JKSE & QE General QSI. Furthermore, none of the model is accurate for volatility forecasting in KSE 100, EGX 30, Tunindex, TASI, BIST 100 and MASI. The GARCH model is acceptable in risk projection for EGX30, BIST 100, as well as Tunindex at the 99% confidence interval, according to the Kupiec Probability of Failure Test. When applied to DFM, the five GARCH Models allow for very accurate volatility prediction. In contrast, volatility forecasting in KSE100, KLCI, TASI, QE General QSI, JKSE, or MASI using any GARCH model is a futile endeavor. It is indicated that no model has predictive capacity to forecast volatility in Tunindex, QSI, DFM, and MASI at 95% CI of Christoffersen's Independence test but volatility in EGX 30 can be forecasted using all models. GARCH, QGARCH, and TGARCH forecast KSE 100 & KLCI volatility better than EGARCH and PGARCH. Volatility in BIST 100 can be anticipated using asymmetrical GARCH Models, but not JKSE. Now discussing Christoffersen's Independence test at 99% CI, KSE100, KLCI, TASI, EGX 30, BIST 100, DFM and JKSE accept null hypothesis, hence all GARCH models are adequate for risk forecasting and asymmetrical GARCH models can anticipate Tunindex volatility. To sum it up, the study focuses on the asymmetric behavior of volatility to both positive and negative shifts in models and the findings on asymmetric testing demonstrated that negative changes have a disproportionately large and forceful effect (robustness) on all stock market returns.
Finally, as per backtesting reports, both symmetric and asymmetric GARCH models work differently for each of stock index and asymmetric GARCH are better at-risk forecasting and capturing leverage effect.

5.2 Recommendations

Keeping in view the findings and discussions, this study supports the supremacy of time- varying GARCH models in effectually forecasting volatility in the stock markets. It is recommended that stock markets showing high volatility clustering in past trends can be effectively predicted using GARCH Models including symmetrical and asymmetrical models. The research comprehends that GARCH Models are appropriate models for Volatility forecasting of EGX 30, DFM, BIST 100, JKSE & KSE 100.

To be most useful, volatility forecasting using GARCH models will allow risk managers to investigate various forces acting on stock markets and the multiple possible outcomes. Therefore, better forecasts lead to improved risk management. It also helps policy maker in planning and designing policies in response to potential catastrophes which is even more crucial and put in place strategies for tolerating and mitigating risks.

Portfolio diversification, risk management, asset allocation, and investment decision-making are all areas that are influenced by the results of these stock market risk forecasting models. Therefore, investor and portfolio/fund managers can use the model's forecasts to assess whether to purchase, hold, or sell the shares of an investment portfolio which attempts to mirror stock market movements resulting in improved decision-making and risk management.

5.3 Limitations

For Further study, conditional value at risk can be estimated on the same data sample. Secondly, this study can also be conducted on other indices. Lastly, the quality of study can be improved by using other GARCH models to the literature.

Bibliography

AbdElaal, M. A. (2011). Modeling and forecasting time varying stock return volatility in the egyptian stock market. *International Research Journal of Finance and Economics*, (18):96–113.

Ahmed, A. E. M. and Suliman, S. Z. (2011). Modeling stock market volatility using garch models evidence from sudan. *International journal of business and social science*, 2(23):43–54.

Alberg, D., Shalit, H., and Yosef, R. (2008). Estimating stock market volatility using asymmetric garch models. *Applied Financial Economics*, 18(15):1201–1208.

Alexander, C. (2008). *Market risk analysis, practical nancial econometrics*. John Wiley & Sons.

ARUNA, U. and ADENOMON, M. (2021). Application of qgarch models to nigeria insurance stocks. *BIMA JOURNAL OF SCIENCE AND TECHNOLOGY (2536-6041)*, 5(02):49–55.

Awartani, B. M. and Corradi, V. (2005). Predicting the volatility of the s&p-500 stock index via garch models: the role of asymmetries. *International Journal of forecasting*, 21(1):167–183.

Badaye, H. K. and Narsoo, J. (2020). Forecasting multivariate var and es using mc-garch-copula model. *The Journal of Risk Finance*, 21(5):493–516.

Bali, T. G., Demirtas, K. O., and Tehranian, H. (2008). Aggregate earnings, firm-level earnings, and expected stock returns. *Journal of Financial and Quantitative Analysis*, 43(3):657–684.

Banumathy, K. and Azhagaiah, R. (2015). Modelling stock market volatility: Evidence from india. *Managing Global Transitions: International Research Journal*, 13(2).

Bentes, S. R. (2015). Forecasting volatility in gold returns under the garch, igarch and figarch frameworks: New evidence. *Physica A: Statistical Mechanics and its Applications*, 438:355–364.

Bollerslev, T. (1986). Generalized autoregressive conditional heteroskedasticity. *Journal of econometrics*, 31(3):307–327.

Bonga, W. G. (2019). Stock market volatility analysis using garch family models: Evidence from zimbabwe stock exchange. *MPRA Paper*, (94201).

Dana, A. (2016). Modelling and estimation of volatility using arch/garch models in jordan's stock market. *Asian Journal of Finance & Accounting*, 8(1):152–167.

Danielsson, J. (2011). *Financial risk forecasting: the theory and practice of forecasting market risk with implementation in R and Matlab*. John Wiley & Sons.

Degiannakis, S., Floros, C., and Dent, P. (2013). Forecasting value-at-risk and expected shortfall using fractionally integrated models of conditional volatility: International evidence. *International Review of Financial Analysis*, 27:21–33.

Ding, Z., Granger, C. W., and Engle, R. F. (1993). A long memory property of stock market returns and a new model. *Journal of empirical nance*, 1(1):83–106.

Ederington, L. H. and Guan, W. (2005). Forecasting volatility. *Journal of Futures Markets: Futures, Options, and Other Derivative Products*, 25(5):465–490.

Elenjical, T., Mwangi, P., Panulo, B., and Huang, C.-S. (2016). A comparative cross-regime analysis on the performance of garch-based value-at-risk models: Evidence from the johannesburg stock exchange. *Risk Management*, 18(2):89–110.

Emenogu, N. G., Adenomon, M. O., and Nweze, N. O. (2020). On the volatility of daily stock returns of total nigeria plc: evidence from garch models, value-at-risk and backtesting. *Financial Innovation*, 6(1):1–25.

Engle, R. F. (1982). A general approach to lagrange multiplier model diagnostics. *Journal of Econometrics*, 20(1):83–104.

Ezzat, H. (2012). The application of garch and egarch in modeling the volatility of daily stock returns during massive shocks: The empirical case of egypt. 96:143–155.

Ezzat, H. (2013). The application of garch methods in modeling volatility using sector indices from the egyptian exchange. 27:68–85.

Fakhfekh, M., Jeribi, A., and Ben Salem, M. (2021). Volatility dynamics of the tunisian stock market before and during the covid-19 outbreak: Evidence from the garch family models. *International Journal of Finance & Economics*, 26:01–14.

Franses, P. H. and Van Dijk, D. (1996). Forecasting stock market volatility using (non-linear) garch models. *Journal of forecasting*, 15(3):229–235.

Gaio, L. E., Pimenta Júnior, T., Lima, F. G., Passos, I. C., and Stefanelli, N. O. (2018). Value-at-risk performance in emerging and developed countries. *International Journal of Managerial Finance*, 14(5):591–612.

Girard, E. and Biswas, R. (2007). Trading volume and market volatility: Developed versus emerging stock markets. *Financial Review*, 42(3):429–459.

Gupta, R. and Guidi, F. (2012). Cointegration relationship and time varying co-movements among indian and asian developed stock markets. *International Review of Financial Analysis*, 21:10–22.

Gzel, F. and Acar, M. (2021). The effects of epidemics on capital markets volatility: A case study of borsa istanbul. *CES Working Papers*, 13(1):50–70.

Harrison, B. and Moore, W. (2011). Nonlinearities in central and eastern european stock markets. *Applied Economics Letters*, 18(14):1363–1366.

Hentschel, L. (1995). All in the family nesting symmetric and asymmetric garch models. *Journal of nancial economics*, 39(1):71–104.

Higgins, M. L. and Bera, A. K. (1992). A class of nonlinear arch models. *International Economic Review*, 33(1):137–158.

Kambouroudis, D. S., McMillan, D. G., and Tsakou, K. (2016). Forecasting stock return volatility: A comparison of garch, implied volatility, and realized volatility models. *Journal of Futures Markets*, 36(12):1127–1163.

Lim, C. M. and Sek, S. K. (2013). Comparing the performances of garch-type models in capturing the stock market volatility in malaysia. *Procedia Economics and Finance*, 5:478–487.

Lin, Z. (2018). Modelling and forecasting the stock market volatility of sse composite index using garch models. *Future Generation Computer Systems*, 79:960–972.

Mandelbrot, B. (1963). New methods in statistical economics. *Journal of political economy*, 71(5):421–440.

Markowitz, H. (1952). The utility of wealth. *Journal of political Economy*, 60(2):151–158.

McNeil, A. J. and Frey, R. (2000). Estimation of tail-related risk measures for heteroscedastic financial time series: an extreme value approach. *Journal of empirical nance*, 7(3-4):271–300.

Mutaju, M. and Pastory, D. (2019). Modeling stock market volatility using garch models case study of dar es salaam stock exchange (dse). 9:138–150.

Naimian, K. (2021). Application of garch type models in forecasting value at risk. *Journal of Forecasting*, 40:737–757.

Najand, M. (2002). Forecasting stock index futures price volatility: Linear vs. nonlinear models. *Financial Review*, 37(1):93–104.

Nelson, D. B. (1991). Conditional heteroskedasticity in asset returns: A new approach. *Econometrica: Journal of the econometric society*, 59(2):347–370.

Nieto, M. R. and Ruiz, E. (2016). Frontiers in var forecasting and backtesting. *International Journal of Forecasting*, 32(2):475–501.

Nurrachmi, R. (2018). Movements of islamic stock indices in selected oic countries. *Al-Muzara'ah*, 6(2):77–90.

Ogege, S. (2016). Gauging the volatility level of stock returns in the nigerian stock market. *The Paci c Journal of Science And Technology*, 17(1):118–120.

Okpara, G. (2015). Downside risk analysis of the nigerian stock market: a value at risk approach. In *A Conference Paper presented at International Science Index, LOS Angeles USA Part XIX*.

Rizvi, S. A. R., Dewandaru, G., Bacha, O. I., and Masih, M. (2014). An analysis of stock market efficiency: Developed vs islamic stock markets using mf-dfa. *Physica A: Statistical Mechanics and its Applications*, 407:86–99.

Sentana, E. (1995). Quadratic arch models. *The Review of Economic Studies*, 62(4):639–661.

Shaik, A. and Syed, A. (2019). Intraday return volatility in saudi stock market: an evidence from tadawul all share index. *Management Science Letters*, 9(7):1131–1140.

So, M. K. and Philip, L. (2006). Empirical analysis of garch models in value at risk estimation. *Journal of International Financial Markets, Institutions and Money*, 16(2):180–197.

Sobreira, N. and Louro, R. (2020). Evaluation of volatility models for forecasting value-at-risk and expected shortfall in the portuguese stock market. *Finance Research Letters*, 32:101098.

Susruth, M. (2017). Application of garch models to forecast financial volatility of daily returns: An empirical study on the indian stock market. *Asian Journal of Management*, 8(2):192–200.

Tamilselvan, M. and Vali, S. M. (2016). Forecasting stock market volitility-evidence from muscat security market using garch models. *International Journal of Commerce and Finance*, 2(1):37–53.

Tripathy, N. and Garg, A. (2013). Forecasting stock market volatility: Evidence from six emerging markets. *Journal of International Business and Economy*, 14(2):69–93.

Vasudevan, R. and Vetrivel, S. (2016). Forecasting stock market volatility using garch models: Evidence from the indian stock market. *Asian Journal of Research in Social Sciences and Humanities*, 6(8):1565–1574.

Zakoian, J.-M. (1994). Threshold heteroskedastic models. *Journal of Economic Dynamics and control*, 18(5):931–955.