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Evaluation of Value-at-Risk and Conditional Value-at-Risk by Using GARCH Model in Pakistan Equity Market

by

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Dedicated to the people I love and admire...My Parents.

CERTIFICATE OF APPROVAL

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Then which of the Blessings of your Lord will you deny.
(Surah Ar-Rehman)
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Abstract

The purpose of the study is to investigate risk forecasting model for evaluation of Value-at- Risk and conditional Value- at- Risk. This study applies GARCH family to estimate the Value At-Risk (VaR) and Conditional Value at- Risk (CVaR) forecast of one day for Pakistan equity market. Primarily, all GARCH based models are applied to daily returns data to capture the VaR and CVaR.. Secondly, extreme value theory GARCH models also used for the estimation of VaR and CVaR. To obtain good estimates of the results, two approaches are used. First is Parametric approach such as GARCH, EGARCH, QGARCH, GJR-GARCH and APGARCH. Second is non- parametric approach such as Historical simulation. The models of Parametric approaches are than evaluated using traditional and dynamic back testing techniques. The study implies daily returns of Pakistan stock market from 1997-2018 perform for Pakistan Equity Market. By comparing all GARCH based models and EVT GARCH based models, GARCH model at 95% confidence level and EVT GARCH Based models at 99% confidence level performs better for true risk forecasting. This study identifies the appropriate GARCH based model to measure the market risk in future and helps the financial institutions and investors to choose appropriate model to measure risk appropriately.

Keywords: Extreme Value Theory (EVT), GARCH Model Back Testing, Risk Forecasting, Value-at-Risk (VaR)

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Abbreviations

APARCH	Asymmetric Power Autoregressive Conditional Heteroskedastic
CVaR	Conditional Value at Risk
EGARCH	Exponential Generalized Autoregressive Conditional Heteroskedastic
EVT	Extreme Value Theory
GARCH	Generalized Autoregressive Conditional Heteroskedastic
GJR-GARCH	Glosten-Jagannathan- Runkle Generalized Autoregressive Conditional Heteroskedastic
GPD	Generalized Pareto Distribution
HS	Historical Simulation
PSX	Pakistan Stock Market
QGARCH	Quadratic Generalized Autoregressive Conditional Heteroskedastic
VaR	Value at Risk
VR	Violation Ratio

Chapter 1

Introduction

1.1 Theoretical Background

In financial institution, risk management plays a vital role. The major issues of various institutions are managing the risk. It is a method that can control and measure the financial situation of any organization. Decision-makers focus on managing the different types of risk methods the market risk, which is associated with losses and occurs due to the fluctuation in market prices of financial assets. (VaR) is the method for estimating the market risk which can also estimate the major losses and confidence level at a specified time period (Jorion, 2000).
Among the risk experts, VaR has been very common due to its unambiguousness and interpretability process. Those losses that could go above the VaR in a given confidence level that are evaluated by (CVaR). Basel (2012) group encourages the use of CVaR in market risk assessment and market risk (Lemonakis, Malandrakis, Garefalakis, & Balla, 2018).
Pritsker (1997) specifies that the efficiency of models of market risk, these must be precise. As "(VaR)" finds the confidence level and extreme loss over a specified period, it can overvalue or undervalue risk under different disciplines. On the contrary, as the comparison of VaR. "(CVaR)" is an appropriate method for the estimation of risk (Altay & Kucukozmen, 2006). For diversifying the portfolio, emerging equity market more attractive due to high average stock returns and

their low relationship with market. Santis (1993) suggests that adding US assets serve as a benchmark for the emerging market in order to improve risk performance. Meanwhile, Bekaert & Harvey, (1995) add that equity investments in the emerging market play a considerable role in the shifting of mean-variance to the left of the tail more efficiently.

Bekaert & Harvey, (1995) and Claessens, Dasgupta, & Glen, (1995) further highlight that market behave play a vital role in an emerging market because these returns create a fatter tail for emerging markets as compared to industrial markets.

According to the VaR, Risk managers should direly have focused on the factors which cause fluctuation in the market and has knowledge about uncertainty in the market. Such risk measurement techniques should be adopted which evaluates risk in the market, market condition, market behavior and the demands of the different markets even and also focuses on the tail of the distribution.

As previous studies focus on the financial dynamics of the world's major stock market but now the trend has been shifted to the emerging market of developing countries (Bekaert & Harvey, 1997).

It is necessary to manage and estimate the market risk due to overcome the sudden significant losses because the market risk is a major concern for financial institutions. Basel introduced the "(VaR)" for the measurement of market risk and it became a more popular tool for estimating the risk. After its amendment, the different experts argue that instead of VaR, ES is important for measuring the market risk. (Artzner, Delbaen, Eber, & Heath, 1999) The purpose of this paper is to identify the different time-varying volatility based VaR and CVaR in Pakistan equity market and then select the suitable GARCH model which is used to evaluate the "Conditional Value at Risk (CVaR)" and "Value at Risk (VaR)".

1.2 Research Gap

Risk estimation is an essential part of any financial institution. Value at risk is considered a necessary tool for the measurement of risk. The risk that comes due

to the adverse movement in market prices of financial assets associated to losses is known as market risk. VaR is the major approach to market risk, that quantifies the risk of loss that can be happen over the specific period of time. Pakistan is an emerging market that contributes to the economy and helps to identify the risk assessment in the Pakistan equity market. This is the pioneer study to evaluate the VAR and conditional VAR in Pakistan Equity Market by using the GARCH model and EVT GARCH model. Financial institutions use this model to evaluate the volatility of returns for market indices and stocks. In previous studies, various distributions such as normal distribution. Student-t, GED, skewed normal and skewed GED are used for the estimation of “Value at risk” and “Conditional value at risk”. This study estimates the market risk that is time-varying of stock prices fluctuate significantly. Therefore, the assumption of risk GARCH model and EVT is used to compare that which GARCH model is most appropriate to evaluate the VaR and Conditional Value at risk in Pakistan Equity market.
The literature shows that a lot of studies are conducted on the importance of VAR in the risk estimation process. The study has contributed to these different ways in the field of measure and management of risk. Firstly, the study contributed to the benefit of investors that they know about the market condition whether the market condition is riskier for investment purposes or less risky. Secondly, it contributed to decision making for the capitalization of the asset. Thirdly, the most important contribution of this study is that it helps to check which VaR and CVAR model is more suitable for their risk estimation.

1.3 Problem Statement

Risk estimation plays a vital role in financial market. Market is basically a major concern for financial institutions. So, the market risk should be measurable and manage. The market risk is the risk that associated to loss that occurs due to the fluctuation in market prices of financial assets. To measure the risk VaR is method for estimating the market risk which can estimate the major losses and confidence level at a given time period (Jorion,2000). Another method is CVaR which can calculate those loses that exceed from VaR at a given time period. The major problem of this study is to measure the risk and level of risk that Pakistan equity market faces currently and in future.

1.4 Research Questions

Research Question 1:
How different time-varying volatility-based values at risk model perform in Pakistan Equity Market?

Research Question 2:
How different time-varying volatility based Conditional Value at risk model perform in Pakistan equity Market?

Research Question 3:
What is the most appropriate model for evaluation of VAR and Conditional Value at risk in Pakistan Equity Market?

1.5 Objectives

Research Objective 1:
To identify the appropriate GARCH based model for estimating VAR in the Pakistan equity market.

Research Objective 2:
To identify the appropriate GARCH based model for estimating Conditional Value at risk in Pakistan Equity Market.

1.6 Significance of the Study

In a financial institution, risk management plays a vital role. Managing risk is a major issue for the various institutions. Risk estimation help to measure and control the financial situation of any organization. Equity market of Pakistan is also facing the unstable condition as the world markets are facing the challenges of economic turmoil. The study is significantly important for financial institutions, risk managers, and investors. This helps the financial institutions to estimate the risk by using the appropriate model . With the passage of time, risk management models are updating and to fill the gap, this study gives the benefit to investors and financial institutions to manage their risk appropriately. By implementing methods of GARCH, this study enables us to know the performance of various GARCH methods for the estimation of risk and after that, it helps to come to know that which the most suitable model for risk measurement.

The purpose of the study was to perform the statistical risk assessment of the Pakistani Equity Market by using the GARCH family that is simple GARCH, EGARCH, GJR-GARCH, QGARCH and APGARCH and EVT model in comparison with the traditional parametric and non-parametric models. This study consists of three parts. In the first part of the study, Value at risk has been analyzed by using the non-parametric (Historical simulation model) and parametric models. The validation of the models is done by the Back-testing technique by using the Kupiec and Christoffersen test. Kupiec POF test reveals that GARCH, GJR-GARCH, QGARCH, and APGARCH models perform better than the EGARCH model at a 95% level of confidence but at 99% level of confidence all models are rejected and did not perform better.

1.7 Plan of the Study

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

Chapter 1: It focuses on the fundamental idea of the study. This section introduces the topic by providing basic information, problem statement, and gap analysis, research question and significance of work.

Chapter 2: This chapter narrates deep investigation of topic including theoretical as well as empirical arguments from past studies.

Chapter 3: This chapter includes the methodology adopted for the investigation of conventional and modern methods and models to estimate risk.
Chapter 4: It elaborates on the outcomes from empirical results and explain the finding on the basis of thesis objectives, the findings are filtered through backtesting techniques.
Chapter 5: This chapter summarizes research outcomes and recommends risk forecasting models according to the Pakistan market condition.

Chapter 2

Literature Review

Financial risk is one of the market risk faced by investors who are committed certain amounts and the chance of loss occured due to fluctuations in the market price in future. The evaluation made by (Zappe, dos Santos, da Silva Ferrão, & Dias, 2013) concluded that the techniques of VaR in market capitalization, during the crisis and non-crisis period work differently. Gilli et al. (2006) stated that during hard times, risk estimation is much dicult and the forecasted returns maybe not reliable as compared to forecasted returns in a normal period. Another study revealed that VaR estimates were on the higher side during the global crisis in dierent countries (McKenna and Metcalfe, 2013).

The previous studies did not favor the estimation of VaR by using the single method because it might over or underestimate risk. It was always recommended to follow more than one method for risk forecasting. Monte-Carlo simulation and the historical simulation performed better in risk-averse organizations, as returns were normally distributed, (Saddique and Khan, 2015). But the risk-takers preferred to use methods that provide smaller VaR estimation.

According to (Jorion, 2000), he described that the confidence level and maximum worst loss can be measured by value at risk at a given time. In order to estimate the most suitable model, Basel introduced a basic model for estimation of VaR initially but the model had major insufficiencies and criticism (Taleb & Jorion, 1997). However, the Basel Committee permitted the institutions for the implementation of internal models that can easily evaluate VaR by using backtesting.

Furthermore, as a tool for risk evaluation, VaR has its problems such as model risk. It means that when the risk is linked with the improperly selected model then this risk is considered the model risk. On the other hand, risk should be aligned with a suitable implementation model. These risks are for all types of risks not only for VaR. The other problem arises due to the non- sub-additively when the number or amount of individual risks does not exceed the cumulative risk.

A measurable tool which is Value at Risk, used to evaluate the possible loss over a given period in a portfolio of assets. Specically, this tool is also developed due to the estimation of unconditional returns distribution of the far-left tail. In past, these criticisms raised due to standard methods of VaR as a risk measure is commonly used and affected on the financial returns that are "the presence of volatility clustering, indicated by high autocorrelation of absolute and squared returns, (ii) excess kurtosis (fat tails) and (iii) skewness in the density of the unconditional returns distribution".

According to Longin & Solnik (1995), the increase in movements of financial returns between markets also increases the volatility. Previous studies highlighted to predict VaR of the portfolio, multivariate models are used in order to achieve forecast improvement and use of more information for the individual asset returns. Bauwens, Laurent, & Rombouts (2006) mentioned that these models can suffer from the "curse of dimensionality" problem thus being more intensive computationally in high dimensional frameworks. This study investigates the regulator that VaR is an appropriate model about forecasting, reporting and pay attention to increased information of the market. Sometimes information related to the asymmetric information that can cause a maximum loss. VaR is helpful to overcome the sudden losses and prevent from the adverse selection of asymmetric information about the possible loss, which provides benefits for the investors that are committed with the future amounts.

Rockafellar and Uryasev, (2000) for the very first time introduce the concept of Conditional VaR. Conditional VaR estimates the measure of loss may occur in tail cases, though VaR improves regarding the size of loss that may happen past the edge. In this manner, the Conditional VaR of a particular portfolio is equivalent to or bigger than the VaR of that portfolio. Conditional VaR rose when VaR neglected to quantify the measure of loss in the condition that VaR exceeded. Contingent incentive in danger is the weighted normal of VaR or expected loss that surpasses the VaR estimation. It is otherwise called Expected shortfall, mean excess over VaR or tail VaR.

Pflug (2000) asserted that conditional VaR is well known risk metric, that follows the theory of intellectual risk estimates planned by Artzner et al., 1999. CVaR is considered as estimation of loss if risk is more than the expected value Alexander, (2009). For example, If VaR is valued at .95% of confidence level, means that there are 5% chances that loss will exceed the desired amount (Allen and Powell, 2009).

Back testing is considered as valuable model from other models due to its extremely prominent features, characterized as accurate models Jorion (2000). Back testing is used to estimate the results of "VaR" and "CVaR" with the expected returns and based on this, the model evaluates the best results that demonstrate the precise level of risk.

Basel committee of banking association demonstrate the risk evaluation best method is beck testing (Pykhtin, 2012). Nieppola (2009) analyzed that VaR models captures the lower risk as compared to the CVaR models (Nath and Samanta, 2003). From all risk evaluation models, he found that Historical simulation is best to capture the risk of equity market. The consequences of the examination by (Kang and Yoon, 2007) found that at 95% confidence level, VaR models always undervalue the risk and they capture the true level of risk.

The strategies for determining Value at Risk are ordered in to parametric and nonparametric in a wide manner. Recorded Simulation is one case of a nonparametric procedure. The semiparametric and parametric technique incorporates "Monte Carlo Simulation" and "Variance-Covariance Method" individually. There is a need to conjecture the mean and unpredictability by some procedure for semiparametric and parametric philosophies. The stock return arrangement is leptokurtic, with overwhelming tails and displays instability grouping. Along these lines, a parametric model of Value at Risk utilizing the mean and instability

estimate gotten by a static procedure isn't right (Khan and Khan, 2018).
Several studies like Isik et al. (2016), Saddique and Khan (2015) use various distributional assumptions like normal distribution and student-t distribution, but the concentration is mostly on central observations or, for states in terms of nancial market, concentration on returns under normal market conditions. Similarly, historical simulation, the non-parametric model makes no assumptions related to the nature of the empirical distribution.
The Value at Risk models, as a device for estimating market risk, have turned out to be well known on the grounds that these models give one single figure which educates us regarding the most noticeably bad conceivable loss, in a given time horizon, with a particular certainty interim. More or less, there are various investigations that support the parametric techniques to figure Value at Risk (Sarma, Thomas, and Shah, 2003). The execution of the semiparametric technique (Monte Carlo Simulation) in anticipating Value at Risk relies on the distributional assumption of returns and the accurate model used to evaluate the mean and the standard deviation of profits (Khindanova, Rachev, and Schwartz, 2001).
VaR was empirically predicted by Zargar and Kumar (2018) in major Asian countries including "Singapore, Malaysia, Hong Kong of China, Indonesia, South Korea, Philippines, Thailand, China, Taiwan of China and India" with number of parametric and non-parametric models to capture the market risk. Then models are evaluated by the back-testing models such as conditional coverage tests an unconditional coverage tests. with dierent competing models, for measuring and managing market risks. These models help to figure out the best VaR models for the markets. The results of the study were mix due to the following two reasons. First, the VaR models always capture the historical data, to forecast the future market. Second, the models rely on some basic assumptions and approximations, that sometimes does not hold in any situation. Therefore, the results of the study are mixed due to some unfavorable situations.
Giot and Laurent (2003) suggested that the Variance-Covariance Method used to evaluate the Value at Risk with unpredictability presence by GARCH model related to electronic returns.

Harmantzis, Miao, and Chien (2006) conduct the study to examine the empirical performance of CoVaR and "VaR" models. The study analyzes the daily returns of stock indexes and currency with ten-year data by using the extreme value theory, peak over threshold method and Generalized Pareto distribution. The results of Backtesting support the fat tail asset returns distributions.

The global nancial crisis of 2007-2008 considered the VaR as the weakest method. Muela, Martın, and Sanz (2017) nd that standard Extreme value (parametric method) outperforms the standard method of VaR calculation. As per Basel accord, Extreme value theory best measures the market risk capital requirement.

The study also highlights that in emerging markets the level of volatility is very high as compared to the developed countries. The rms that are operating in the emerging countries should consider the standard Extreme value method for risk calculation.

Danielsson and De Vries (2000) compare the four dierent models of (GARCH normal, GARCH t, HS, EVT) for equities, bond, commodities, and foreign exchange to generate daily 99% VaR In this case, the performance of HS and EVT is found better than the GARCH Normal and GARCH t distribution. Danielsson and De Vries (2000) report that GARCH with normal distribution assumption does not perform well as compared to the GARCH-t distribution assumption.

The execution of VaR and CVaR models ought to be assessed because the dependability of each evaluated model depends on its exactness. Monetary organizations must play out their exactness assessments normally to affirm the unwavering quality of evaluated hazard. The weight of inside and outside gatherings (e.g., financial specialists, controllers, ranking directors, and so forth.) additionally require foundations for the precision evaluation of their hazard models (Blanco and Oks, 2004).

While writing information no widespread model providing the ideal evaluation of the VaR. Various research papers seeing use of various methodologies in created monetary markets affirm this, for example, "Manganelli and Engle (2001), Christoffersen, et al. (2001), Angelidis, et al. (2004), Wong, et al. (2002), Alexander and Leigh (1997), Harmantzis, et al. (2006), Embrechts, et al. (1998), McNeil, et al. (2005), Guermat and Harris (2002)".

Then again, there are not many papers perceiving the examination of VaR models in creating budgetary markets. Gençay and Selçuk (2004) investigate the quantile estimation and parameter models of VaR stock trade files creating Eastern and Central European nations where outcomes showing that summed up Pareto distributions and unexpected value theory are essential instruments in risk the executives in creating nations.

Žiković (2007) detected various ways for estimation of VaR in case of new entities for EU participation. In money related markets of these nations on the grounds that the profits show the presence of substantial heteroscedasticity asymmetry and tails, the use of VaR models are not effective enough.

In 2009, further inquiries followed by Žiković analyzed that the profits of stock-trade lists of VaR models of Croatian and Turkish with the opening of global economic reserve. Anelić (2010) observed with 5% level of significance, the dissected models give estimations of VaR under the stable economic situations of "Slovenian, Croatian, Serbian and Hungarian markets", while, under the instability of market situation with 1% level of significance, examined models give evaluation of VaR parameters. Djaković (2010) examined the exhibition of unexpected price with the day by day stock behaves of four diverse developing markets "Serbian, Croatian, Slovenian and Hungarian stock records", and inferred that EVT method ought to combine reliable observing, with uncommon attention on the job of ideal authority assurance.

Nikolić-orić and orić (2011) examined the record of stock exchange in money market and analyze that GARCH models shared through offensive price top over-limit strategy, decline the mean estimation of VaR, just as that given models are superior to IGARCH model and Risk Metrics technique. Additionally, Mladenović, and Miletić (2012), in view of examination of stock-trade records in Central and Eastern European nations "Bulgaria, Czech Republic, Hungary, Croatia, Romania, and Serbia", arrived at resolution that the technique of unexpected value theory is marginally superior to GARCH model with respect to the computation of VaR, however broad proposal is to utilize the two methodologies for better estimating of market risk. In so far, the Montenegrin securities exchange has not been examined in exact writing as of not long ago, so the primary commitment of this paper is to increase the constrained experimental research on estimation of VaR and anticipating in rising money related markets.

Chapter 3

Research Methodology

In this study, different models and approaches are used for the estimation of VaR and CVaR. Two types of approaches are used for this study one is a non-parametric approach and the other is the parametric approach. The parametric approach includes GARCH models such as GARCH, EGARCH, GJR-GARCH, APGARCH and QGARCH and EVT GARCH model. The non-parametric approach includes only one that is a historical simulation.

3.1 VaR Estimation through Non-Parametric Model

3.1.1 Historical Simulation

Historical simulation is a non- parametric approach, which is widely used by the market to calculate the daily and quarterly VaR Historical simulation is very advantageous for the market to calculate VaR and CVaR because it is not complex to the changes in market situation. This method is used for the forecasting of risk will be on the basis of past returns and also provide better weightage to all past observations. The historical simulation model forecasts the VaR by using a percentile function. Its relative assumption is whatever trend of returns is in past, will continue in future as well. Historical simulation gives equal weightage to all past observation. This method provides better estimates in the absence of structural breaks. But the financial data is highly volatile, every time the trend may not be the same in future as in past this method is less responsive to odd outlier, which makes it better estimator as compared with parametric models. This is helpful for portfolio investments because, as compared with other models, it captures non-aligned dependence directly. Historical Simulation is applied for finding dynamic forecasted value at risk and compared with other methodologies to obtain the best methodology.

$$VAR_t = -R_t^p \tag{3.1}$$

$\mathrm{R}_t^p Is$ the path percentile of sample t. It is referred to as historical simulation (HS), based on historical return data.

3.1.2 VaR Estimation through Parametric Model

The parametric model assumes that the data is normally distributed. This may not exist in the financial market all the time because market conditions did not remain the same it fluctuates and due to increased volatility in financial markets data may have fat tails. Parametric approaches follow the underlying model's assumptions to estimate the parameters of VaR and CVaR calculations.

1. GARCH

Bollerslev (1986) proposed the GARCH model in the context of variance. This model captures the volatility dynamics and estimates of the VaR and CVaR. In this case, volatility is not constant due to the fluctuation of the prices in the market. GARCH model introduced in 1982 by Robert F.Engle, to evaluate the volatility in financial markets. This model is preferable than others because it gives accurate result to predict time varying prices and rates of financial instruments. GARCH model has been widely used in modeling of the conditional volatility in time series data and assumes that good news and bad news have same effect on future conditional volatility meanwhile it depends on the squared past. The conditional variance of the GARCH model can be written as:

$$\sigma_t^2 = \omega + \Sigma_{i=1}^q \alpha_i \varepsilon_{t-1}^2 + \Sigma_{j-1}^p \beta_{j=1}^p \beta_j \sigma_{t-j}^2 \qquad (3.2)$$

The impact of positive and negative on the conditional variance are same in GARCH model. So GARCH model is incapable to express the Leverage Effects. The conditional variance of GARCH model is not only linear function of lagged conditional variance but also a linear function of lagged squared residuals.

2. EGARCH

In 1991, Nelson proposed the EGARCH model. It focusses the asymmetric effects of data. He observed that EGARCH model can reduce the main disadvantages of GARCH models. It means the negative relationship between future and current returns which is omitted by the GARCH model assumption. The equation of conditional variance of E GARCH model is written as:

$$log(\sigma_t^2) = \omega + \Sigma_{i=1}^q \left[\alpha_i z_{t-i} + \gamma_i \left(|z_{t-i}| - \sqrt{2/\pi}\right)\right] + \Sigma_{j-i}^p \beta_j log\left(\sigma_{t-j}^2\right) \qquad (3.3)$$

where the coefficients capture the size and sign effect.

For the EGARCH model positivity limitations are not necessary since the logarithm is positive. Asymmetric behavior depends on the coefficient. If the positive news has larger effect on the negative news. This model identifies the asymmetric behavior of the time varying variance to shocks and confirms that the variance is always positive at the same time. When the logarithm is greater than the mean and error term would also greater means $\epsilon_{(t-1)} >$ This means that effect of negative news has more than positive news. In EGARCH model this sign γ_i shows leverage effect or parameter and tells the negative and positive shock. In most cases a negative shock increases the uncertainty as compared to positive shock. Leading to uncertain future, a negative shock suggests the bad news in financial market. Therefore, for bearing high risk in their investments, shareholders would require higher expected returns.

3. GJR-GARCH

Glosten, Jagannathan, and Runkle (1993) proposed the GJR-GARCH model to capture the asymmetry property of financial data in finding the conditional heteroskedasticity.

$$(\sigma_t^2) = \omega + \Sigma_{i=1}^{q}[\alpha_i + \gamma_i I_{(\epsilon t-j} > 0)]\epsilon_{t-i}^2 + \Sigma_{j-1}^{p}\beta_j\sigma_{t-j}^2 \quad (3.4)$$

where α, β and γ are constant parameters. This model tells about positive and negative shock, good and bad news and capture the asymmetric effects by the constant parameter. The good news in the financial market exists if the error term is greater than zero and if it is less than zero it means the bad news exists in the financial market.

4. QGARCH

Sentana (1995) proposed the Quadratic GARCH (QGARCH) model to assume the asymmetric effects of negative and positive shocks. This model can represent the formalized facts present in financial returns data better than the GARCH (1,1) model.

$$(\sigma_t^2) = \omega + \Sigma_{i=1}^{q}\alpha_i\epsilon_{t-i}^2 + \Sigma_{j=1}^{p}\beta_j\sigma_{t-j}^2 + \Sigma r_i\epsilon_{t-i} \quad (3.5)$$

5. APGARCH

Ding, Granger, and Engle (1993) carried the APARCH (Asymmetric power ARCH Model). This model represents the Leverage Effects, kurtosis and fat tails. The APARCH model identifies the asymmetry in return volatility as the GJR-GARCH model. It tells about the comparison of negative and positive returns. Returns are negative if volatility tends to increase as compared to positive returns.

The general structure is:

$$(\sigma_t^{\varphi}) = \omega + \Sigma_{i=1}^{q}\alpha_i\epsilon_{t-i}^{\varphi} + \Sigma_{j=1}^{p}\beta_j\sigma_{t-j}^{\varphi} \quad (3.6)$$

where ξ, ω, αj, γj and β_i are the parameters which shows the leverage effect. When a negative information has a stronger impact than the positive information on the price volatility, the leverage effect exists. It also tells about good and bad news. The indicator function takes a value of 1 if the error term is greater than zero it represents that in financial market, bad news are greater than the good news and it should be significant and have a negative sign.

3.2 VaR Estimation Through EVT

After applying the conventional VaR models, the next step is to apply extreme value theory to estimate VaR for the left tail of the distribution. Mostly, the two main approaches followed by EVT include generalized extreme value distribution (GEV) which is captured under BMM (Block maxima model), while another one is said to be generalized Pareto distribution (GPD) which covers peak over threshold (POT) models. By comparing these two models, the block maxima model is a traditional and old technique as compared with a peak over the threshold model. Here, in this study, the extreme value theory calculates three parameters like:

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

• Location parameter: It is used to represent the location of the distribution, which means if the value of the location parameter is negative, then the tail is on the left side and vice versa.

• Scale parameter: The scale of the distribution is measured through standard deviation. It tells about is on the higher side or on the lower side.

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

So, VaR for extreme events will be:

$$VaR^{p}_{t+1} = \mu + \frac{\sigma}{\xi}\left[[\frac{n}{N_{\mu}}(1-p)]^{\xi} \right] \tag{3.7}$$

3.3 Backtesting

It is a statistical technique that is used to compare the risk models and also help to improve their weaknesses by providing the information and causes of weaknesses. The purpose of Back-testing is to predict that the values calculated by the VaR are the correct measure of risk or not. Back-testing is helpful to cover the errors in the calculation of VaR that can arise via sampling error, data problems, model errors or any other specification errors. It prevents the underestimation and overestimation of risk. In this study, Back-testing is used to validate the models of VaR and CVaR.

As per the Basel Committee requirements, the VaR violations at 95% and 99% confidence level are used for Backtesting. It is hard to Backtest conditional value at risk models because CVar models require estimates of the tail expectation to the CVaR forecast.

3.4 Violation Ratio

One of the most common tools of backtesting is the violation ratio. In this, the observed numbers of Var violations are compared with the expected violations of Var. The formula is as:

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

It is the conventional method of backtesting the accuracy of forecasting models, as the models provide true forecasting of risk or not. In that case, if a model estimates minimum risk, but violation ratio suggests that the risk was underestimated. So that model may not be adopted for forecasting. The idea value for violations ratio will be equivalent to 1, explains the number of observed violations is equal to the number of expected violations. But in financial data, it is not always possible to get exactly 1. Danielson (2011) suggests a rule of thumb with a range of acceptance of violation ratio (0.8 to 1.2). Most of the times the results of violation ratio are considered as good forecasting techniques, and a decision is made on violation ratio.

3.5 VaR Volatility

Volatility means instability. Another back-testing technique is to estimate the volatility in any model. The parameter used to check volatility is the standard deviation of VaR. This method of backtesting is adopted more for the normally distributed return series. One of the reasons includes, the statistical properties of the normal distribution are calculated by setting the benchmark with mean and standard deviation. Despite this feature, the volatility in risk may not be applied to all other risk forecasting models except for normal distribution as it may not provide exact and appropriate volatility. The alignment of miscalculated volatility may also depend on unique applications. When the motive is not to estimate the extreme conclusion, the volatility is the better estimator to check the reliability of models as compared with other backtesting techniques. This technique suggests that a model with minimum volatility means minimum standard deviation should be selected.

3.6 Backtesting Var Methodologies

The log of daily returns of Pakistan stock market used to examine the performance of GARCH models. Kupiec test and Christoffersen test used to measure the VaR models. In the two-stage Backtesting procedure, the best performing model must satisfy the Kupiec and Christoffersen test.

3.6.1 Kupiec (POF) Test

In 1995, Kupiec test is introduced to investigate the fluctuation in the binomial test, or it is the degree of failure. Kupiec test is followed by the χ^2 distribution at 1 degree of freedom. The model will be accepted, if the amount of likelihood ratio is less than chi-square value. If the LR is greater than the chi-square value, the model inaccuracy and the decision of null hypothesis rejection will be made. At 95% and 99% level of confidence, the null hypothesis will be rejected if LR>3.84. The null hypothesis states that "the observed failure rate is equal to the failure rate that is suggested by the confidence interval".

The formula of LR is:

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

Where x represents the number of times a model failed, N represents the "number of observations" and p = "VaR level (confidence level)".

The value does not exceed a critical value, the null hypothesis is accepted that model is suitable for the forecasting of risk.

3.6.2 Christoffersens Test

Christoffersen (1998) develop a conditional coverage test. The probability of Christoffersen independence test examines that today exception depends on the result of the past day. In this test, the log-likelihood ratio is used as in the Kupiec test but with the statistics of independence of exceptions. In this case, the likelihood ratio of the independence test is compared with the chi-square value at one degree of freedom. The null hypothesis is, that the LR > χ^2 model deemed incorrect. Under the null hypothesis, the occurrence of violations should be independent over time.

$$LR = -2log\left(\frac{(1-\pi)^{T000+T10}\pi^{T01+T11}}{(1-\pi01)^{T00}\pi01^{T01}(1-\pi11)^{T10}\pi11^{T11}}\right) \tag{3.9}$$

Where

$$\pi = \frac{T01+T11}{T00+TO1+T10+T11} \tag{3.10}$$

T00 represents a time period with no failure, proceed by time period with no failure.

T10 represents a time period with failure, proceeds by time period with no failure.

T01 represents a time period with no failure, proceed by time period with failure.

T11 represents a time period with failure, proceed by time period with failure.

1 represents the probability of failure on period t, given that a failure occurred on period t 1=T11 divided by (T10+T11).

$\pi 0$ represents the probability of failure on period t, given that a failure occurred on period t 1= T01 divided by (T00+T01).
represents the probability of failure on period t = (T01+T11/(T00+T01+ T10 + T11).
Christoffersen helps to inspect the reason for the failure of the test due to clustered violations, inaccurate coverage or both. Campbell, Lo, and MacKinlay (1997) suggest applying the coverage and independence test separately because sometimes the model does not pass the joint test. The null hypothesis assumes to have no clustering, means the probability of violation of tomorrow does not depend on today's identified violation. Otherwise, the null hypothesis is rejected and reported time period clustering between violations is identified.

3.7 Conditional Value at Risk (CVaR)

Alexander (2009) states the amount of loss exceeds from the VaR over the risk horizon and level of significance, CVaR captures these losses that exceeds from the VaR.

$$CVaR_{ha} = \mu_h + \alpha^{\alpha-1}\varphi(\varphi^{-1}(\alpha))\sigma_h........ \tag{3.11}$$

Where represents the standard normal density and this sign shows distribution function. Thus, -1 () is the quantile and (-1()) represents the highest amount of standard normal density. The following formula can be used to evaluate the historical or nonparametric CVaR (Alexander, 2009).

$$CVaR_{ha} = -E(X_h|X_h < -VaR_{ha})........ \tag{3.12}$$

By averaging all returns which are lower than negative Historical Simulation VaR, CVaR.

3.8 Sample

For the analysis, the data samples forming the basis for the analysis of this study is the daily closing stock market indices. The sample period is 1997-2018. The closing stock price indices consist of five working days. The data for stock indices are matched with each other in terms of dates in order to have daily analyses. The data of 21 years from 1997-2018 of the PSX index is collected from the Pakistan stock exchange market. The returns are calculated by using this formula:

Rt=ln(Pt/Pt-1) Where

R represents the return earned for the day "t"

Pt represents the price of the index at day "t".

Pt-1 represents the price of index at previous day "t-1"

Chapter 4

Results and Findings

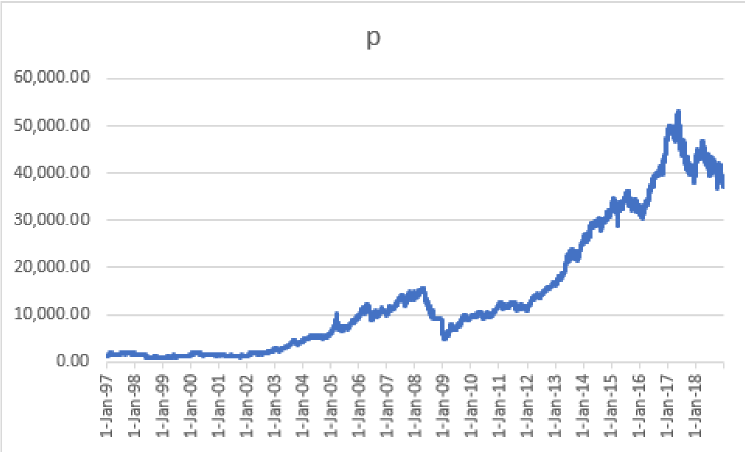
4.1 Descriptive Statistics

Table 4.1 exhibits a description of the daily returns of the Pakistan equity market (PSX). Mean and median are central tendencies and provide information about the average return. The value of Mean is 0.06% on a daily basis. The median is 0.09%. The maximum loss in a day is -13.2%. The standard deviation value is 1.49%. The maximum return in this study is 12.26%. Skewness shows that data is negatively skewed. Kurtosis value is 9.28 that is higher than 3 it means data is peak and has fat-tailed. Jarque -Bera is used to seeing that whether data is normally distributed. The value of Jarque-Bera is 9005.46. The high value of the Jarque-Bera statistic indicates that data is non-normal which is a common feature of future time series.

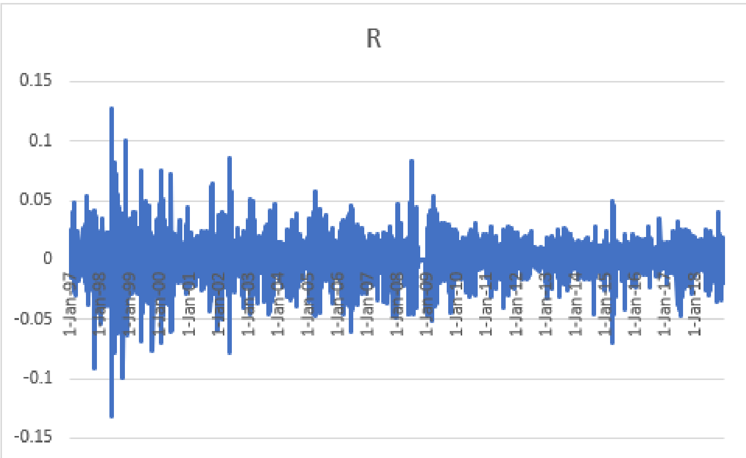
Table 4.1: Descriptive Statistics

	Mean	**Median**	**Max**	**Min**	**Std. Dev**	**Kurtosis**	**Skewness**	**Jarque-Bera**
PSX	0.006	0.001	0.128	-0.132	0.015	9.289	-0.344	9005.468

4.2 Graph of Prices of PSX



The above graph shows the prices of PSX from the year 1997 to 2018. The behavior of prices is constant from the year 1997 to 2003. But in 2004 it goes up to the year 2008 and after that, it becomes a decline in the year 2009. After 2012 the prices increase and shows better performance of the market till the year 2014. In 2016 it declines, In 2017 the prices increase again and then in 2018 they decline and show weaker conditions in the market.



The above graph shows the graphical information about the returns of PSX yearly. In the year 1997 -98 it shows that is less volatile. But after 1998 it becomes more volatile in the market. From the years 2001 to 2014 shows that the returns are less volatile. in some years reported that returns are less volatile and in a suitable range but in some years, it reports that returns are highly volatile. The following graph shows that the return of the index is quietly stable around the mean value.

4.3 Value at Risk Estimation Through Historical Simulation

VaR is used to express the potential loss suffered by any investment in the portfolio. Table 4.2 shows the result of VaR estimation by using the Historical simulation (Non-Parametric) model at 95% and 99% confidence interval.

4.4 Value at Risk Estimation Through Historical Simulation

VaR is used to express the potential loss suffered by any investment in the portfolio. Table 4.2 shows the result of VaR estimation by using the Historical simulation (Non-Parametric) model at 95% and 99% confidence interval.

Table 4.2: VaR Estimation using Historical Simulation

	VAR 95%	VaR 99%
PSX	-0.02488	-0.04437

At a 95% confidence level, the historical simulation reports the risk of 2.4% in PSX. It means the potential loss for one day to the investor is 2.4% i.e, there are 95% chances that the loss will not exceed 2.4%.

At a 99% confidence level, the historical simulation reports the risk of 4.4% in PSX. It means that there are 99% chances that loss in the Pakistan market will not exceed 4.4% in a day.

4.5 Var Estimation Through GARCH

Table 4.4 represents the results of VaR estimation under parametric based GARCH models at 95% and 99% confidence intervals.

• **GARCH**

GARCH is a statistical model that is used to analyze the volatility in different types of financial data. This study evaluates the VaR and CVaR in the Pakistan equity market, so this model tells about the impact of past prices behavior on the volatility of current price behavior.

Table 4.3: Estimation of Volatility by GARCH

Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	0.0010	0.0001	7.0524	0.0000
R(-1)	0.1068	0.0144	7.4212	0.0000
	Variance Equation			
C	6.18E-06	2.93E-07	21.09103	0.0000
RESID(-1)$\hat{2}$	0.163135	0.007099	22.98075	0.0000
GARCH(-1)	0.815517	0.005777	141.1774	0.0000

Table: 4.3, reports the value of R(-1) is significant it means that from today's return we can forecast the future's market returns. The value of RESID(-1)^2 shows the past price behavior influences the current volatility, this value is significant and positive it means that past price behavior can be forecast the current volatility of the market. The value of GARCH(-1) shows the volatility persistence in market. The sum of two coefficients of RESID(-1)^2 and GARCH(-1) is closer to 1 it means that the persistence of volatility exists and transmitted in the next year it is long run in nature.

4.5.1 VaR and CVaR Estimation Using GARCH based Model

The table 4.4 reports the result of VaR and CVaR estimation by using GARCH based models with "95% and 99% confidence level".

Table 4.4: VaR and CVaR Estimation using GARCH Based Model

PSX	**95%**	**99%**
VaR	-0.022	-0.0313
CVaR	-0.032	-0.038

Table: 4.4, reports the results of the estimation of value at risk and conditional value at risk by using the GARCH model. At a 95% confidence level, the VaR of PSX is 2.2%. It indicates that there are 95% chances that loss will not exceed 2.2% in a day. The value at risk at a 99% confidence level is 3.13% indicates that there is only a 1% chance that loss will exceed 3.13% in a day.
At a 99% confidence level, the result of the estimation of CVaR indicates that the average expected loss is 3.8% which is quite high as compared to the 95% confidence level. At a 95% confidence level, the PSX market faces expected loss which is 3.2%.

4.5.2 Violation Ratio

Violation Ratio is the basic tool used to compare the expected number of violations with actual VaR. Violation Ratio is one of the primary methods of calculations of model accuracy. In this section violation is forecasted, it is used to identify the model that has better predictable performance. The value of the violation ratio should be 1 or nearest to 1.

Table 4.5: Violation Ratio Using GARCH Model

PSX	**Confidence level 95%**	**Confidence level 99%**
Violation Ratio	0.948	0.345

Table: 4.5, reports the violation ratio of the GARCH model at 95% and 99% confidence level. At a 95% confidence level, the violation ratio is 0.948, which is nearest to (between $0.80 - 1.20$) and reports that expected violations are equivalent to the observed ones. This GARCH model provides the true forecasting of risk with a 95% confidence level. As compared with the 99% confidence level, the value of violation ratio is 0.345 which is less than 1 and reports that the expected violations are less equivalent to observed violations. So the GARCH model is weaker for risk forecasting with 99% confidence level. The risk forecasting with 95% confidence interval, the models perform much better, as the violation ratio is equivalent to 1 explaining that the expected violations are equal to the observed ones.

4.5.3 VaR Volatility

Volatility refers to the market uncertainty. It is used to measure risk if volatility is lower the model is reliable for VaR estimation. Table 4.6 reports VaR volatility at 95% and 99% confidence level for the GARCH model.

Table 4.6: VaR Volatility Using GARCH Model at 95% and 99% confidence level

PSX	**95%**	**99%**
GARCH	0.011	0.015

With a 95% confidence level, in the PSX market, the GARCH model is considered to be the less volatile model as their volatility is 1.1 %. With the increase in the confidence interval, the VaR Volatility also increases. At 99% confidence interval it reports that the volatility is 1.5% that is more volatile than the 95% confidence level.

4.5.4 Kupiec POF Test – Unconditional Coverage Test for GARCH Model

In this study, the Backtesting test has been done by using the unconditional coverage test proposed by Kupiec (1995). The dynamic backtesting has been conducted for all models of parametric and EVT models at 95% and 99% confidence level. Although, the assumption of distribution is different for each model and the performance of each model is also different based on assumptions The table 4.6 reports the results of the unconditional coverage test by Kupiec with 95% and 99% confidence level. Kupiec explains that the "VaR model" is rejected, if the data suggests that the probability of exceptions is different than p. For 95% the value is 3.84, whereas it is 6.635 for 99%confidence levels. This test is used to relate the expected violations with observed number of violations. The model said to be accepted or may provide true forecasting of risk if the LR is less than 3.84 for a 95% confidence level and 6.635 for a 99% confidence level.

Table 4.7: Kupiec POF Test Using GARCH Model at 95% and 99% Confidence Level

PSX	**95% (LR)**	**Critical value**	**99%(LR)**	**Critical value**
GARCH	0.76	3.84	23.37	6.635

The **Table: 4.7**, reports Kupiec POF test at 95% and 99% confidence interval. In the GARCH model, the likelihood ratio is in a range that is 0.76 and less than the critical value which is 3.84 with a 95% confidence level. It means that if LR $<$ 3.84 at 95% confidence interval the model is accepted for forecasting the risk. At 99% confidence level, the value of likelihood is not in the range that is 23 and more than the critical value which is 6.635. It means that if the value of LR$>$ critical value, this model is not acceptable for estimating the risk. As a comparison from the 95% confidence level, this GARCH model is accepted for estimating the risk because its value of LR is less than a critical value. So the GARCH model is reliable only with a 95% confidence level.

4.5.5 Christoffersen's Independence Test for VaR Conventional Models

Another backtesting test has been applied, the conditional coverage and independence test Christoffersens (1998). This test is developed to check the cluster. The focus is to check whether violations happen one after the other to make cluster at one point of time, or the violations behave independently. The null hypothesis assumes to have no clustering, means the probability of violation of tomorrow does not depend on today's identified violation. Otherwise, the null hypothesis is rejected and reported time period clustering between violations will be identified.

The following table 4.8 reports the independence test at a 95% confidence interval on the GARCH model that is a time-varying volatility model. In the GARCH model, the likelihood ratio is more than 3.84, which shows that the null hypothesis is rejected in the market. It means that the probability of volatility of tomorrow depends on today's volatility and the market will not respond in the future.

Table 4.8: Christoffersens Test Using GARCH Model at 95% and 99% Confidence Level

PSX	LR (95%)	Critical value	LR (99%)	Critical value
GARCH	4.782	3.84	1.013	6.635

Table 4.8 reports that the value of likelihood is 1.013 which is less than the critical value that is 6.635 with 99% confidence level. However, clustering is observed at a 95% confidence level its LR statistic is more than critical value or chi-square.

4.6 EGARCH

Nelson (1991) proposed the EGARCH to capture the asymmetric effects of data. He observed that his EGARCH model can reduce the disadvantage of GARCH models. It means the negative relationship between current and future returns which is omitted by the GARCH model assumption. It tells us about the size and sign effects of market, bad and good news in the market, small and big shock and tells about persistent volatility. **Table 4.9** reports the result of the mean and

Table 4.9: Estimation of Volatility using EGARCH Model

Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	0.0011	0.0001	13.4179	0.0000
R(-1)	0.1078	0.0138	7.8070	0.0000
	Variance Equation			
C(3)	-0.742593	0.024803	-29.93987	0.0000
C(4)	0.308342	0.010187	30.26759	0.0000
C(5)	-0.064803	0.006877	-9.423699	0.0000
C(6)	0.941619	0.002556	368.3867	0.0000

variance equation. The value of R(-1) is significant it means that from today's return we can forecast the future's return. Invariance equation the value of C(3) shows the coefficient, this value is significant it means that constantly does not change. C(4) shows the size effect, this value is positive and significant it means that big shock creates more volatility and small shock creates less volatility.
C(5) shows the sign effect, this value is negative and significant, it means that bad news creates more volatility in market than good news.
C(6) tells about the persistence of volatility, this value is positive and significant it means that there is the volatility persistence in the market and transmitted to the next year and it is long run in nature.

4.6.1 Estimation of VaR and CVaR using EGARCH Model

The table 4.10 represents the estimation of VaR and CVaR through the EGARCH model at 95% and 99% confidence level.

TABLE 4.10: VaR and CVaR Estimation using EGARCH Model

PSX	**95%**	**99%**
VaR	-0.021	-0.0309
CVaR	-0.034	-0.042

Table 4.10 reports the results of the estimation of value at risk and conditional value at risk by using the EGARCH model. At a 95% confidence level, the VaR of PSX is 2.1%. It indicates that there are 95% chances that loss will not exceed 2.1% in a day. The value at risk at a 99% confidence level is 3% indicates that there is only a 1% chance that loss will exceed 3% in a day.
At a 99% confidence level, the result of the estimation of CVaR indicates that the average expected loss is 4.2% which is quite high as compared to the 95% confidence level. At a 95% confidence level, the PSX market faces expected loss which is 3.4%.

4.6.2 Violation Ratio

Violation Ratio is used to compare the expected number of violations with actual VaR. It is one of the primary methods of calculations of model accuracy. In this section violation is forecasted, it is used to identify the model that has better predictable performance. The value of the violation ratio should be 1 or nearest to 1.

The following table 4.11 reports the violation ratio of the EGARCH model at 95% and 99% confidence level. At a 95% confidence level, the violation ratio is 0.948, which is nearest to (between 0.80 – 1.20) and reports that expected violations are equivalent to the observed ones. This EGARCH model provides the true forecasting of risk with a 95% confidence level. As compared with the 99% confidence level, the value of violation ratio is 0.31 which is less than 1 and reports that the expected violations are less equivalent to observed violations. So the EGARCH model is weaker for risk forecasting with 99% confidence level. The risk forecasting is better in 95% confidence interval, as the violation ratio is equivalent to 1 explaining that the expected violations are equal to the observed ones.

Table 4.11: Violation Ratio Using EGARCH Model

PSX	**95%**	**99%**
Violation Ratio	0.866	0.31

4.6.3 VaR Volatility

Volatility refers to the market uncertainty. It is used to measure risk if volatility is lower the model is reliable for VaR estimation. Table 4.12 reports VaR volatility at 95% and 99% confidence level for the EGARCH model.

Table 4.12: VaR Volatility Using EGARCH Model at 95% and 99% Confidence Level

PSX	95%	99%
EGARCH	0.009	0.0139

With a 95% confidence level, in the PSX market, the EGARCH model indicates VaR volatility is 0.9 %. With the increase in the confidence interval, the VaR Volatility also increases. At 99% confidence interval it reports that the volatility is 1.4% that is more volatile than the 95% confidence level. This indicates that the model is more stable at a 95% confidence level.

4.6.4 Kupiec POF Test

The table 4.13 reports the results of the unconditional coverage test by Kupiec with 95% and 99% confidence level. Kupiec explains that the "VaR model" is rejected, if the data suggests that the probability of exceptions is different than p. For 95% the value is 3.84, whereas it is 6.67for 99%confidence levels. This test is used to relate the observed violations with expected number of violations. The model said to be accepted or may provide true forecasting of risk if the LR is less than 3.84 for a 95% confidence level and 6.67 for a 99% confidence level.

Table 4.13: Kupiec POF Test Using EGARCH Model at 95% and 99% confidence level

PSX	**95%**	**Critical Value**	**99%**	**Critical value**
EGARCH	5.25	3.84	15.28	6.635

The **Table 4.13** reports the Kupiec test likelihood ratio at 95% and 99% confidence interval. In the EGARCH model, the likelihood ratio is 5.25, which is more than the critical value (3.84) at a 95% confidence level. It means that if LR >3.84 at a 95% confidence interval the model is not accepted for forecasting the risk.

At 99% confidence level, the value of likelihood is not in the range that is 15.28 and greater than the critical value which is 6.635. It means that if the value of LR> critical value, this model is not acceptable for estimating the risk. This EGARCH model is not accepted for estimating the risk because its value of LR is more than the critical value at both 95% and 99% confidence level.

4.6.5 Christoffersen's Test

Another backtesting test has been applied, the conditional coverage and independence test Christoffersens (1998). This test is developed to check the cluster. The main focus is to check whether violations happen one after the other to make cluster at one point of time, or the violations behave independently. The null hypothesis assumes to have no clustering, means the probability of violation of tomorrow does not depend on today's identified violation. Otherwise, the null hypothesis is rejected and reported time period clustering between violations will be identified.

The following table 4.14 reports the independence test at a 95% confidence interval on the EGARCH model that is a time-varying volatility model. In the EGARCH model, the likelihood ratio is more than 3.84, which shows that the null hypothesis is rejected in the market. It means that the probability of volatility of tomorrow depends on today's volatility and the market will not respond in the future.

Table 4.14: Christoffersen Test Using EGARCH Model at 95% and 99% Confidence Level

PSX	**95%**	**Critical value**	**99%**	**Critical value**
EGARCH	6.872	3.84	0.113	6.635

The above table reports, at a 99% confidence level, the value of likelihood is 1.13 which is less than the critical value that is 6.635. It means no clustering found. In the case of the EGARCH model, the volatility clustering is observed at a 95% confidence level.

4.7 GJR-GARCH

GJR- GARCH is also known as TGARCH. This model tells about the asymmetric behavior of the market, a sign of the market (good and bad news) and tells about the difference between actual and expected returns of the market.

Table 4.15: Estimation of Volatility using GJR-GARCH Model

Variable	**Coefficient**	**Std. Error**	**z-Statistic**	**Prob.**
C	0.0008	0.0002	5.0470	0.0000
R(-1)	0.1182	0.0146	8.1117	0.0000
		Variance Equation		
C	6.61E-06	3.11E-07	21.29626	0.0000
RESID(-1)$\hat{2}$	0.118317	0.007304	16.19835	0.0000
RESID(-1)$\hat{2}$*(RESID(-1)<0)	0.091125	0.011811	7.715293	0.0000
GARCH(-1)	0.811675	0.005782	140.3829	0.0000

The value of R(-1) is significant and positive it means that current returns can be forecasted from past returns. If actual returns are more than expected then it shows the good news in the market. And if actual returns are less than expected it shows bad news. In the above table the value of RESID(-1)^2*(RESID(-1)<0 is positive and significant it means that bad news is more effective than good news. This shows the asymmetric behavior of the market and the volatility of bad news is different from the good news. The value of GARCH(-1) is positive and significant it means there is the persistence of volatility exist in the market and transmitted in next year.

4.7.1 Estimation of VaR and CVaR using GJR-GARCH Model

The table 4.17 reports the estimation of VaR and CVaR by using GJR-GARCH at 95% and 99% confidence level.

Table 4.16: VaR and CVaR Estimation through GJR-GARCH

PSX	**95%**	**99%**
VaR	-0.022	-0.0313
CVaR	-0.032	-0.038

Table 4.16, reports the results of the estimation of value at risk and conditional value at risk by using the GJR-GARCH model. At a 95% confidence level, the

VaR of PSX is 2.2%. It indicates that there are 95% chances that loss will not exceed 2.2% in a day. The value at risk at a 99% confidence level is 3.13% indicates that there is only a 1% chance that loss will exceed 3.13% in a day.
At a 99% confidence level, the result of the estimation of CVaR indicates that the average expected loss is 3.8% which is quite high as compared to the 95% confidence level. At a 95% confidence level, the PSX market faces expected loss which is 3.2%.

4.7.2 Violation Ratio

Violation Ratio is used to compare the expected number of violations with actual VaR. It is one of the primary methods of calculations of model accuracy.
Table 4.17 reports the violation ratio of the GJR-GARCH model at 95% and 99% confidence level. At a 95% confidence level, the violation ratio is 0.948, which is nearest to (between 0.80 – 1.20) and reports that expected violations are equivalent to the observed ones. This GJR-GARCH model provides the true forecasting of risk with a 95% confidence level. As compared with the 99% confidence level, the value of violation ratio is 0.344 which is less than 1 and reports that the expected violations are less equivalent to observed violations. So GJR- GARCH model is weaker for risk forecasting at a 99% confidence level. The risk forecasting with a 95% confidence interval, the models perform much better, as the violation ratio is equivalent to 1 explaining that the expected violations are equal to the observed ones.

Table 4.17: Violation Ratio using GJR-GARCH

	Confidence level 95%	Confidence level 99%
Violation Ratio	0.948	0.344

4.7.3 VaR Volatility

Volatility refers to the market uncertainty. It is used to measure risk if volatility is lower the model is reliable for VaR estimation.

TABLE 4.18: Var Volatility Using GJR-GARCH at 95% and 99% Confidence Level

PSX	95%	99%
VaR Volatility	0.011	0.0157

Table 4.18 reports VaR volatility at 95% and 99% confidence level for the GJR-GARCH model. With a 95% confidence level, in the PSX market, the GJR-GARCH model considered to be a volatile model as its volatility is 1.1%. With the increase in the confidence interval, the VaR Volatility also increases. At 99% confidence interval it reports that the volatility is 1.6% that is more volatile than the 95% confidence level. The reported VaR volatility shows that the GJR-GARCH model shows more volatility at 99% as compare to volatility at a 95% confidence level.

4.7.4 Kupiec POF Test

This test is used to compare the observed violations with the expected number of violations. The model said to be accepted or may provide true forecasting of risk if the LR is less than 3.84 for a 95% confidence level and 6.635 for a 99% confidence level.
The table 4.19 reports the results of the unconditional coverage test by Kupiec with the confidence level at 95% and 99%. Kupiec explains that the VaR model is rejected, if the data suggests that the probability of exceptions is different than p. For 95% the value is 3.84, whereas it is 6.67for 99%confidence levels.

TABLE 4.19: Kupiec POF Test Using GJR-GARCH at 95% and 99% Confidence Level

PSX	95%	Critical Value	99%	Critical value
GJR-GARCH	0.766	3.84	23.37	6.635

The above table reports the Kupiec test at 95% and 99% confidence interval. In the GJR-GARCH model, the likelihood ratio is in the range that is 0.76 and less than the critical value which is 3.84 at a 95% confidence level. It means that if LR

< 3.84 at 95% confidence interval the model is accepted for forecasting the risk. At 99% confidence level, the value of likelihood is not in the range that is 23.37 and more than the critical value which is 6.64. It means that if the value of LR$>$ critical value, this model is not acceptable for estimating the risk. As a comparison from the 95% confidence level, this GARCH model is accepted for estimating the risk because its value of LR is less than the critical value. So the GARCH model is reliable only with a 95% confidence level.

4.7.5 Christoffersen's Test

Another backtesting test has been applied, the conditional coverage and independence test Christoffersens (1998). This test is developed to check the cluster. The main focus is to check whether violations happen one after the other to make cluster at one point of time, or the violations behave independently. The null hypothesis assumes to have no clustering, means the probability of violation of tomorrow does not depend on today's identified violation. Otherwise, the null hypothesis is rejected and reported time period clustering between violations will be identified.

The following table 4.21 reports the independence test at a 95% confidence interval on the GJR-GARCH model that is a time-varying volatility model. In the GARCH model, the likelihood ratio is greater than 3.84, which shows that the null hypothesis is rejected. It means that the probability of volatility of tomorrow depends on today's volatility and the market will not respond in the future.

Table 4.20: Christoffersen's Test Using GJR_GARCH at 95% and 99% Confidence Level

PSX	**95%**	**Critical value**	**99%**	**Critical value**
GJR-GARCH	4.782	3.84	1.013	6.635

The above table reports, at a 99% confidence level, the value of likelihood is 1.013 which is less than the critical value that is 6.635. It means no clustering found. However, volatility clustering is observed at a 95% confidence level.

4.8 QGARCH

Table 4.21: Estimation of Volatility using QGARCH Model

Variable	**Coefficient**	**Std. Error**	**z-Statistic**	**Prob.**
C	0.000741	0.000153	4.832893	0
R(-1)	0.108006	0.014526	7.435451	0
	Variance Equation			
C	6.48E-06	3.25E-07	19.92071	0
RESID(-1)$\hat{2}$	0.165617	0.007288	22.72606	0
GARCH(-1)	0.811313	0.005755	140.9872	0
Q(-1)	-0.00074	8.91E-05	-8.304088	0

The above table shows the mean and variance equation. the value of R(-1) is positive and significance it means that past returns influence current returns. Invariance equation, The value of RESID(-1)^2 shows the past price behavior influences the current volatility, this value is significant and positive it means that past price behavior can be used to predict the current volatility of the market. The value of GARCH(-1) shows the persistence of volatility in the market. Their coefficients of RESID(-1)^2 and GARCH(-1) are closer to 1 it means that the persistence of volatility exists and transmitted to the next year and it is long run in nature. The value of Q(-1) is significant it means that nonlinearity exists in it.

4.8.1 Estimation of VaR and CVaR Using QGARCH Model

The table 4.22 represents the estimation of VaR and CVaR by using the QGARCH model at 95% and 99% confidence level.

Table 4.22: Estimation of VaR and CVaR Using QGARCH Model

PSX	**Confidence level 95%**	**Confidence level 99%**
VaR	-0.022	-0.031
CVaR	-0.032	-0.039

Table 4.22 reports the results of the estimation of value at risk and conditional value at risk by using the QGARCH model. At a 95% confidence level, the VaR

of PSX is 2.2%. It indicates that there are 95% chances that loss will not exceed 2.2% in a day. The value at risk at a 99% confidence level is 3.1% indicates that there are only 1% chances that loss will exceed 3.1% in a day.
At a 99% confidence level, the result of the estimation of CVaR indicates that the average expected loss is 3.9% which is quite high as compared to the 95% confidence level. At a 95% confidence level, the PSX market faces expected loss which is 3.2%.

4.8.2 Violation Ratio

The following table 4.23 reports the violation ratio of the QGARCH model at 95% and 99% confidence level. At a 95% confidence level, the violation ratio is 0.899, which is in range (between 0.80 – 1.20) and reports that expected violations are equivalent to the observed ones. This QGARCH model provides the true forecasting of risk with a 95% confidence level as compared to the 99% confidence level, the value of violation ratio is 0.340 which is less than 1 and reports that the expected violations are not equivalent to observed violations. So the QGARCH model is weaker for risk forecasting at a 99% confidence level. The risk forecasting with a 95% confidence interval, the models perform much better, as the violation ratio is equivalent to 1 indicating that the expected violations are equal to the observed ones.

Table 4.23: Violation Ratio using QGARCH Model

PSX	**Confidence level 95%**	**Confidence level 99%**
Violation Ratio	0.899	0.34

4.8.3 VaR Volatility

Volatility refers to the market uncertainty. It is used to measure risk if volatility is lower the model is reliable for VaR estimation. Table 4.24 reports VaR volatility at 95% and 99% confidence level for the QGARCH model.

TABLE 4.24: VaR Volatility Using QGARCH Model at 95% and 99% Confidence Level

PSX	**Confidence level 95%**	**Confidence level 99%**
VaR Volatility	0.011	0.0156

With a 95% confidence level, the QGARCH model has its volatility at 1.1 %. With the increase in the confidence interval, the VaR Volatility also increases. At 99% confidence interval it reports that the volatility is 1.6% that is more volatile than the 95% confidence level. The reported VaR volatility shows that the QGARCH model shows more volatility at 99% and less volatile at a 95% confidence level.

4.8.4 Kupiec POF Test

The table 4.25 reports the results of the unconditional coverage test by Kupiec with the confidence level at 95% and 99%. Kupiec explains that the VaR model is rejected, if the data suggests that the probability of exceptions is different than p. For 95% the value is 3.84, whereas it is 6.67 for 99% confidence level. This test is used to compare the observed violations with the expected number of violations. The model said to be accepted or may provide true forecasting of risk if the LR is less than 3.84 for a 95% confidence level and 6.635 for a 99% confidence level.

TABLE 4.25: Kupiec POF Test Using QGARCH Model at 95% and 99% Confidence Level

PSX	**95%**	**Critical Value**	**99%**	**Critical value**
Q GARCH	1.912	3.84	15.3	6.635

The above table 4.25 reports the Kupiec POF test at 95% and 99% confidence interval. In the QGARCH model, the likelihood ratio is in the range that is 1.912 and less than the critical value which is 3.84 at a 95% confidence level. It means that if LR $<$ 3.84 at 95% confidence interval the model is accepted for forecasting the risk.

At 99% confidence level, the value of likelihood is not in the range that is 15.3

and more than the critical value which is 6.64. It means that if the value of LR> critical value, this model is not acceptable for estimating the risk. As a comparison from the 95% confidence level, this GARCH model is accepted for estimating the risk because its value of LR is less than the critical value. So the GARCH model is reliable only with a 95% confidence level.

4.8.5 Christoffersen's Test

Another backtesting test has been applied, the conditional coverage and independence test Christoffersens (1998). This test is developed to check the cluster. The focus is to check whether violations happen one after the other to make cluster at one point of time, or the violations behave independently. The null hypothesis assumes to have no clustering, means the probability of violation of tomorrow does not depend on today's identified violation. Otherwise, the null hypothesis is rejected and reported time period clustering between violations will be identified. The following table 4.26 reports the independence test at a 95% confidence interval on the QGARCH model that is a time-varying volatility model. In the QGARCH model, the likelihood ratio is more than 3.84, which shows that the null hypothesis is rejected in the market. It means that the probability of volatility of tomorrow depends on today's volatility and the market will not respond in the future.

Table 4.26: Christoffersen's Test Using QGARCH Model at 95% and99% Confidence Level

KSE	95%	Critical value	99%	Critical value
Q GARCH	5.953	3.84	0.113	6.635

The above table reports, the value of likelihood is 1.13 which is less than the critical value that is 6.635 at a 99% confidence level. It means no clustering found. In the case of QGARCH like the time-varying model, the market responds more in the future because of past volatility as compared to the 95% confidence level.

4.9 APGARCH

TABLE 4.27: Estimation of Volatility Using APGARCH Model

Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	0.000777	0.000145	5.34459	0
R(-1)	0.116176	0.014149	8.210789	0
	Variance Equation			
C(3)	9.54E-05	2.82E-05	3.386063	0.0007
C(4)	0.170259	0.006621	25.71603	0
C(5)	0.183406	0.0221	8.299042	0
C(6)	0.822008	0.005409	151.9659	0
C(7)	1.414108	0.062594	22.5918	0

APGARCH tells about bad news and good news in the market, small and big shock and persistent volatility it also tells about the size and signs effect of the market. In the above table C(4) shows significant and also negative signs exists it means that it shows the difference between small and a big shock. The value of C(5) is positive and significant it means that big shack creates more volatility than a small shack. C(6) shows significant and negative sign exists in it that shows bad news creates more volatility than the good news in the market. The value of C(7) is significant and positive it means that there is persistent volatility in the market.

4.9.1 Estimation of VaR and CVaR Using APGARCH Model

The table 4.28 reports the estimation of VaR and CVaR by using APGARCH model at 95% and 99% confidence level.

TABLE 4.28: VaR and CVaR Estimation using APGARCH Model

PSX	95%	99%
VaR	-0.022	-0.031
CVaR	-0.033	-0.0395

Table 4.28 reports the results of the estimation of value at risk and conditional value at risk by using the APGARCH model. At a 95% confidence level, the VaR of PSX is 2.2%. It indicates that there are 95% chances that loss will not exceed 2.2% in a day. The value at risk at a 99% confidence level is 3.1% indicates that there are only 1% chances that loss will exceed 3.1% in a day.
At a 99% confidence level, the result of the estimation of CVaR indicates that the average expected loss is 3.95% which is quite high as compared to the 95% confidence level. At a 95% confidence level, the PSX market faces expected loss which is 3.3%.

4.9.2 Violation Ratio

The following table 4.29 reports the violation ratio of the GARCH model at 95% and 99% confidence level. At a 95% confidence level, the violation ratio is 0.919, which is near to 1 (between 0.80 – 1.20) and reports that expected violations are equivalent to the observed ones. This APGARCH model provides the true forecasting of risk with a 95% confidence level. As compared with the 99% confidence level, the value of violation ratio is 0.315 which is less than 1 and reports that the expected violations are less equivalent to observed violations. So the APGARCH model is weaker for risk forecasting at a 99% confidence level. The risk forecasting with a 95% confidence interval, the models perform much better, as the violation ratio is equivalent to 1 explaining that the expected violations are equal to the observed ones.

Table 4.29: Violation Ratio Using APGARCH Model

PSX	**Confidence level 95%**	**Confidence level 99%**
Violation Ratio	0.919	0.315

4.9.3 VaR Volatility

Volatility refers to the market uncertainty. It is used to measure risk if volatility is lower the model is reliable for VaR estimation.

TABLE 4.30: VaR Volatility at 95% and 99 % Confidence Level

PSX	95%	99%
APGARCH	0.011	0.0159

Table 4.30 reports VaR volatility at 95% and 99% confidence level for the APGARCH model. With a 95% confidence level, in the PSX market, the APGARCH model considered to be the volatile model as its volatility is 1.1 %. With the increase in the confidence interval, the VaR Volatility also increases. At 99% confidence interval it reports that the volatility is 1.6% that is more volatile than the 95% confidence level.

4.9.4 Kupiec POF Test

The table 4.31 reports the results of the unconditional coverage test by Kupiec with the confidence level at 95% and 99%. Kupiec explains that the VaR model is rejected, if the data suggests that the probability of exceptions is different than p,. For 95% the value is 3.84, whereas it is 6.67 for 99% confidence level. This test is used to compare the observed violations with the expected number of violations. The model said to be accepted or may provide true forecasting of risk if the LR is less than 3.84 for a 95% confidence level and 6.67 for a 99% confidence level.

TABLE 4.31: Kupiec POF test Using APGARCH Model at 95% and 99% Confidence Level

PSX	95%	Critical Value	99%	Critical value
APGARC H	2.957	3.84	22.28	6.635

The **Table 4.31** reports Kupiec test at 95% and 99% confidence interval. In the APGARCH model, the likelihood ratio is in the range that is 2.95 and less than the critical value which is 3.84 at a 95% confidence level. It means that if LR $<$ 3.84 at 95% confidence interval the model is accepted for forecasting the risk.

At 99% confidence level, the value of likelihood is not in the range that is 22.28 and more than the critical value which is 6.64. It means that if the value of LR$>$

critical value, this model is not acceptable for estimating the risk. As a comparison from the 95% confidence level, this GARCH model is accepted for estimating the risk because its value of LR is less than a critical value. So the APGARCH model is reliable only with a 95% confidence level.

4.9.5 Christoffersen's Test

Another backtesting test has been applied, the conditional coverage and independence test Christoffersens (1998). This test is developed to check the cluster. The main focus is to check whether violations happen one after the other to make cluster at one point of time, or the violations behave independently. The null hypothesis assumes to have no clustering, means the probability of violation of tomorrow does not depend on today's identified violation. Otherwise, the null hypothesis is rejected and reported time period clustering between violations will be identified.

The following table 4.32 reports the independence test at a 95% confidence interval on the APGARCH model that is a time-varying volatility model. In the APGARCH model, the likelihood ratio is more than 3.84, which shows that the null hypothesis is rejected in the market. It means that the probability of volatility of tomorrow depends on today's volatility and the market will not respond in the future.

Table 4.32: Christoffersens Test Using APGARCH Model

PSX	**95%**	**Critical value**	**99%**	**Critical value**
APGARCH	5.447	3.84	0.243	6.635

The above table reports, at a 99% confidence level, the value of likelihood is 0.243 which is less than the critical value that is 6.635. It means no clustering found. In the case of APGARCH like the time-varying model, the market responds more in the future because of past volatility as compared to the 95% confidence level.

4.10 VaR Estimation Through EVT Model

The financial markets are highly volatile, and the extreme movement may happen. The investors are not concerned with all distribution, either they are more interested in tails. The focus of extreme value theory is to analyze the tail region. The distinctive feature of extreme value theory as compared to earlier parametric and non-parametric models is that it estimates the extreme events that happened on tail extremes, instead of estimation of the whole distribution. The main concern of extreme value theory is to study the behaviour of extreme outcomes on both the left and right tail. For risk analysis, only the left tail is analyzed.

The use of the Extreme Value approach is used to compute the VaR at tail distributions at a confidence level of 95% and 99%. The Extreme value theory is getting popularity due to its focus on the empirical tail distribution data for the prediction of extreme events.

- **Generalized Pareto Distribution Parameters and VaR Estimation**

The results of GPD parameters and standard error estimates of the left tail of the return distributions. The test is conducted on two quantiles q = (0.95 and 0.99). The estimation of parameters is done by the GPD estimation method. The estimates for the shape and scale parameters with the standard error of shape and scale parameters. The shape parameter is greater than zero indicating heavy-tailed data. The threshold is chosen to be 95% of the empirical distribution. Parametric estimation of POT with Threshold , Number of exceedances, Negative log-likelihood estimates, Maximum Likelihood Estimates of shape and scale with Standard error. For estimation of VaR through EVT this study used the standardized residual values. Then estimates the threshold, scale and shape parameters and compute the Var at 95% and 99% level of confidence.

Table 4.33: Estimation of VaR Using EVT GARCH Model

PSX	**VaR (95%)**	**VaR (99%)**
GARCH	-0.026	-0.0364
EGARCH	-0.0254	-0.0354
GJR-GARCH	-0.0259	-0.0364
QGARCH	-0.0265	-0.0369
APGARCH	-0.0257	-0.036

The expected potential loss under the GARCH model is reported by the Pakistan market at 95% and 99% of the confidence level. The above table 4.8.1 reports the average loss for PSX is 2.6% with a 95% confidence level, and 3.6% at 99% confidence interval. With a 95% confidence level, the predicted average loss is reported by EGARCH is 2.5% for the Pakistani market. The average expected loss is 2.7% using the QGARCH model.

With a 99% confidence level, the expected loss is 3.5% by using the EGARCH model as compared to other models such as GARCH, GJR-GARCH, QGARCH, and APGAR. The average expectation of loss is 3.7% reported by PSX in a day.

4.11 Backtesting Results (Kupiec and Christoffersen's)

In this study, two types of backtesting have been applied the Kupiec (1995) conditional coverage test and P. Christoffersen, Diebold and Schuermann (1998). The backtesting has been conducted for all the models of Parametric, non- parametric and EVT models at 95% and 99% level of confidence. Although the assumptions of distribution are different for each model and performance of each model is also different based on assumptions.

4.11.1 Kupiec POF Test

Kupiec (1995) developed the likelihood ratio to find out whether the value at risk model is to be rejected or not. Kupiec test examines that the observed number of violations is equal to the expected number of percentage violations.

TABLE 4.34: Kupiec POF test Using EVT GARCH models at 95% and 99% Confidence Level

PSX	95%	Critical Value	99%	Critical value
GARC H	7.954	3.84	1.99	6.635
EGARCH	17.87	3.84	4.023	6.635
GJR-GARCH	3.627	3.84	1.602	6.635
QGARCH	20.88	3.84	4.653	6.635
APGARCH	5.884	3.84	2.912	6.635

The above table reports the results of the Kupiec POF test at 95% and 99% confidence level.

At a 95% confidence level, the likelihood ratios of GARCH based models such as GARCH, EGARCH, QGARCH and APGARCH are greater than critical values, if LR> critical value which is 3.84 it means these models are not acceptable for true forecasting of risk. In this case, GJR-GARCH model is acceptable its value of LR is less than the critical value.

At 99% confidence level, all values of LR< chi-square value which is 6.635. it means the Kupiec test is suitable for measuring the risk under the EVT model at 99% confidence level.

4.11.2 Christoffersens Independence Test for EVT GARCH Models

Christoffersen's test is used to measures the dependency between consecutive days. The backtesting approach will help to find out the clustering effect of an event. That is the influence extends to more than a day or not.

At a 95% level of confidence, clustering is found in the case of GARCH based models and the null hypothesis is rejected. All GARCH models are not suitable

TABLE 4.35: Christoffersen's Test Using EVT GARCH Models at 95% and 99% Confidence Level

PSX	95%	Critical value	99%	Critical value
GARCH	5.388	3.84	0.72	6.635
EGARCH	7.32	3.84	0.979	6.635
GJR-GARCH	-8.1	3.84	0.673	6.635
QGARCH	8.24	3.84	1.05	6.635
APGARCH	7.2	3.84	0.848	6.635

and their values of LR> 3.84.

At a 99% level of confidence, all models report that no clustering is found, and the null hypothesis is accepted because their values of LR $<$ 6.635 and these models are appropriate to measure the risk.

4.12 Comparison and Results

TABLE 4.36: VaR and CVaR Estimation using GARCH based Models and EVT Models

PSX	VaR -95%	CVaR -95%	VaR -99%	CVaR -99%	EVT -95%	EVT -99%
GARCH	-0.0220	-0.0321	-0.0313	-0.0380	-0.0260	-0.0364
EGARCH	-0.0210	-0.0338	-0.0309	-0.0416	-0.0254	-0.0354
GJR-GARC	-0.0220	-0.0321	-0.0313	-0.0380	-0.0259	-0.0364
QGARCH	-0.0220	-0.0323	-0.0313	-0.0393	-0.0265	-0.0369
APGARCH	-0.0220	-0.0329	-0.0312	-0.0395	-0.0257	-0.0360

The above **Table 4.36** reports an estimation of VaR by using GARCH based models. At a 95% confidence level, the highest risk of PSX is 2.2% by using GARCH, GJR-GARCH, QGARCH, and APGARCH as compared to EGARCH, which shows risk at 2.1%.

The same trend is observed for a 99% confidence level, the risk of PSX is 3.13% by using GARCH, GJR-GARCH, QGARCH, and APGARCH. The risk is 3% by using the EGARCH model.

At a 95% confidence level, the average expected losses are 3.3%, 3.4% using EGARCH and APGARCH models, which is quite high as compared to other GARCH based models 95% confidence level. The average expected loss is 3.2 % at a 95% level of confidence.

At 99% confidence level the average expected losses are 3.9%, 4.2% and 4% using EGARCH, QGARCH, and APGARCH, which shows higher risk as compared to GARCH and GJR-GARCH, which shows that the expected loss is 3.8%.

The use of EVT GARCH based models for estimating the forecasted risk at 95% and 99% confidence level. The expected potential loss under EVT GARCH based models are reported by the Pakistan market at 95% and 99% of confidence level. The above table reports the loss for PSX is 2.5% using the EGARCH model and the expected loss reported 2.7% using the QGARCH model with a 95% confidence level.

At 99% confidence level, the expected loss is 3.5% using the EGARCH model and the expected loss reports 3.7% using the QGARCH model, which is quite high as compared to other GARCH based models.

As a comparison from the 95% confidence level, the average predicted loss is reported by EGARCH is 2.5% for the Pakistani market. The expected loss is 2.7% using QGARCH model.

Table 4.37: VaR Volatility Using GARCH based Models at 95% and 99% Confidence Level

PSX	**VaR Volatility 95%**	**VaR Volatility 99%**
GARCH	0.011	0.0157
EGARCH	0.009	0.0139
GJR-GARCH	0.011	0.0157
QGARCH	0.011	0.0157
APGARCH	0.011	0.0159

Volatility refers to market uncertainty. It is used to measure risk if volatility is lower, the suggested model is reliable for VaR estimation. The above table reports VaR volatility at 95% and 99% confidence interval for parametric GARCH based models.

With a 95% confidence interval, in PSX EGARCH model is a less volatile model as its volatility is 0.009 which is near to 1. The other GARCH based models like GARCH, GJR-GARCH, QGARCH and APGARCH reported more volatility in VaR i.e 1.1%.
The reported VaR volatility shows EGARCH is the best suited model for risk forecasting, as there is less volatility in VaR results as compared to other GARCH based models with the confidence interval of 95%.
With the increase in confidence interval, the VaR volatility also increases. At 99% confidence level, all VaR volatilities are greater than 1% which are 1.6%, and 1.4% by using all GARCH based models and did not use for true risk forecasting with 99% confidence level as compared to 95% confidence level.

Table 4.38: Violation Ratio Using GARCH based Models at 95% and 99% Confidence Level

PSX	**Violation Ratio 95%**	**Violation Ratio 99%**
GARCH	0.948	0.345
EGARCH	0.866	0.315
GJR-GARCH	0.948	0.345
QGARCH	0.899	0.341
APGARCH	0.919	0.315

Violation ratio is used to compare the expected number of violations with actual VaR The above table 4.38 shows the violation ratio of GARCH based models with the confidence level of 95% and 99%. At a 95% confidence level, in all GARCH based models like GARCH, EGARCH, GJR-GARCH, QGARCH and APGARCH most of all violation ratios are nearest to 1 and these models can be used by Pakistan market for true VaR forecasting. At 99% confidence level, in GARCH based models all violations ratios are above range, which shows that expected violations are not equal with the actual. These models cannot use for true risk forecasting with a 99% confidence level.
Generally, the reported violation ratios are much better as all are in range and

may use for true risk forecasting of the Pakistani market with the confidence level of 95%.

Table 4.39: Kupiec POF test Using GARCH based Models and EVT Models

PSX	**LR -95%**	**EVT -95%**	**Critical value**	**LR -99%**	**EVT -99%**	**Critical value**
GARCH	0.766	7.954	3.84	23.37	1.99	6.635
EGARCH	5.25	17.87	3.84	15.28	4.023	6.635
GJR-GARCH	0.766	3.627	3.84	23.37	1.6	6.635
QGARCH	1.912	20.88	3.84	15.3	4.653	6.635
APGARCH	2.957	5.884	3.84	22.28	2.912	6.635

Kupiec explains that if the data suggests that the probability of exceptions is different than p, the VaR model is rejected. For 95% the value is 3.84, whereas it is 6.67for 99% confidence levels. This test is used to compare the observed violations with the expected number of violations. The model said to be accepted or may provide true forecasting of risk if the LR is less than 3.84 for a 95% confidence level and 6.67 for a 99% confidence level.

The above table 4.39 reported the likelihood ratios of GARCH based models and EVT models and show results which model is accepted. At a 95% confidence level, the likelihood ratios of GARCH based models such as GARCH, GJR-GARCH, QGARCH, and APGARCH are 0.76,0.76, 1.912 and 2.95 which are less than the critical value that is 3.84. It means these ratios are in a range which explains that these models may be used for risk assessment except the EGARCH model as its likelihood ratio is more than 3.84. Hence, this EGARCH model may not be used for the estimation of VaR.

The Kupiec test results look worst using EVT models, the likelihood ratios of all GARCH based models are greater than the critical value except GJR-GARCH model at 95%. It means that the number of expected violations is more or less equal to the observed ones.

At 99% confidence level, all likelihood ratios of all models are less than the critical value which is 6.635. It means that these GARCH based models are reliable for estimation of risk and the null hypothesis is accepted.

TABLE 4.40: Christoffersens Test Using GARCH based Models and EVT Model

PSX	**LR -95%**	**EVT -95%**	**Critical value**	**LR -99%**	**EVT -99%**	**Critical value**
GARCH	4.782	5.388	3.84	1.013	0.72	6.635
EGARCH	6.872	7.32	3.84	0.113	0.979	6.635
GJR-GARCH	4.782	-8.1	3.84	1.013	0.673	6.635
QGARCH	5.953	8.24	3.84	0.113	1.05	6.635
APGARCH	5.447	7.2	3.84	0.243	0.848	6.635

The **Table: 4.40**, reports the dependence test at 95% and 99% confidence level on parametric GARCH based models. In GARCH based models the likelihood ratios are more than 3.84 with a 95% confidence interval, which states that the null hypothesis is rejected in the Pakistani market. At 99% confidence level, in GARCH based models all likelihood ratios are less than the critical value which is 6.635, which explains that the null hypothesis is accepted, and the market responded more in future because of past volatility as compared to 95% confidence interval.

In EVT models, the likelihood ratios of the GARCH based models are greater than the critical value that is 3.84 at a 95% confidence level. This GARCH models are not suitable for true risk forecasting and the null hypothesis is rejected.

At 99% confidence level in EVT models, all likelihood ratios of GARCH based models are less than critical values which report that the null hypothesis is accepted.

Chapter 5

Discussion and Conclusion

5.1 Conclusion

The purpose of the study was to perform the statistical risk assessment of the Pakistani Equity Market by using the GARCH family that is simple GARCH, EGARCH, GJR-GARCH, QGARCH and APGARCH and EVT model in comparison with the traditional parametric and non-parametric models. This study consists of three parts. In the first part of the study, Value at risk has been analyzed by using the non-parametric (Historical simulation model) and parametric models. The validation of the models is done by the Back-testing technique by using the Kupiec and Christoffersen test. Kupiec POF test reveals that GARCH, GJR-GARCH, QGARCH, and APGARCH models perform better than the EGARCH model at a 95% level of confidence but at 99% level of confidence all models are rejected and did not perform better.

Christoffersen independent test results are quite different from the Kupiec test. At the 99% confidence level, all of the models pass the Christoffersen test and considered as the reliable method of risk forecasting while, at 95%, all models did not pass the test and did not consider as the reliable method of risk forecasting.

In the second part, the conditional value at risk has been analyzed by using parametric models. EGARCH model is not suitable in conditional value at risk at a 95% confidence level as compare to 99% confidence interval.

For estimation of violation volatility EGARCH model is more appropriate as compared to other models at 95% and 99% level of confidence but in the estimation of violation ratio, all models pass the violation ratio for estimating the Pakistan market risk at 95% and 99% level of confidence.
Backtesting techniques used by a number of scholars but not yet found to be appropriate. That is the reason, market Regulation does not rely on the CVAR results, but the comparison of VaR and CVAR is used by the market.
The third section contains the evaluation of VaR through the Extreme Value theory. The backtesting result shows that all GARCH based models at a 95% level of confidence are not appropriate for forecasting the riskas compared to 99% level of confidence, all models show the appropriate result that confirmed by the Backtesting. As a comparison of GARCH based models and EVT models, EVT GARCH Based models perform well by using the Kupiec test and Christoffersen test it reported better results for estimating the results at 99% confidence level. These models are best and suitable for forecasting market risk.

5.2 Recommendation

Based on the findings and analysis, it is recommended that the GARCH based models are better methods of risk estimation at 95% confidence level. This study used EVT GARCH models for estimating market risk. It is recommended that the EVT GARCH based models are reliable method for measuring the forecasting market risk at 99% confidence level. While comparing the results of simple GARCH family models from the EVT model, it is considered that a better model for risk assessment of extreme events is a simple GARCH based models at 95% confidence level and EVT GARCH based models at 99% confidence level . These models perform better for VAR calculation in the Pakistan Equity Market.
The following recommendations according to the investors are:

1. This study provides the risk measures of market to the investors for better decision making.

2. Based on given evaluation, investors will be able to choose right investments.
3. This study also helps the investors to choose right time for investment based on market volatility.

5.3 Limitations

The back-testing of conditional value at risk is not done in this study. However, the same could be done by using different back-testing techniques like; violation ratio, volatility, Kupiec test and Christoffersens test.
It is a future direction for the scholars to perform the back-testing of the Conditional value at risk (CVaR) and improve the literature.

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