CAPITAL UNIVERSITY OF SCIENCE AND TECHNOLOGY, ISLAMABAD

A Statistical Risk Assessment of Pakistani Banking Stocks and its Extreme Tail Behavior

by

Ume Rubab

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

in the

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Dedicated to my parents

CAPITAL UNIVERSITY OF SCIENCE & TECHNOLOGY
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CERTIFICATE OF APPROVAL

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Abstract

The goal of this study is the investigation of statistical risk analysis methodologies, by using the Extreme value theory in comparison with parametric and non-parametric models. Extreme value theory is concerned with the probabilistic and statistical behavior of rare events. This study has focused on the risk assessment of Value at risk of time series data in financial risk management. In order to obtain good estimates of the results, two-stage approaches are used. First, the parameters of the Generalized Pareto distribution and Block maxima method are calculated then, their estimation of VaR is done by choosing the threshold. Additionally, the performance of Extreme value theory compared with the parametric and non-parametric methodologies through robust Backtesting. Backtesting of each distributional assumption is performed at three confidence levels. The Backtesting (Kupiec Test) of va;ue at risk models under the parametric and non-parametric assumption suggest that Historical simulation perform better than the other models. The results of Christoffersen test suggest that GARCH is one of the models that perform better than the other models. The Backtesting results of Extreme value theory suggest that GARCH (1, 1) is a weaker method from the other methods while comparing with static Extreme value theory, Parametric and Non-Parametric models.

Keywords: Extreme value theory, Parametric models, Non-parametric models, Dynamic POT, Kupiec test, Christoffersen test.

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Abbreviations

ABL	Allied Bank Limited
AKBL	Askari Bank Limited
BAFL	Bank Al-Falah Limited
BAHL	Bank Al-Habib Limited
BOK	Bank of Khyber Limited
BOP	Bank of Punjab
BMM	Block maxima method
BIPL	Bank Islami Pakistan Limited
CoVaR	Conditional Value at Risk
EWMA	Extreme weighting moving average
EVT	Extreme value theory
ES	Expected Shortfall
FABL	Faysal Bank Limited
GPD	Generalized Pareto Distribution
GARCH	Generalized autoregressive conditional heteroscedasticity
HS	Historical simulation
HBL	Habib Bank Limited
HMB	Habib Metropolitan Bank Limited
JSBL	JS Bank Limited
MCB	Muslim Commercial Bank Limited
MEBL	Meezan Bank Limited
MLE	Maximum likelihood estimate
NBP	National Bank of Pakistan
POT	Peak over threshold

POF	Proportion of failure
SBL	Samba Bank Limited
SILK	Silk Bank Limited
SNBL	Soneri Bank Limited
SCBPL	Standard Chartered Bank Limited
SMBL	Summit Bank Limited
UBL	United Bank Limited
VaR	Value at Risk

Chapter 1

Introduction

1.1 Theoretical Background

Financial risk management is a major domain in finance that focuses on the risk assessment, measurement, and management to create value. The main concern of the financial risk management is to assess the risk for the investor's interest and develop a financial instrument and investment strategies for hedging the negative events. Since risk can be described by the Variance and it comes from the low or high forecasted values. To capture the risk, an organized tool for risk assessment comes in early 1980's that was VaR (Zhang, 2017).

Value at risk (VaR) is used to measure the financial risk that is based on loss distribution. Baumol (1963) uses the VaR to examining the model named as expected gain confidence limit. In 1994 JP Morgan proposes the risk metrics based on the VaR measure. As per the Basal accord II, VaR was considered as the basic tool of risk measurement in the financial institutions Rocco (2014). Since that time, VaR is used as a risk measurement tool in the financial sector. Since many years VaR plays a very important role in risk management, risk calculation, financial control and financial reporting. VaR measures the risk of the portfolio for a certain period of time at a particular confidence interval.

VaR is widely used in the risk assessment of the banking sector but it has some limitations. First, it provides no information that how much loss a portfolio will face. It ignores the risk at the left tail. Second, the VaR model does not follow the concept of additivity. The measure of VaR of asset one and VaR of asset two are not subject to addition. Due to lack of sub-additivity of VaR, the portfolio creates the higher value of credit risk. During the global financial crisis, the investors that lose their money realized that the improper use of VaR and lack of understanding cause this crisis. Some investors focus on the tail risk and caught off in it.

A big number of investors adopted the risk measure of conditional value at risk (CoVaR). It is designed to measure the extreme loss and it is the extension of VaR that provides the amount of loss in a given loss event. Conditional value at risk also known as a mean shortfall, mean excess loss or VaR tail. VaR is good to measure the frequency of loss while CoVaR measures the amount of loss in a given time period. To measure the CoVaR, "a weighted average of the VaR estimate and expected losses beyond VaR" are calculated (Kidd, 2012).

CoVaR is a better measurement tool than VaR because it takes into account the tail distribution that measures the coherent risk (Artzner, Delbaen, Eber, & Heath, 1999). Conditional value at risk is also known as an expected shortfall and also termed as VaR average. It accounts for 100% that "what happens in the tail beyond the VaR".

The relationship of VaR and CoVaR is shown in the following graph.

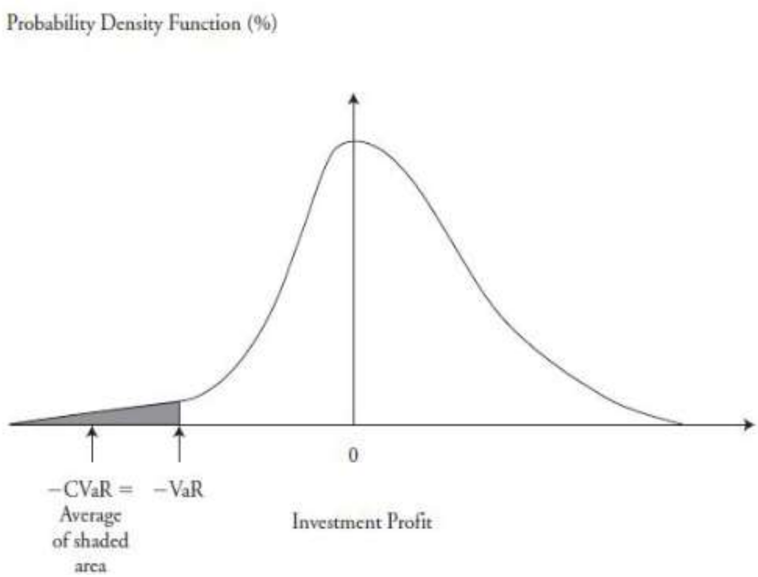

Figure 1.1: Conditional value at risk in term of probability density function.

CoVaR quantifies the tail risk and it is better than VaR because it follows the sub-additive principle. Rockafellar and Uryasev (2000) argue that when portfolio risk is measured by using the non-parametric approach, the portfolio risk can be optimized by CoVaR. The reliability of the CoVaR model depends on the accuracy of the tail model used. The bank is a risk-taking enterprise. It is expected by the banks that relevant information of risk will be disclosed in the market that will help the investors to make their investment save (M. Linsley & J. Shrives, 2005).

Central banks across the globe are making efforts to stabilize the banking system, especially after the global financial crisis of 2008-09. The effect of 2008 global turmoil can be seen in the financial sector. Micro-prudential and macro-prudential regulations are based on a measure of risk. The most common measure that used in the financial institutions and in the micro-prudential regulations is the VaR measurement assumptions based on of normal distribution of the stock returns undervalue the risk while the actual returns distributions show heavier tails. The CoVaR is used to measure the systematic risk of each bank that contributed to the overall systematic risk. Peak over threshold method of Extreme Value Theory measures the tail of the observations by using the Generalized Pareto distribution (GPD) of those observations that lie beyond the threshold (McNeil & Frey, 2000).

The functioning of a modern market economy is based on the strength of the banking sector and other financial institutions that are closely monitored by supervisors and regulators in addition to the ordinary investor. Financial institutions and supervisors in monitoring process use the traditional tools of risk measurement or use the rating of the banks done by the Moody's and standard poor's on the basis of services and their repaying abilities. Some investors use the scoring models by using the accounting information provided by the institutions in their annual reports (Byström, 2006).

In the banking sector, operational risk is considered as most important due to new requirements of the Basel accord. International scholars and researchers have studied the various models of operational risk calculation like the Bayesian method, VaR, and extreme value method. Now, the banking industry has started to use a new kind of statistical risk assessment models and techniques to quantify the risk. Cope, Mignola, Antonini, and Ugoccioni (2009) measure the operational risk by using the Extreme Value theory and believe that risk assessment calculation depends on the shape, scale and position characteristics of the loss distribution.

As per Basel accord III, every bank has to decide that which statistical model they will use to calculate risk. In banking history, rare events occur many times and in future, it is also the possibility that these extreme events will occur. In statistics, extreme value statistics deals with the rare extreme events (Mager, 2012).

In financial risk management, the assessment of extreme events is crucial for the regulators and investors. A statistical distribution that used in the risk assessment of historical data fits well. Statistical risk assessment helps to quantify the risk and make a useful contribution to decision making under uncertainty. Banks, brokerage firms, investment firms, and regulators are concerned with the appropriate risk measurement tool that adequately captures the risk faced by the firms. Pakistani banking sector risk management practices, policies and procedures are at a nascent stage. So, this study is useful for Pakistani banking sector to manage and improve their risk management practices.

1.2 Research Gap

Historically, VaR models are used in the forecasting of risk in the financial sector. Extreme tail behavior is observed in the physical sciences and its evidence is found in the literature. In 1980, the main focuses start on the extreme events when an unprecedented extreme event, Black Monday occurred. Over the period, the financial risk forecasting gets attention. But in finance, the main focus is done on the extreme tail behavior and in this regard, a number of studies apply these techniques and find out that these are applicable in the financial sector. Pakistan is an emerging market and its banking sector is the largest sector that contributes to the economy and this study help to identify the statistical risk assessment of Pakistani banking stocks and their extreme behaviors. This is the pioneer study looking at the extreme value behavior of the Pakistani banking stocks in comparison with the traditional methods of forecasting. The focus of the study is on tail risk characteristics and in-depth univariate extreme value analysis.

1.3 Research Questions

Pakistani banking industry is a very important part of the economy that contributes to the growth of the country. After the global financial turmoil of 2008, greater emphasis is done to identify the risk exposure under the extreme values and its extreme tail behavior. Therefore, there is a need to statistically analyze the risk assessment of Pakistan banking stock under extreme value. The study attempts to answer the following research questions.

- Does extreme value theory be helpful to calculate the Extreme risk measure in Pakistani banking stock?
- Is the Pakistani banking stocks are characterized by extreme tail distributions as described by EVT?
- Is Generalized Pareto distribution model fits the observed distributions of Extreme values?
- Which method is more appropriate, parametric, non-parametric or EVT?

1.4 Objectives of the study

- To evaluate the various methods of estimation of VaR.
- To identify the appropriate model for estimation of risk of Pakistani banking stocks under extreme events.
- To quantify the tail risk in the Pakistani banking stocks.
- To analyze the GPD model for extreme events.
- To suggest recommendations based on empirical findings.

1.5 Significance of the Study

Risk management is considered as good management practices. Financial institutions are exposed to various types of risks like (credit risk, default risk, interest rate risk, liquidity risk, currency risk and regulatory risk). The study is significantly important for policymakers, regulatory authorities, financial institutions, risk managers, and investors. This helps the financial institutions to measure the risk by using the appropriate model. With the passage of time, risk management models are updating and to fill the gap, this study helps the investors and financial institutions to manage their risk appropriately. It also helps to identify the upcoming shocks in the market and to make the appropriate measures to manage the risk. Previous studies constitute that the shock of 2007-08 is the result of inappropriate measures of risk management. Pakistan is an emerging market and banking sector plays an important role. The economy of the country depends on the banking sector, so it is significantly important for banks to manage the risk by using the updated models.

1.6 Contribution of the Study

The study has contributed in three different ways in the field of financial risk management. First, the study contributed to the empirical literature of the financial risk management. Secondly the study contributed in the methodology of the risk assessment under extreme events of Pakistani banking stocks. Thirdly, the study provides evidence to the financial practitioners that which model performs best for risk assessment of financial institutions and recommended the model that is suitable for the banking sector in Pakistan.

1.7 Plan of the Study

The plan of the study is organized in chapters as follows. Chapter 2 introduces the theoretical results of VaR and Expected shortfall under the asymptotic distribution of extreme events, parametric and non-parametric assumptions. Chapter 3 describes the methodology of the study that consists of sample information and models used in this study. Chapter 4 describes the results of VaR and Expected shortfall under Parametric, non-parametric and extreme value assumptions with analysis and backtesting results. Chapter 5 provides the robust conclusion and recommendation.

Chapter 2

Literature Review

2.1 VaR and Expected Shortfall

In this section, VaR and ES are compared on the basis of risk management of banking institutions and examine that how Basel requirements are affected by the banks choice of risk measure.

Embrechts, Puccetti, Rüschendorf, Wang, and Beleraj (2014) advocate the use of Expected shortfall at the level of 2.5% instead of VaR at 1% level. The Basel committee of banking supervision recently proposed the Expected shortfall as better measurement tool than the VaR as the Expected shortfall is becoming the most prominent tool in the banking sector; the accuracy of the Expected shortfall is also becoming vital.

Andersson, Mausser, Rosen, and Uryasev (2001) use the CVAR, in the measurement of credit risk by using the Monte Carle method to generate the returns of bonds. Then the assessment of risk did in linear programming to get the minimum CVAR. In this study, the CVAR found as a better method than VaR for measurement of all types of risks like market risk or operational risk etc. Yao, Wen, and Luan (2013) measure the operational risk of state-owned commercial banks of China by using the Peak over Threshold method to calculate the VaR and the ES for the capital requirement in one year of operations.

Kuester, Mittnik, and Paolella (2006) work on the NASDAQ index by using the GARCH under Student-t distribution model, GARCH under skewed Student-t distribution model, GARCH-EVT, and HS model. In this study, GARCH-EVT found to be the best model on the basis number of exceedances in the out of sample model.

Lazar and Zhang (2017) quantify the risk by using the Expected shortfall due to imperfect VaR forecasts. Conditional coverage test and unconditional coverage tests are used in the calculation of Expected shortfall and compare the VaR and Expected shortfall models. The results figure out that Expected shortfall is less affected by model risk as compared to VaR Specification and estimation errors are found in the VaR and removed by using the Backtesting measures.

VaR models ignore the extreme events at the left tail of the probability distribution. To address this issue, researchers and practitioners used the GPD or BMM that can be calculated by Extreme Value Theory- the specialized branch of statistics that uses the extreme information. In literature, the main focus is on the Extreme Value Theory and its statistical importance in the Banking sector. This section consists of the literature of the semi-parametric model, in comparison with non-parametric and parametric models.

2.2 Extreme Value Theory and VaR

Extreme value Theory is used for the modeling of extreme events (fat tails), instead of whole distribution Jurgilas (2012). EVT Is developed by Fisher and Tippett (1928). The Extreme Value Theory (EVT) is a statistical technique that is concerned with extreme observations of random variables. For the measurement of tail risk, it is widely used for the return distribution of monetarist assets. There are two methods that can be used for the identification of extreme returns named the “Block Maxima method” and “Peak over Threshold” method. In the Block Maxima method, the period of observation is divided into blocks such as weeks or months. In each block, the maximum observation will be considered as extreme returns. In the Block Maxima method, only the extreme observation is considered and others are neglected while the Peak over threshold method considered the other observations that exceed the specific threshold as extreme observations (Paul & Sharma, 2017).

The tail distribution of stock returns before and after a global financial crisis is compared by Uppal and Ullah Mangla (2013). Uppal (2013) Uses the extreme value theory model to represent that model does not provide the tail risk in the "United States and the United Kingdom" during the global financial turmoil. Hence, EVT can better perform in the emerging markets. Most of the studies use the EVT in the discussion of the global financial crisis in developed and emerging markets. After the Asian financial crisis of 1998, Gencay and Selcuk (2004) use the Extreme Value Theory models for emerging markets.

Onour and Sergi (2010) conduct a study on the gulf corporation countries, "Saudi Arabia, Kuwait and the United Arab Emirates" for estimation of extreme risks in these three markets. By using the S&P 500 index. The study applied the Generalized Pareto distribution and found it appropriate measurement tool of risk. The study conducted by Djakovic, Andjelic, and Borocki (2011) on four emerging markets "(Serbian, Croatian, Slovenian, and Hungarian stock indexes)" uses the extreme value theory to analyze the performance of EVT with daily stock returns.

Bhattacharyya and Ritolia (2008) also suggest that EVT model is appropriate for the risk assessment of emerging stock returns. Qayyum and Nawaz (2010) also used the EVT to measure the stock index returns for the period of 1993-2009. Uppal and Mudakkar (2014) suggest that there is a need to modernize the risk forecast models in Pakistan in a timely fashion while considering the structural transition in the country.

da Silva and de Melo Mendes (2003) analyze the ten Asian stock markets by using the extreme value theory to find out the asymptotic distribution of extreme events. They find that extreme value theory is a better approach than the traditional method of capital requirement calculations. Embrechts, Resnick, and Samorodnitsky (1999) calculate the securitization of risk and alternative risk transfer by using the extreme value theory as a best methodological tool for measurement.

Gencay and Selcuk (2004) analyze the parametric and non-parametric models on the central and eastern European countries. The results add in the literature that EVT under generalized Pareto distribution models are good for risk management in emerging markets. Longin (2005) use the US stock market data and analyzed that EVT is the most accurate model for the return distribution of asset calculation. By focusing on the tail of the distribution, it helps to select the better. Assaf (2009) used the conditional generalized Pareto distribution model and state that it is a successful model for emerging markets.

Gjika and Horvath (2013) apply the GARCH model to estimate the modified CO-VaR on US banking data and analyzed that depository institution contributes more toward the systematic risk and before the crisis, the systematic risk of all insurance groups, broker-dealers, and non-depository institutions increased. Saddique and Khan (2015) calculate the risk factors by using the VaR at Pakistani banks from (2004-13). The results conclude that banks should not focus on the single method of risk calculation because it leads toward the under or overestimation of risk. In this study, Parametric, non-parametric and Monte Carlo simulation models present the different results from each other.

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

The global financial crisis of 2007-2008 considered the VaR as the weakest method. Muela, Martín, and Sanz (2017) find 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 firms that are operating in the emerging countries should consider the standard Extreme value method for risk calculation.

Fama (1976) also suggest that the distribution of stock daily returns is heavy-tailed instead of normal distribution. Mandelbrot (1966) is the first one that identifies the fat tail and excess peakedness of underlying stocks. Këllezi and Gilli (2003) also, study the EVT by using the BMM and POT method to calculate the VaR and Expected Shortfall. Mignola and Ugoccioni (2005) believe that Extreme Value Theory is useful to ensure the operational risk and it depends on the shape, scale, and position of the loss distribution.

The health of the banking sector is widely monitored by the regulators, investors, and supervisors. For this purpose, they often use the rating of the banks done by the Moody's and Standard & Poor's. Some use the accounting information that is also based on the scoring models. The scoring models and accounting information's are based on the historical cost that is not the best predictor of future market risks. Mwamba, Hammoudeh, and Gupta (2017) perform the comparative analysis of conventional and Islamic stock market by using the extreme value distribution (BMM and POT) method. The results show that Islamic stocks are less risky than the conventional stocks and Block Maxima method perform better than the Peak over threshold method.

Furió and Climent (2013) model the tail distribution to predict the frequency of asset stock returns by comparing the GARCH type models with Extreme value theory. The results indicate that traditional GARCH type models are less accurate than the Extreme value theory results by using the Student-t distribution for sample estimation.

Ozun, Cifter, and Yılmazer (2010) Uses the filtered extreme-value theory (EVT) model to forecast stock returns and compare the predictive performance of this model with other conditional volatility models. The performances of the filtered EVT models are compared to those of GARCH with student-t distribution, GARCH with skewed student-t distribution, and FIGARCH by using alternative back-testing algorithms, namely, "Kupiec test, Christoffersen test, Lopez test, Diebold and Mariano test, root mean squared error (RMSE), and h-step". The results indicate that filtered EVT performs better in terms of capturing fat-tails in stock returns than parametric VaR models.

Poon, Rockinger, and Tawn (2003) identify and model the joint-tail distribution based on multivariate extreme value theory. The results show that the multivariate approach is the most efficient and effective way to study extreme events such as systemic risk and crisis. Neftci (2000) uses in-sample and out-of-sample data, to perform extreme distribution theory and results surprisingly well in capturing both the rate of occurrence and the extent of extreme events in financial markets. In fact, the statistical theory of extremes appears to be a more natural and robust approach to risk management calculations.

Chinhamu, Huang, Huang, and Hammujuddy (2015) uses the backtesting techniques to confirm the effectiveness of risk measures, of VaR and Expected shortfall models. The results of the study support that EVT provides the effective mean of tail risk measure of VaR and Expected Shortfall. Huang and Lin (2004) worked on the number of models including EWMA, Normal distribution, APARCH-Normal distribution, and student-t distribution. At a lower 95% confidence level, APARCH-normal distribution model outperforms the rest of the models and at a high confidence level of 99%, APARCH-student performs best on the stock returns of the Taiwan Index.

A study conducted by Ozun et al. (2010), compared the Value at risk and Expected shortfall models by using the parametric and non-parametric models. Semi-parametric models (Extreme Value Theory Models) outperform at ISE 100 Index. McNeil and Frey (2000) also reached the same conclusion that Extreme Value theory models outperform the GARCH-Normal distribution, GARCH-t distribution models.

2.3 Non-parametric Models

Historical simulation is the traditional method used by a series of papers also called non-parametric by Hull and White (1998) and Barone, Barone-Adesi, and Castagna (1998). Most of the banks still prefer the use of Historical simulation instead of Monte-Carlo or variance-covariance method. The main reason is that historical VaR does not need to make any parametric assumption. Historical simulation ignores the structural breaks and clustering in volatility.

Danielsson and de Vries (1997) observe that underestimation/overestimation of VaR by Historical simulation is different in case of individual stock instead of a portfolio. Ouyang (2009) examine the performance of five models (EXMA, EQMA, GARCH (1,1), HS, EVT(POT) by using the stock returns of Shanghai and Shenzhen index. Ouyang (2009) compare these models and reported that Historical Simulation is the best performer model that is matched by the EVT method.

Danielsson and De Vries (2000) compare the four different 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.

2.4 Parametric Models

Value at risk and Expected Shortfall models assume that the return distributions can be approximated by a certain parametric distribution. The estimation of VaR and ES under parametric conditions depends on the estimation of conditional mean, variance, and distribution assumed for standardized residuals. Another conditional variance model used in this study is EWMA (Exponential weighting moving average). Sometimes the assumption of normal distribution leads to underestimation of value at risk. Most of the studies used the student-t distribution instead of normal distribution. The assumption of normal distribution makes the skewness and kurtosis high that leads toward the underestimation of risk (Nadarajah, 2005).

Chapter 3

Data and Methodology

3.1 Population and Sample of the Study

There are 20 banks listed on the Pakistan stock exchange. The time frame of each bank is listed below. Daily data of banking stock is collected from Pakistan stock exchange (PSX).

S. No.	Banks	Time frame	No. of Observations
1	ABL	1998-2017	3111
2	AKBL	2005-2017	4871
3	BAFL	1998-2017	3393
4	BAHL	2004-2017	4870
5	BOK	1998-2017	2957
6	BOP	2006-2017	2974
7	BIPL	2006-2017	4878
8	FABL	1998-2017	4872
9	HBL	2007-2017	2611
10	HMB	1998-2017	4874
11	JSBL	2007-2017	2734
12	MCB	1998-2017	4872
13	MEBL	2002-2017	3957
14	NBP	2008-2017	3982

S. No.	Banks	Time frame	No. of Observations
15	SBL	2002-2017	3446
16	SILK	2009-2017	2711
17	SNBL	1998-2017	4063
18	SCBPL	2008-2017	2507
19	SMBL	2007-2017	4871
20	UBL	2005-2017	3130

3.2 Research Methodology

In this study, three approaches of VaR and ES are used that is a parametric approach (4 models), non-parametric (1 model) and Extreme Value theory approach (3, static and Dynamic models). The parametric model includes the Normal, Student-t, EWMA, and GARCH, while non-parametric models include only one Historical simulation model. The semi-parametric approach consists of static POT, BMM, and Dynamic POT method.

3.2.1 Extreme Value Theory (EVT)

The focus of the study is on the risk assessment of Pakistani banking stocks by using the Extreme Value Theory approach. The study has used the extreme events particularly negative returns. In EVT, two distributions are important such as Peak over Threshold method (POT) and Block Maxima method. If an investor invests in banking stocks, this will translate the part of the investment that an investor can lose.

3.2.2 GPD (Peak Over Threshold)

Generalized Pareto distribution is the more natural method to calculate the threshold μ in a given sample. It considered the extreme observations above μ. also called the excess distribution over the threshold μ. the access distribution over the threshold μ in a given Variable X, with distribution function F is

$$F(\mu, x) = P(X - \mu \leq x | X > \mu) = \frac{F(x+\mu) - F(\mu)}{1 - F(\mu)} \quad 0 \leq x < xF - \mu$$

Generalized Pareto Distribution lies in a family of the continuous probability distribution. To model the tails of distributions, three parameters are used "(location μ, scale β, and shape)".

$$G(\varepsilon, \beta, \mu) = \begin{cases} 1 - \left(1 + \frac{\varepsilon(x-\mu)}{\beta}\right) - \frac{1}{\varepsilon} & \text{for} \varepsilon \neq 0 \\ 1 - exp\left(-\left(\frac{x-\mu}{\beta}\right)\right) & \text{for} \varepsilon = 0 \end{cases}$$

The cumulative probability distribution function of GPD is given as

$$F(e, \mu, \beta) = 1 - \left(\frac{1 + e(x-\mu)}{\beta}\right)$$

In extreme value theory Pickands-Balkema-de Han theorem that provides the asymptotic distribution of tail distribution of random variable x. while the distribution of F and x are unknown. Balkema and De Haan (1974) and Pickands III (1975) uses the large class of underlying distribution function F and large that F is analyzed by GPD.

3.2.3 Block Maxima Method

The block maxima method in Extreme Value Theory divides the observation period into a non-over-lapping period of equal size and observed the maximum value in each period. The extreme value of each period incorporates the high risk in the portfolio. There are the negative values that deal with the risk. In literature, the block Maxima is considered as a weaker method than POT. Block maxima are easy to apply because the extreme events occur in each block. In this location parameter is μ and scale parameter is σ.

$$F(\varepsilon, \mu, \sigma) = \begin{cases} exp\left(-1 + \frac{\varepsilon(x-\mu)}{\sigma}\right) - \frac{1}{\varepsilon} & \text{for} \varepsilon \neq 0 \\ 1 - exp\left(-\left(\frac{x-\mu}{\sigma}\right)\right) & \text{for} \varepsilon = 0 \end{cases}$$

If $\varepsilon > 0$ will be a Frechet family

$\varepsilon = 0$ Distribution becomes Gumbel

$\varepsilon < 0$ Distribution becomes Weibull

These density functions are called the standard extreme value distribution.

The EVT deals with extreme losses and its analysis developed on negative stock returns.

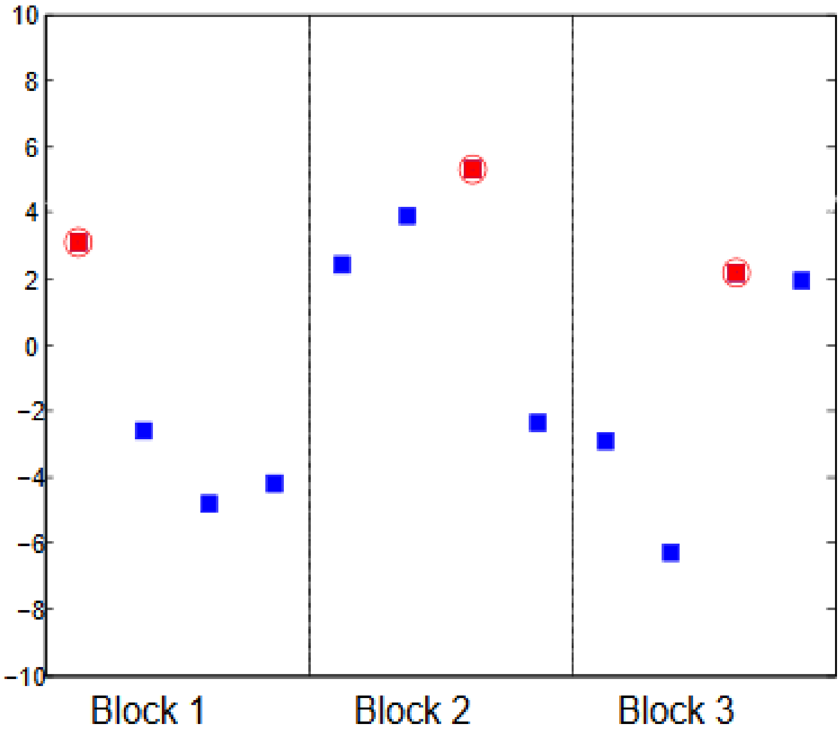

FIGURE 3.1: Block Maxima.

3.3 Non-parametric Model

Nonparametric methods are widely used due to its simplistic assumptions of normality. (Cheung & Powell, 2012) suggested the non-parametric approach to calculating the VaR because it is unlikely that stock returns always follow the parametric distribution.

3.3.1 Historical Simulation

A historical simulation is a non-parametric approach that is widely used by the banks to calculate the daily and quarterly VaR Historical simulation is very advantageous for the banks to calculate VaR because it is not sensitive to the changes in the market conditions. It follows some limitations like the assumption of market factors are constant and it requires a large historical sample.

$$\mathrm{VAR} = F^{-1}(cl) = x_{(i)}$$

Expected shortfall has resolved the problem of subadditivity and provides more information about the tail. Conditional value at risk measures the potential size of the loss exceeding the VaR For random Variable X, the Expected Shortfall is the expected size of loss that exceeds VaR

$$E(S\alpha) = E(X|X > \mathrm{VAR}\alpha)$$

Artzner et al. (1999) argue that the conditional value at risk is the opposite of VaR, is a coherent risk measure. Expected Shortfall from the historical simulation approach is estimated as the mean return in the moving window, that exceed the VaR estimate. There is a problem with the HS method to estimate the ES that how many past periods include in the moving window. Few observations create sampling error and by using too many observations react slowly in the true distribution. Taylor (2007) propose the exponentially weighted quantile regression to solve the problem of ES by taking the cost function.

$$\text{ES} = \sum_{i=(ncl)}^{n} \frac{Xn_{(i)}}{n - [ncl]}$$

3.4 Parametric Estimation Models

Parametric approaches follow the underlying probability distribution assumption to estimate the parameters for VaR and ES calculation.

3.4.1 Normal Distribution

The normal distribution is one of the standard methods of VaR calculation in finance. In case of normal distribution, the VaR is simply as

$$\text{VAR}_\alpha = \mu + \sigma\Phi^{-1}(\alpha)$$

Where μ is the mean of population ion, $F\,(ut)$ is the left tail quantile and σ_t is the volatility as the measure of dispersion. It is observed that volatility increased in the global financial crisis and eventually returned to their actual level after the crisis as it was before the crisis.

$$\text{ES}_\alpha = \mu + \sigma\frac{\emptyset(\Phi^{-1}\,(\alpha))}{1-\alpha}$$

Where Φ is the standard normal distribution function and $\emptyset$ is the density function (Embrechts, Frey, & McNeil, 2005).

3.4.2 Student-t Distribution

To better estimate the risk, if the log returns of time series are leptokurtic, the natural choice is the student-t distribution. The standard student-t distribution has zero mean and Variance is calculated by the degree of freedom. For the Student-t distribution, expressions for the VaR and ES are presented by (McNeil & Frey, 2000) and (Embrechts et al., 2005).

$$\mathrm{VAR}_{\alpha} = \mu + \sigma t v^{-1}(\alpha)$$

$$\mathrm{ES}_{\alpha} = \mu + \sigma \frac{gv(tv^{-1}(\alpha))}{1-\alpha} \frac{v + (tv^{-1}(\alpha))^2}{v-1}$$

Where tv is the distribution function and gv is the density function of student-t distribution.

3.4.3 Exponentially Weighted Moving Average (EWMA)

The EWMA methodology applies exponentially declining weights to the underlying Variance and covariance of the stock returns. A higher value of λ bears more persistent reaction to a shock. JP Morgan uses the standard market risk metric of λ=0.94. The covariance matrix, with the assumption of conditional normality, is used to calculate the VaR (Monetary & Department, 2007).

$$h_t = \lambda h_{t-1} + (1-\lambda)\, r_{t-1}$$

where,

h_t = Variance of the asset at time t

r_{t-1}= Return at time $t-1$

In this method, the conditional variance with the assumption of normality is calculated at 95% and 99%. JP Morgan uses the EWMA to estimate the volatility from the following formula.

$$\sigma^2_{n=\lambda\sigma^2_{n-1}} + (1-\lambda)\, \mu^2_{n-1}$$

3.4.4 GARCH

The GARCH model was proposed by (Bollerslev, 1986), to take the variance into account. It captures the volatility dynamics and estimates the VaR and ES estimates. In this case, volatility is not constant and modeled it GARCH (1,1) model.

$$\sigma t^2 = \alpha_0 + \alpha_1 r_{t-1}^2 + \beta_1 \sigma_{t-1}^2$$

GARCH model is fitted by the maximum likelihood, and coefficient of the model is estimated on the 500 previous values. The values of VaR and ES can be estimated as follow

$$\text{VAR} = \sigma_{t+1} \in q$$

$$\text{ES} = \sigma_{t+1} E[\in \mid \in > \in q]$$

$\in q$ is the upper quantile of the marginal distribution of $\in t$.

3.5 Backtesting

Back-testing 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 from the underestimation and overestimation of risk. In this study, Back-testing is used to validate the models of VaR and Expected Shortfall accuracy.

As per the Basel Committee requirements, the VaR violations at 95%, 97.5%, and 99% confidence level are used for Backtesting. It is hard to Backtest the Expected

Shortfall models because ES models require estimates of the tail expectation to the ES forecast.

3.5.1 Violation Ratio

One of the most common tools of Back-testing is violation ratio. In this, the observed numbers of VaR violations are compared with expected.

$$\text{VR} = \frac{\text{Observed number of violations}}{\text{Expected number of violations}} = \frac{vi}{p \times Wt}$$

VR>1 = VaR model under-forecast risk

VR<1 = VaR model over-forecast risk

3.6 Backtesting VaR Methodologies

The study analyzes the performance of various VaR and ES models by using the log of daily returns of twenty Banking stocks. VaR models are tested by using the conditional coverage test (Kupiec test) and Unconditional Christoffersen test. In the two-stage Backtesting procedure, the best performing model must satisfy the Kupiec and Christoffersen test.

3.6.1 Kupiec (POF) Test

Kupiec is the conditional Backtesting technique that is used to validate the VaR models.

The null hypothesis of the POF test is as follows

$$H_{OP} = P^{\sim} = \frac{X}{T}$$

Where

P = Proportion of failure

$P^{\sim}$ = Observed failure rate

X = Number of exceptions

T = Number of observations

The null hypothesis states that "the observed failure rate is equal to the failure rate that is suggested by the confidence interval".

Kupiec test is followed by the χ^2 distribution at 1 degree of freedom. If the amount of likelihood is less than chi-square value, the model will be accepted. If the LR is greater than the critical value, the decision of null hypothesis rejection and model inaccuracy will be made. At the 5% significance level of test, the null hypothesis is rejected it LR>3.84.

The likelihood ratio test is expressed from the following formula

$$\mathrm{LR} = -2\ln\frac{(1-P)^{T-x}\times P^{x}}{\left(1-\frac{x}{T}\right)^{T-x}\times\left(\frac{x}{T}\right)^{x}}$$

POT test considers the number of exceptions and it is important to calculate the number of exceptions. In this, daily losses of the stock returns are calculated and then compare to the forecasted VaR If, the value of the daily loss is greater than the calculated VaR, violation occurs. Once the numbers of exceptions for each level of confidence are calculated, the POF test is applied. When the sample size will be larger, the power of the test increases. One of the shortcomings of the model is that it ignores the time when the losses occur. It leads toward the failure of the model in case of violation clustering. That is the reason the Christoffersen test is used to resolve any short-comings in the model.

3.6.2 Christoffersen Test

P. F. Christoffersen (1998) develop the conditional coverage test. The probability of Christoffersen independence test examines that the today exception depends on the outcome of the previous day. In this test, 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 independence test is compared with the chi-square value at one degree of freedom. The null hypothesis of independence test is a follows

$$H_0 = \pi \wedge 01 = \pi \wedge 11$$

The null hypothesis is, that LR $> \chi^2$ model deemed incorrect. Under the null hypothesis, the occurrence of violation should be independent over time.

$$\text{LRind} = -2 \ln \left(\frac{(1-\pi)^{T00+T10} \times \pi^{T01+T11}}{(1-\pi 01)^{T00} \pi 01^{T01} (1-\pi 11)^{T10} \pi 11^{T11}} \right)$$

Where

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

Christoffersen help to inspect the reason for the failure of the test due to clustered violations, inaccurate coverage or both. Campbell, Lo, and MacKinlay (1997) suggest to apply the coverage and independence test separately because sometimes model does not pass the joint test.

Chapter 4

Results and Discussion

4.1 Descriptive Statistics

Table 4.1 reports the summary of statistics of daily negative returns of 20 Pakistani banking stocks listed on the Pakistan stock exchange (PSX). The negative mean loss of (BIPL, BOK, JSBL, SBL, SCBPL, SILK, and SMBL) experiences negative shocks. The returns of (ABL, AKBL, BAFL, BAHL, BOP, FABL, HMB, MCB, MEBL, SNBL) are positively skewed and (BIPL, BOK, HBL, JSBL, NBP, SBL, SCBPL, SILK, SMBL, UBL) are negatively skewed, indicating that they are non-symmetric.

The high excess kurtosis of each stock indicates the fat tail distribution of the stock returns. Although, all stocks have non-normally distributed returns, BAHL, BOK, HBL, HMB, NBP, SILK banks have more leptokurtic return distributions and fatter tails than other banks stocks returns. To check the normality of loss distribution, the Jarque-Bera test has been performed. The grater statistics of the test gives an evidence of non-normality of the data. The extreme fat tail of stock returns series provides the positive motivation for the estimation of VaR models applications.

Table 4.1: Summary statistics.

	Mean	**Med**	**Max**	**Min**	**Std. Dev.**	**Skew**	**Kurt**	**Jarque-Bera**
ABL	0.0003	0.00	0.095	-0.203	0.021	-0.647	9.363	5465
AKBL	0.0001	0.00	0.187	-0.377	0.025	-1.740	28.647	135960
BAFL	0.0000	0.00	0.096	-0.288	0.024	-1.263	18.048	32915
BAHL	0.0002	0.00	0.138	-0.351	0.023	-4.510	60.401	685081
BIPL	-0.0002	0.00	0.187	-0.146	0.031	0.611	6.729	1897
BOK	-0.0003	0.00	0.257	-0.234	0.031	0.460	10.312	6731
BOP	0.0001	-0.00	0.234	-0.408	0.035	-0.675	15.672	33009
FABL	0.0002	0.00	0.158	-0.209	0.027	-0.250	8.191	5520
HBL	-0.0001	-0.00	0.095	-0.215	0.020	-0.930	12.836	10902
HMB	0.0001	0.00	0.115	-0.464	0.025	-3.650	55.343	567218
JSBL	-0.0003	-0.00	0.311	-0.288	0.036	0.771	10.977	7520
MCB	0.0005	0.00	0.157	-0.163	0.025	-0.268	6.951	3227
MEBL	0.0005	0.00	0.113	-0.257	0.023	-0.414	10.546	9502
NBP	0.0004	0.00	0.516	-0.283	0.026	0.487	59.287	525809
SBL	-0.0002	0.00	0.358	-0.199	0.040	0.536	8.007	3765
SCBPL	-0.0003	0.00	0.135	-0.119	0.025	0.046	5.492	702
SILK	-0.0002	0.00	0.693	-0.528	0.037	1.976	60.342	559294
SMBL	-0.0010	-0.00	0.309	-0.217	0.039	1.073	10.520	6388
SNBL	0.0000	0.00	0.186	-0.337	0.027	-1.407	22.878	81805
UBL	0.0003	0.00	0.095	-0.245	0.0217	-1.246	16.76	25538

4.2 VaR Under Parametric and Non-parametric Assumptions

Table 4.2 presents the results of VaR calculation under Historical simulation model below.

Table 4.2: VaR under HS method.

Historical Simulation (Non-Parametric)			
	VaR@95%	**VaR@97.5%**	**VaR@99%**
ABL	-0.0336	-0.0510	-0.0512
AKBL	-0.0376	-0.0510	-0.0608

	VaR@95%	VaR@97.5%	VaR@99%
BAFL	-0.0399	-0.0510	-0.0550
BAHL	-0.0269	-0.0392	-0.0512
BOK	-0.0476	-0.0620	-0.0862
BOP	-0.0510	-0.0654	-0.0654
BIPL	-0.0481	-0.0608	-0.0782
FABL	-0.0440	-0.0513	-0.0690
HBL	-0.0315	-0.0500	-0.0782
HMB	-0.0332	-0.0487	-0.0552
JSBL	-0.0512	-0.0657	-0.0894
MCB	-0.0445	-0.0513	-0.0721
MEBL	-0.0351	-0.0479	-0.0590
NBP	-0.0420	-0.0512	-0.0513
SBL	-0.0611	-0.0817	-0.1037
SILK	-0.0480	-0.0598	-0.0833
SNBL	-0.0385	-0.0511	-0.0667
SCBPL	-0.0445	-0.0510	-0.0632
SMBL	-0.0546	-0.0701	-0.0960
UBL	-0.0358	-0.0490	-0.0513

At 95% confidence level, the Historical simulation method reports the highest risk of 6.1% in SBL. It means that there are 95% chances that the loss will not exceed 6.1%. Historical simulation reports that BAHL has the lowest risk of 2.8%. The potential loss for one day to the investor is lower in this stock. It means that SBL is the riskiest bank in the portfolio and BAHL is the least risky bank.

At 97.5% confidence level, the Historical simulation method reports the highest risk of 8.2% for SBL. It means that there is a 97.5% chance that the loss will not exceed 8.2%. Historical simulation reports that BAHL has the lowest risk of 3.9%. The potential loss for one day to the investor is lower in this stock. It means that SBL is the riskiest bank in the portfolio and BAHL is the least risky bank at the 97.5% level of confidence.

At 99% confidence level, the Historical simulation method reports the highest risk of 10.4% at SBL. It means that there is a 99% chance that the loss will not exceed 10.4%. Historical simulation reports that BAHL has the lowest risk of 5.1%. The potential loss for one day to the investor is lower in this stock. It means that SBL is the riskiest bank in the portfolio and BAHL is the least risky bank at the 99% level of significance. The Historical simulation method reports that the level of risk increases as the level of confidence increased.

4.3 Value at Risk (Parametric Methods)

Table 4.3: VaR under Normal and Student-t Model.

Normal & Student-t VaR (Parametric Estimation)						
	VaR 95%		**VaR@97.5%**		**VaR@99%**	
	NORM	**T-DIST**	**NORM**	**T-DIST**	**NORM**	**T-DIST**
ABL	-0.0345	-0.0319	-0.0411	-0.0442	-0.0488	-0.0651
AKBL	-0.0418	-0.0353	-0.0498	-0.0503	-0.0592	-0.0773
BAFL	-0.0396	-0.0358	-0.0472	-0.0485	-0.0561	-0.0695
BAHL	-0.0381	-0.0278	-0.0454	-0.0405	-0.0539	-0.0645
BOK	-0.0721	-0.0466	-0.0859	-0.0665	-0.1021	-0.1026
BOP	-0.0581	-0.0498	-0.0691	-0.0717	-0.0821	-0.1121
BIPL	-0.0511	-0.0470	-0.0609	-0.0669	-0.0723	-0.1031
FABL	-0.0452	-0.0413	-0.0539	-0.0573	-0.0641	-0.0847
HBL	-0.1136	-0.0310	-0.1354	-0.0446	-0.1607	-0.0699
HMB	-0.0405	-0.0326	-0.0482	-0.0493	-0.0572	-0.0828
JSBL	-0.0591	-0.0528	-0.0703	-0.0724	-0.0835	-0.1057
MCB	-0.0418	-0.0387	-0.0498	-0.0531	-0.0591	-0.0774
MEBL	-0.0381	-0.0348	-0.0453	-0.0481	-0.0537	-0.0709
NBP	-0.0421	-0.0351	-0.0501	-0.0500	-0.0595	-0.0770
SBL	-0.0661	-0.0605	-0.0786	-0.0850	-0.0933	-0.1285
SILK	-0.0607	-0.0466	-0.0723	-0.0687	-0.0858	-0.1112
SNBL	-0.0447	-0.0380	-0.0533	-0.0543	-0.0632	-0.0839

	VaR 95%		VaR@97.5%		VaR@99%	
	NORM	**T-DIST**	**NORM**	**T-DIST**	**NORM**	**T-DIST**
SCBPL	-0.0413	-0.0391	-0.0492	-0.0541	-0.0852	-0.0798
SMBL	-0.0642	-0.0559	-0.0762	-0.0784	-0.0905	-0.1182
UBL	-0.0671	-0.0331	-0.0798	-0.0451	-0.0947	-0.0652

At the 95% confidence level, the risk of HBL is higher at 11.4% followed by a normal distribution. ABL is diagnosed as a least risky bank at a value at risk of 3.5%. At the 97.5% confidence interval, HBL reports the risk of 13.5% and ABL risk is 4.1%. At the 99% confidence level, the maximum risk of HBL is 16% and the minimum risk diagnosed by the model is 4.8% in ABL.

The student t model considers the SBL as the riskiest bank at 6% and least risk bank diagnosis by the model is BAHL at 2.8%. The maximum risk diagnosis by the model is 8.5% of SBL and minimum risk calculated by the model is 4% of BAHL. At the 99% confidence level, the maximum risk diagnosis by the model is 12.9% in SBL and minimum risk calculated by the model is 6.4% in BAHL.

At the 95% level, The VaR estimates of the normal VaR are higher than the student t distribution. The difference in result is based on the difference of the assumptions. The results at 97.5% and 99% confidence level, VaR estimates of Normal distribution are lower than the student t distribution means that normal VaR always underestimates the risk. Roccioletti (2015) also found that normal VaR is lower than the student t VaR at 97.5% and 99% and Normal VaR always underestimates the risk.

Table 4.4: VaR calculations under EWMA and GARCH model.

	EWMA & GARCH					
	VaR-95%		**VaR-97.5%**		**VaR-99%**	
	EWMA	**GARCH**	**EWMA**	**GARCH**	**EWMA**	**GARCH**
ABL	-0.0249	-0.0316	-0.0297	-0.0377	-0.0352	-0.0448
AKBL	-0.0298	-0.0380	-0.0355	-0.0453	-0.0421	-0.0538
BAFL	-0.0255	-0.0314	-0.0303	-0.0375	-0.0361	-0.0445

	VaR-95%		VaR-97.5%		VaR-99%	
	EWMA	**GARCH**	**EWMA**	**GARCH**	**EWMA**	**GARCH**
BAHL	-0.0304	-0.0599	-0.0362	-0.0714	-0.0429	-0.0848
BOK	-0.0574	-0.0645	-0.0685	-0.0768	-0.0813	-0.0912
BOP	-0.0304	-0.0394	-0.0362	-0.0470	-0.0431	-0.0558
BIPL	-0.0331	-0.0545	-0.0393	-0.0650	-0.0467	-0.0772
FABL	-0.0647	-0.0839	-0.0771	-0.1000	-0.0916	-0.1187
HBL	-0.0281	-0.0619	-0.0335	-0.0738	-0.0398	-0.0876
HMB	-0.0349	-0.0367	-0.0416	-0.0438	-0.0494	-0.0520
JSBL	-0.0319	-0.0387	-0.0381	-0.0462	-0.0451	-0.0548
MCB	-0.0269	-0.0342	-0.0321	-0.0407	-0.0381	-0.0484
MEBL	-0.0254	-0.0308	-0.0303	-0.0367	-0.0361	-0.0436
NBP	-0.0239	-0.0421	-0.0285	-0.0501	-0.0338	-0.0595
SBL	-0.0964	-0.0828	-0.1148	-0.0987	-0.1363	-0.1171
SILK	-0.0253	-0.0363	-0.0302	-0.0432	-0.0358	-0.0513
SNBL	-0.0297	-0.0460	-0.0354	-0.0549	-0.0421	-0.0651
SCBPL	-0.0312	-0.0381	-0.0372	-0.0454	-0.0441	-0.0539
SMBL	-0.0324	-0.0444	-0.0386	-0.0529	-0.0458	-0.0628
UBL	-0.0296	-0.0456	-0.0352	-0.0591	-0.0418	-0.0711

At 95% confidence level, the EWMA method reports the highest risk of 9.6% in SBL. It means that there is the maximum potential for loss is 9.6%. EWMA reports that ABL has the lowest risk of 2.5%. The potential loss for one day to the investor is lower in this stock. It means that SBL is the riskiest bank in the portfolio and ABL is the least risky bank. At 95% confidence level, the GARCH model reports the highest risk of 8.3% in FABL. It means that there is the maximum potential for loss is 8.3%. Historical simulation reports that MEBL has the lowest risk of 3%. The potential loss for one day to the investor is lower in this stock. It means that FABL is the riskiest bank in the portfolio and MEBL is the least risky bank.

At 97.5% confidence level, EWMA method reports the highest risk of 11.5% in SBL. It means that there is the maximum potential for loss is 11.5%. Historical simulation reports that NBP has the lowest risk of 2.9%. The potential loss for one day to the investor is lower in this stock. It means that SBL is the riskiest bank in the portfolio and NBP is the least risky bank. At 97.5% confidence level, the GARCH model reports the highest risk of 10% at FABL. It means that there is the maximum potential for loss is 10%. Historical simulation reports that MEBL has the lowest risk of 3.7%. The potential loss for one day to the investor is lower in this stock. It means that FABL is the riskiest bank in the portfolio and MEBL is the least risky bank.

At 99% confidence level, EWMA method reports the highest risk of 13.6% at SBL. It means that there is the maximum potential for loss is 13.6%. Historical simulation reports that NBP has the lowest risk of 3.4%. The potential loss for one day to the investor is lower in this stock. It means that SBL is the riskiest bank in the portfolio and NBP is the least risky bank. At 99% confidence level, the GARCH model reports the highest risk of 11.9% at FABL. It means that there is the maximum potential for loss is 11.9%. Historical simulation reports that MEBL has the lowest risk of 4.4%. The potential loss for one day to the investor is lower in this stock. It means that FABL is the riskiest bank in the portfolio and MEBL is the least risky bank.

The risk estimated by the EWMA is lower than the GARCH model at three confidence levels of 95%, 97.5%, and 99%. While comparing the results of EWMA and GARCH, it is concluded that EWMA forecast the risk lower than the GARCH model.

4.3.1 Violation Ratio and Volatility

Violation Ratio is one of the primary methods of model accuracy calculations. In this section, Violation, and volatilities are forecasted to check the model that performs best.

Table 4.5: Violation ratio under EWMA, N.dist, HS, T.DIST and GARCH.

Violation Ratio					
VR-95%					
	EWMA	**N.DIST**	**HS**	**T.DIST**	**GARCH**
ABL	1.88	0.88	0.77	1.33	1.42
AKBL	1.60	1.01	1.12	0.91	1.33
BAFL	0.92	0.93	1.00	1.30	0.79
BAHL	0.73	0.51	0.97	0.56	0.54
BOK	0.83	0.7	1.00	1.06	0.64
BOP	0.81	0.94	1.11	1.05	0.74
BIPL	0.94	0.84	0.98	1.38	0.75
FABL	0.86	0.87	1.09	1.33	0.76
HBL	0.73	0.63	0.95	0.61	0.65
HMB	0.86	0.73	0.92	0.78	0.68
JSBL	0.79	0.57	0.83	1.08	0.56
MCB	0.99	1.12	0.95	1.38	0.91
MEBL	0.94	0.79	0.94	1.24	0.81
NBP	0.94	1.10	0.95	1.15	0.76
SBL	1.05	0.89	1.09	1.50	0.93
SILK	0.81	0.65	0.97	0.83	0.57
SNBL	1.46	1.19	1.03	0.93	1.37
SCBPL	1.18	1.09	0.92	1.51	1.13
SMBL	0.85	0.65	0.91	0.84	0.59
UBL	1.74	1.33	0.80	1.92	1.52

Violation ratio is the primary tool of Backtesting that compare the observed frequency and expected number of violations. In the EWMA model, the violation ratio is greater than 1 in the case of (ABL, AKBL, SNBL, and UBL) that under forecasted the risk at 95% confidence level. Other banking stocks are a clear indication of perfect modeling. The model of normal distribution violation ratio in case of each stock is fairly modeled except the stock of UBL that is underestimated by the model. The forecasting of historical simulation is a clear indication of perfect modeling. The model of student t distribution under forecasted the risk of (ABL, BAFL, BIPL, MCB, and UBL). There is not a model that overestimated the risk of banking stocks at 95% confidence level.

At the 95% confidence level, the model that performs better than the other models is a Historical simulation and Normal Distribution.

TABLE 4.6: Volatility ratio under EWMA, N.dist, HS, T.DIST, and GARCH.

VOLATILITY 95%					
	EWMA	**N.DIST**	**H.S**	**T.DIST**	**GARCH**
	VOL	**VOL**	**VOL**	**VOL**	**VOL**
ABL	0.018	0.013	0.006	0.027	0.021
AKBL	0.023	0.011	0.009	0.010	0.029
BAFL	0.014	0.010	0.012	0.047	0.015
BAHL	0.018	0.009	0.008	0.011	0.023
BOK	0.052	0.037	0.012	0.055	0.032
BOP	0.019	0.013	0.011	0.033	0.022
BIPL	0.020	0.010	0.011	0.026	0.021
FABL	0.015	0.008	0.010	0.004	0.014
HBL	0.010	0.010	0.010	0.012	0.009
HMB	0.017	0.009	0.008	0.010	0.021
JSBL	0.020	0.012	0.012	0.044	0.017
MCB	0.013	0.010	0.011	0.028	0.014
MEBL	0.013	0.008	0.009	0.008	0.011
NBP	0.017	0.007	0.011	0.025	0.022
SBL	0.023	0.007	0.007	0.033	0.020
SILK	0.023	0.012	0.010	0.048	0.032
SNBL	0.024	0.010	0.015	0.011	0.034
SCBPL	0.011	0.007	0.007	0.020	0.010
SMBL	0.022	0.022	0.009	0.011	0.017
UBL	0.018	0.014	0.003	0.023	0.020

To implement the VaR estimation, EWMA λ=0.94 is used to capture the volatilities.

Volatility is an appropriate risk measure states that lower volatility supports the reliable VaR model. At the 95% confidence level, the EWMA forecasted the maximum value of volatility in the stock of BOK. It means that EWMA is a weaker method for the risk assessment of BOK stock. Normal distribution model also forecasted the high volatility in the BOK stock while others stock has lower volatility and model is considered as stable for them. The volatility forecasted by the Historical simulation method is lower as compared to the EWMA and Normal distribution. It is considered a stable method. The volatility calculated by the t. distribution method is high for the BOK stock and considers the weaker method for that stock. GARCH volatility is also high as compared to the other models and it is considered as a weaker method. GARCH forecasted high volatility in the SNBL stock means that it is the riskiest stock for investment. The method is not stable for the risk estimation of the SNBL stock. The most appropriate model at the 95% confidence level is suggested as the Historical Simulation method.

Table 4.7: Violation ratio under EWMA, N.dist, HS, T.DIST and GARCH.

VR 97.5%					
	EWMA	**N.DIST**	**HS**	**T.DIST**	**GARCH**
ABL	1.15	0.93	0.87	0.71	0.97
AKBL	1.06	0.77	1.05	0.68	0.83
BAFL	1.11	0.80	1.20	1.10	1.01
BAHL	0.95	0.54	0.95	0.47	0.62
BOK	0.99	0.86	1.03	1.00	0.81
BOP	1.00	0.81	1.00	0.45	0.77
BIPL	1.14	1.06	0.99	1.25	0.93
FABL	0.96	0.97	0.96	0.65	0.81
HBL	1.00	0.80	0.93	0.45	0.78
HMB	1.15	0.65	0.85	0.53	0.76
JSBL	0.79	0.61	0.73	1.08	0.59
MCB	1.29	1.06	0.91	1.73	1.11
MEBL	1.18	0.94	0.97	1.09	0.83
NBP	1.19	1.57	1.02	1.56	0.95

	EWMA	N.DIST	HS	T.DIST	GARCH
SBL	1.19	1.25	1.11	1.79	1.15
SILK	0.87	0.68	0.86	0.76	0.63
SNBL	1.03	0.80	1.08	1.12	0.81
SCBPL	1.39	1.28	0.81	1.73	1.37
SMBL	0.88	0.62	0.84	0.76	0.58
UBL	1.29	0.88	1.08	1.84	1.06

In the EWMA model, the violation ratio is greater than 1 in the case of (SCBPL) that under forecasted the risk at 97.5% confidence level. Other banking stocks are a clear indication of perfect modeling. The model of normal distribution violation ratio in case of each stock is fairly modeled except the stock of NBP that is underestimated by the model. The forecasting of Historical Simulation is a clear indication of perfect modeling. The model of student t distribution under forecasted the risk of (MCB, NBP, SBL, SCBPL and UBL). There is not a model that overestimated the risk of banking stocks at 97.5% confidence level. GARCH model also performs better than the student t model and one violation occurs at SCBPL stock that is also diagnosed by the EWMA, and student t distribution.

At the 97.5% confidence level, Historical simulation, EWMA, normal distribution, and GARCH Perform better than the student t model.

Table 4.8: Volatility ratio under EWMA, N.dist, HS, T.DIST, and GARCH.

VOLATILITY 97.5%					
	EWMA	**N.DIST**	**HS**	**T.DIST**	**GARCH**
	VOL	**VOL**	**VOL**	**VOL**	**VOL**
ABL	0.0155	0.0109	0.0094	0.0363	0.0178
AKBL	0.0197	0.009	0.0065	0.0136	0.0242
BAFL	0.0168	0.0121	0.0115	0.0630	0.0173
BAHL	0.0215	0.0104	0.0094	0.0142	0.0268
BOK	0.0617	0.0442	0.0201	0.0736	0.0384
BOP	0.0221	0.0157	0.0227	0.0446	0.0257
BIPL	0.0241	0.0119	0.0146	0.0352	0.0244

	EWMA	N.DIST	HS	T.DIST	GARCH
	VOL	**VOL**	**VOL**	**VOL**	**VOL**
FABL	0.0183	0.0093	0.0110	0.0050	0.0161
HBL	0.0116	0.0122	0.0097	0.0162	0.0102
HMB	0.0202	0.0103	0.0091	0.0138	0.0246
JSBL	0.0241	0.0138	0.0169	0.0599	0.0200
MCB	0.0160	0.0114	0.0145	0.0373	0.0161
MEBL	0.0149	0.0095	0.0114	0.0102	0.0133
NBP	0.0197	0.0083	0.0054	0.0330	0.0261
SBL	0.0270	0.0080	0.0132	0.0451	0.0232
SILK	0.0274	0.0139	0.0159	0.0647	0.0386
SNBL	0.0205	0.0080	0.0093	0.0152	0.0284
SCBPL	0.0125	0.0088	0.0098	0.0267	0.0122
SMBL	0.0265	0.0082	0.0134	0.0149	0.0199
UBL	0.0147	0.0114	0.0084	0.0309	0.0168

At the 97.5% confidence level, EWMA, Normal distribution, student-t and GARCH diagnosis the BOK, the riskiest stock due to high volatility. Historical simulation diagnosed the BOP as the riskiest stock. At the 97.5% confidence level, all of the five models perform well as compared to the 95% confidence level results.

Table 4.9: Violation ratio at 99% level of significance.

	VR 99%				
	EWMA	**N.DIST**	**HS**	**T.DIST**	**GARCH**
	VR	**VR**	**VR**	**VR**	**VR**
ABL	0.90	1.00	0.93	0.53	0.79
AKBL	0.81	0.81	1.04	0.66	0.75
BAFL	1.59	1.28	1.17	1.16	1.38
BAHL	1.60	0.82	0.98	0.69	0.94
BOK	1.33	1.13	1.25	1.04	0.97
BOP	1.64	1.30	0.89	0.48	1.18
BIPL	1.55	1.59	1.43	0.81	1.02

	EWMA	N.DIST	HS	T.DIST	GARCH
	VR	**VR**	**VR**	**VR**	**VR**
FABL	1.28	1.44	1.03	0.70	1.17
HBL	1.47	1.23	1.28	0.59	1.37
HMB	1.53	0.94	0.75	0.57	1.07
JSBL	1.34	0.94	0.67	1.27	1.12
MCB	1.65	1.25	0.75	1.69	1.33
MEBL	1.27	1.30	1.07	1.04	0.92
NBP	1.90	0.95	1.01	0.91	1.49
SBL	1.80	1.87	1.32	2.10	1.66
SILK	1.32	0.95	1.07	0.60	0.81
SNBL	0.87	0.65	0.99	1.17	0.66
SCBPL	1.54	1.36	0.63	1.85	1.36
SMBL	1.25	0.80	0.90	0.54	0.75
UBL	0.99	1.02	0.99	2.08	0.97

At the 99% confidence level, more violations occur at EWMA, Normal, Student t and GARCH model, and fewer violations occur at Historical simulation model. It means that as the confidence level increases, the number of violations also increases. While evaluating these models, 97.5% confidence level is best to calculate the risk for all stocks. At the 99% confidence level, each model underestimates the risk except the Historical simulation method.

Table 4.10: Volatility ratio at 99% level of significance.

	VOL 99%				
	EWMA	**N.DIST**	**H.S**	**T.DIST**	**GARCH**
	VOL	**VOL**	**VOL**	**VOL**	**VOL**
ABL	0.0130	0.0091	0.0119	0.0518	0.0150
AKBL	0.0166	0.0076	0.0088	0.0191	0.0203
BAFL	0.0200	0.0145	0.0117	0.0898	0.0206
BAHL	0.0256	0.0123	0.0133	0.0201	0.0318
BOK	0.0732	0.0525	0.0263	0.1044	0.0457

	EWMA	**N.DIST**	**H.S**	**T.DIST**	**GARCH**
	VOL	**VOL**	**VOL**	**VOL**	**VOL**
BOP	0.0263	0.0187	0.0380	0.0634	0.0305
BIPL	0.0286	0.0142	0.0221	0.0504	0.0290
FABL	0.0218	0.0111	0.0132	0.0070	0.0192
HBL	0.0138	0.0145	0.0075	0.0229	0.0121
HMB	0.0240	0.0123	0.0151	0.0196	0.0293
JSBL	0.0287	0.0164	0.0213	0.0855	0.0238
MCB	0.0191	0.0136	0.0191	0.0534	0.0192
MEBL	0.0178	0.0114	0.0136	0.0146	0.0159
NBP	0.0234	0.0099	0.0036	0.0469	0.0311
SBL	0.0320	0.0096	0.0289	0.0647	0.0276
SILK	0.0326	0.0166	0.0284	0.0924	0.0459
SNBL	0.0172	0.0067	0.0081	0.0216	0.0238
SCBPL	0.0149	0.0105	0.0180	0.0381	0.0145
SMBL	0.0315	0.0097	0.0196	0.0214	0.0237
UBL	0.0124	0.0096	0.0107	0.0439	0.0141

The results of volatility at a 99% confidence level are the same as compared to the other confidence levels of 95% and 97.5%. BOK is considered as the riskiest stock and models underestimate the risk of the stock.

Historical simulation Perform well than the other models (EWMA, N.dist, T-dist., and GARCH) at the 95% significance level because the model has the best minimum violation ratio and is less volatile. Historical simulation and Normal Distribution model has minimum violation ratio and lower volatility as compared to other models at the 97.5% significance level. At the 99% significance level, fewer violations occur in the Historical simulation model as compared to other models and in case of volatility Historical Simulation is considered the less volatile model.

4.3.2 Backtesting Results (Kupiec and Christoffersen Test)

In this study, Two types of Backtesting has been applied, the conditional coverage test Kupiec (1995) and Independence test P. Christoffersen, Diebold, and Schuermann (1998). The dynamic Backtesting has been conducted for all models of parametric, non-parametric and EVT models at 95%, 97.5% 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. In this, the rolling window procedure is used that is twofold. It is good to assess the stability of model over time and the accuracy of forecasting. The rolling window of 500 observations has been used.

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

TABLE 4.11: Kupiec's-POF test at the 95% significance level.

Kupiec's-POF test						
confidence level 95%						
	Test static					Critical Value
	LR-of					χ^2
	EWMA	N.DIST	HS	GARCH	student t	
ABL	37.64	40.81	53.30	181.48	0.01	3.84
AKBL	27.66	0.00	0.00	87.25	0.00	3.84
BAFL	6.95	45.89	47.67	10.16	0.00	3.84
BAHL	0.00	48.19	0.00	0.00	51.85	3.84
BOK	16.60	12.64	0.02	97.42	0.89	3.84
BOP	0.00	0.00	0.00	16.34	0.00	3.84
BIPL	3.91	3.53	0.12	36.97	17.97	3.84
FABL	19.88	0.00	0.00	114.18	0.00	3.84
HBL	15.82	16.74	1.09	83.37	0.38	3.84
HMB	0.00	19.43	0.00	173.27	0.00	3.84
JSBL	21.72	25.04	4.24	63.44	0.04	3.84

	Test static					Critical Value
	LR-of					χ^2
	EWMA	N.DIST	HS	GARCH	student t	
MCB	0.00	0.00	0.00	0.00	0.00	3.84
MEBL	7.19	9.28	0.99	83.86	43.86	3.84
NBP	7.01	0.00	0.74	122.76	0.00	3.84
SBL	1.92	1.69	0.99	10.15	19.02	3.84
SILK	29.50	26.69	0.87	178.11	8.31	3.84
SNBL	0.00	32.88	0.00	154.92	0.00	3.84
SCBPL	0.11	1.04	1.06	15.95	27.14	3.84
SMBL	12.43	6.58	42.00	0.96	2.96	3.84
UBL	0.24	0.05	0.00	0.45	42.93	3.84

At the 95% confidence level, the likelihood ratio calculated by the EWMA model is highest for a stock return that is 37.64, 27.66 reject the model. It means that the EWMA model is not reliable for (ABL, BOK, FABL, HBL, JSBL, SILK, and SMBL) risk assessment. In this case, the EWMA model does not perform well. Violation ratios are very high that clearly implying rejection. The highest likelihood ratio calculated for the Normal distribution model is 48.19 of BAHL. The model is not reliable for the risk assessment of (ABL, BAFL, BAHL, BOK, HBL, HMB, FBAL, JSBL, SILK, and SMBL) because their likelihood ratios are greater than the critical value of 3.84.

The POF test predicts that Historical Simulation model is not reliable for the risk assessment of the (ABL, BAFL, JSBL, and SMBL) stock returns. For these results, it can be said that VaR estimation underestimates the risk. The POF test predicts that the GARCH model is reliable for the risk assessment of four stocks (BAHL, MCB, SMBL, and UBL) stock returns. GARCH is the model that is rejected at the 99% confidence level for most of the stocks. It means that it is not a reliable model for risk assessment of the banking stocks. The POF test predicts that student t model is not reliable for the risk assessment of the (BAHL, BIPL, MEBL, SBL, SILK, SCBPL, UBL) stock returns. For these results, it can be said that VaR estimation underestimates the risk.

The calculated likelihood ratios at the 95% confidence level, it is identified that the observed rate of failure is different from the confidence interval rate failure. For this test, Historical Simulation is the reliable model and EWMA, normal distribution, student-t, GARCH is not considered the reliable model for risk assessment of banking stocks at 95% level. At the highest level of confidence, more violations occurred and the models that were reliable at 95% are rejected at the 99% level.

TABLE 4.12: Christofferson's Independence Test at 95% confidence level.

Christofferson's Test						
confidence level 95%						
	Test static					Critical Value
	LR-IND					χ^2
	EWMA	N.DIST	HS	GARCH	student t	
ABL	2.07	20.18	7.13	7.31	6.17	3.84
AKBL	32.45	0.00	0.00	49.67	0.00	3.84
BAFL	8.58	2.94	3.22	19.95	0.00	3.84
BAHL	0.00	8.19	0.00	0.00	17.36	3.84
BOK	0.60	16.90	16.53	16.52	11.71	3.84
BOP	0.00	0.00	0.00	31.25	0.00	3.84
BIPL	2.94	4.30	2.06	0.33	2.39	3.84
FABL	44.51	0.00	0.00	0.05	0.00	3.84
HBL	10.15	24.94	26.25	0.75	43.38	3.84
HMB	9.82	21.52	0.00	0.10	0.00	3.84
JSBL	0.00	0.48	0.55	0.08	2.03	3.84
MCB	0.00	0.00	0.00	0.00	0.00	3.84
MEBL	9.10	42.42	35.65	0.03	60.49	3.84
NBP	64.56	0.00	132.23	0.29	0.00	3.84
SBL	0.14	1.53	0.09	3.83	1.67	3.84
SILK	11.16	32.13	32.52	0.93	37.21	3.84
SNBL	0.00	39.17	0.00	16.83	0.00	3.84
SCBPL	0.01	0.86	1.51	0.89	2.94	3.84
SMBL	0.02	4.28	1.21	0.03	0.07	3.84
UBL	3.97	57.51	25.33	4.36	76.09	3.84

At the 95% confidence level, the results of Christoffersen are much better than the Kupiec test. The reason is that Kupiec test follows the frequency of the distribution and ignores the dynamics of the time. Each model fails to assess the risk of UBL stock. Christoffersen test reveals that volatility clustering is present in the EWMA, normal, student-t and HS model. That is the reason, these models does not pass the Christoffersen test except GARCH.

TABLE 4.13: Kupiec's-POF test at 97.5% confidence level.

Kupiec's-POF test						
confidence level 97.5%						
	Test static					Critical Value
	LR-cov					χ^2
	EWMA	N.DIST	HS	GARCH	student t	
ABL	0.14	0.43	2.86	77.82	0.09	5.02
AKBL	0.00	3.14	0.90	10.53	1.57	5.02
BAFL	0.05	19.99	15.56	1.54	8.09	5.02
BAHL	0.00	10.82	4.99	0.88	35.21	5.02
BOK	5.82	1.05	0.02	68.24	0.62	5.02
BOP	0.00	4.15	0.00	6.03	53.71	5.02
BIPL	1.91	0.11	0.03	38.61	8.38	5.02
FABL	13.81	0.24	0.79	99.13	2.31	5.02
HBL	3.39	3.39	0.64	49.69	2.40	5.02
HMB	8.84	16.54	3.31	96.42	10.41	5.02
JSBL	6.53	10.11	5.77	40.31	0.07	5.02
MCB	7.19	0.87	1.46	1.48	0.00	5.02
MEBL	8.10	1.13	1.13	74.33	37.72	5.02
NBP	0.98	21.56	0.05	89.25	14.92	5.02
SBL	1.06	4.40	0.56	9.51	27.71	5.02
SILK	12.61	10.93	2.38	107.61	6.74	5.02
SNBL	7.61	5.46	0.05	93.43	1.50	5.02
SCBPL	0.19	2.84	4.11	32.48	31.98	5.02
SMBL	31.17	4.31	15.22	5.14	3.30	5.02
UBL	2.85	0.63	0.52	0.05	30.46	5.02

At the 97.5% confidence level, the likelihood ratio calculated for the EWMA model is highest for SMBL stock return that is 31.17, reject the model. It means that the EWMA model is not reliable for (BOK, HMB, JSBL, MCB, MEBL, SILK, SNBL, and SMBL) risk assessment. Violation ratios are very high that clearly implying rejection.

The highest likelihood ratio calculated for the normal distribution model is 21.56 of NBP. The model is not reliable for the risk assessment of (BAFL, BAHL, HMB, JSBL, NBP, SBL, SILK, SMBL and SNBL) because their likelihood ratios are greater than the critical value of 5.02.

The POF test predicts that Historical simulation model is not reliable for the risk assessment of the (BAFL, JSBL, and SMBL) stock returns. For these results, it can be said that VaR estimation underestimates the risk.

The POF test predicts that the GARCH model is reliable for the risk assessment of (BAFL, BAHL, SBL, MCB, SMBL, and UBL) stock returns. GARCH is the model that is rejected at the 97.5% confidence level for most of the stocks. It means that it is not a reliable model for risk assessment of the Pakistani banking stocks.

The POF test predicts that student t model is not reliable for the risk assessment of the (BAFL, BAHL, BOP, BIPL, HMB, MCB, MEBL, NBP, SBL, SILK, SCBPL, and UBL) stock returns. For these results, it can be said that VaR estimation underestimates the risk.

The calculated likelihood ratios at the 97.5% confidence level, it is identified that the observed rate of failure is different from the confidence interval rate failure. For this test, Historical Simulation is the reliable model and EWMA, normal distribution, student t, GARCH is not considered the reliable model for risk assessment of banking stocks at 97.5% level. They fail the Kupiec POF test.

TABLE 4.14: Christofferson's Independence Test at 97.5% confidence level.

Christofferson's Test						
confidence level 97.5%						
	Test static					Critical Value
	LR-ind					χ^2
	EWMA	N.DIST	HS	GARCH	student t	
ABL	7.31	2.07	20.18	7.13	6.63	5.02
AKBL	0.00	56.40	50.61	58.27	24.01	5.02
BAFL	0.42	0.00	0.86	6.06	16.98	5.02
BAHL	0.00	1.54	9.26	7.45	4.69	5.02
BOK	3.85	14.63	14.59	0.00	12.59	5.02
BOP	33.15	31.90	66.06	0.93	51.67	5.02
BIPL	11.94	13.76	12.15	1.86	0.31	5.02
FABL	13.85	117.54	74.99	2.38	101.81	5.02
HBL	1.47	37.84	36.85	3.65	12.31	5.02
HMB	1.29	14.92	3.84	2.24	13.25	5.02
JSBL	0.14	0.31	0.11	2.44	0.43	5.02
MCB	7.76	72.47	41.31	2.22	0.00	5.02
MEBL	3.30	33.66	34.05	3.69	39.04	5.02
NBP	24.32	243.12	69.53	3.99	138.24	5.02
SBL	5.76	6.72	7.58	0.03	9.86	5.02
SILK	9.14	25.65	18.33	4.33	27.03	5.02
SNBL	5.16	24.71	23.50	0.00	35.90	5.02
SCBPL	0.00	1.48	1.51	2.02	2.02	5.02
SMBL	0.36	2.77	6.79	0.36	0.10	5.02
UBL	4.25	3.81	6.28	0.05	53.37	5.02

At the 97.5% confidence level, the GARCH model passes the Christoffersen test, while other model does not pass the test. It means that GARCH is the reliable model for the risk assessment of Pakistani banking stocks.

Table 4.15: Kupiec-POF test at a 99% confidence level.

Kupiec-POF test						
confidence level 99%						
	Test static					Critical Value
	LR-POF					χ^2
	EWMA	N.DIST	HS	GARCH	Student T	
ABL	28.99	25.56	14.94	20.97	2.00	6.63
AKBL	0.25	0.01	0.12	30.08	0.72	6.63
BAFL	97.35	20.73	19.21	84.04	0.15	6.63
BAHL	85.20	0.42	4.90	30.95	6.16	6.63
BOK	0.12	0.42	0.42	41.23	0.04	6.63
BOP	15.42	3.70	0.24	1.48	23.68	6.63
BIPL	0.10	6.38	2.08	20.33	1.20	6.63
FABL	0.76	4.93	0.51	0.31	0.83	6.63
HBL	0.05	2.09	0.40	8.89	2.18	6.63
HMB	0.12	0.17	0.33	23.42	2.94	6.63
JSBL	0.25	0.25	4.62	23.02	1.06	6.63
MCB	15.50	4.29	0.32	4.88	80.10	6.63
MEBL	2.13	0.97	0.23	25.08	4.89	6.63
NBP	0.29	0.23	2.27	33.36	0.29	6.63
SBL	0.71	14.25	1.39	2.70	17.44	6.63
SILK	2.89	0.01	0.05	45.99	1.60	6.63
SNBL	0.04	1.17	0.07	38.15	0.00	6.63
SCBPL	0.46	1.99	4.42	14.18	19.61	6.63
SMBL	5.83	1.93	0.83	8.83	4.95	6.63
UBL	7.82	3.07	0.21	3.07	48.85	6.63

At the 99% confidence level, the likelihood ratio calculated for the EWMA model is highest for BAFL stock return that is 97.35, reject the model. It means that the EWMA model is not reliable for (ABL, BAHL, BAFL, BOP, MCB, SMBL, and UBL) risk assessment. In this case, the GARCH model does not perform well. Violation ratios are very high that clearly implying rejection.

The highest likelihood ratio calculated for the normal distribution model is 25.56 of ABL. The model is not reliable for the risk assessment of (ABL, BAFL, BIPL, and SBL) because their likelihood ratios are greater than the critical value of 6.63. The overall performance of the Normal distribution model is reliable because it passes the Kupiec test.

The POF test predicts that Historical simulation model is not reliable for the risk assessment of the (ABL, and BAFL) stock returns. For these results, it can be said that VaR estimation underestimates the risk. Overall the performance of the Historical Simulation method is good as compared to the other four models.

The POF test predicts that the GARCH model is reliable for the risk assessment of four stocks (BOP, FABL, MCB, SBL, and UBL) stock returns. GARCH is the model that is rejected at the 99% confidence level for most of the stocks. It means that it is not a reliable model for risk assessment of the banking stocks.

The POF test predicts that student t model is not reliable for the risk assessment of the (BAHL, BOP, MCB, MEBL, SBL, SCBPL, SMBL, and UBL) stock returns. For these results, it can be said that VaR estimation underestimates the risk. The results are consistent with the Danielsson and De Vries (2000) that the GARCH model does not perform well under the normal distribution assumption.

The calculated likelihood ratios at the 99% confidence level, it is identified that the observed rate of failure is different from the confidence interval rate failure. For this test, Historical Simulation, EWMA, normal distribution, student t are the reliable models and GARCH is not considered the reliable model for risk assessment of banking stocks at 99% level.

Table 4.16: Christofferson's Independence Test at 99% confidence level.

Christofferson's Test						
confidence level 99%						
	Test static					Critical Value
	LR-IND					χ^2
	EWMA	N.DIST	HS	GARCH	Student t	
ABL	2.07	20.18	7.13	7.31	3.75	6.63
AKBL	14.83	11.44	32.61	4.43	8.25	6.63
BAFL	8.58	2.94	3.22	19.95	8.94	6.63
BAHL	10.32	0.34	3.77	10.21	1.71	6.63
BOK	5.65	0.96	19.98	0.00	5.54	6.63
BOP	22.67	20.35	59.48	2.01	33.21	6.63
BIPL	10.94	13.67	17.18	6.16	0.80	6.63
FABL	0.83	67.22	18.57	0.83	36.68	6.63
HBL	1.61	38.51	21.72	4.38	5.51	6.63
HMB	0.39	0.64	0.77	3.67	1.33	6.63
JSBL	1.70	0.00	0.00	7.43	2.18	6.63
MCB	7.18	7.09	0.77	0.04	81.79	6.63
MEBL	0.00	11.73	5.13	5.96	10.09	6.63
NBP	16.89	34.02	24.72	6.28	36.47	6.63
SBL	1.57	13.40	22.18	2.00	28.20	6.63
SILK	17.95	18.77	30.06	8.36	33.78	6.63
SNBL	6.43	13.27	11.86	0.00	0.00	6.63
SCBPL	0.00	0.72	0.00	5.39	3.57	6.63
SMBL	0.00	2.79	2.35	0.00	3.90	6.63
UBL	0.16	0.45	1.03	0.00	27.01	6.63

The table above shows the result of Christoffersen test at 1% significant level. The results show that all of the models fail the Christofferson's test for banking stock returns of AKBL, NBP, and SILK. EWMA and GARCH pass the Christofferson's test for most of the stocks as compared to the Normal, Student t and Historical

Simulation. The results compared to the Kupiec test are quite different because Kupiec test rejects the GARCH model but Christoffersen test passes the GARCH model as a reliable one.

4.4 Expected Shortfall Under the Parametric and Non-parametric Assumption

Table 4.17 shows the results of Expected Shortfall for Historical simulation method at 95%, 97.5%, and 99% confidence level.

Table 4.17: ES under the HS method.

Historical Simulation (Non-Parametric)			
	ES@95%	ES@97.5%	ES@99%
ABL	-0.0511	-0.0602	-0.0737
AKBL	-0.0605	-0.0761	-0.1110
BAFL	-0.0573	-0.0679	-0.0933
BAHL	-0.0555	-0.0795	-0.1308
BOK	-0.0785	-0.1042	-0.1542
BOP	-0.0816	-0.1086	-0.1554
BIPL	-0.0669	-0.0802	-0.0986
FABL	-0.0638	-0.0784	-0.1071
HBL	-0.0512	-0.0620	-0.0782
HMB	-0.0596	-0.0793	-0.1224
JSBL	-0.0753	-0.0935	-0.1181
MCB	-0.0608	-0.0722	-0.1002
MEBL	-0.0528	-0.0651	-0.0852
NBP	-0.0600	-0.0710	-0.1014
SBL	-0.0890	-0.1086	-0.1331
SILK	-0.0737	-0.0944	-0.1350
SNBL	-0.0636	-0.0820	-0.1202
SCBPL	-0.0578	-0.0675	-0.0852
SMBL	-0.0801	-0.0995	-0.1279
UBL	-0.0517	-0.0608	-0.0757

At 95% confidence level, Historical simulation method reports that there are 95% chances that the loss will not exceed 8.9% in SBL. It means that there is the maximum potential for loss is 8.9%. Historical simulation reports that ABL has the lowest risk of 5.11%. The potential loss for one day to the investor is lower in this stock. It means that SBL is the riskiest bank in the portfolio and ABL is the least risky bank.

At 97.5% confidence level, Historical simulation method reports the highest risk of 10.9% at SBL and BOP. It means that there are 2.5% chances that the loss will exceed 10.9%. Historical simulation reports that ABL has the lowest risk of 6%. The potential loss for one day to the investor is lower in this stock. It means that BOP is the riskiest bank in the portfolio and ABL is the least risky bank.

At 99% confidence level, the historical simulation method reports the highest risk of 15.5% at BOP. It means that there are 1% chances that the loss will exceed 15.5%. Historical simulation reports that ABL has the lowest risk of 7%. The potential loss for one day to the investor is lower in this stock. It means that BOP is the riskiest bank in the portfolio and ABL is the least risky bank.

Table 4.18 Expected shortfall under Normal and student t distribution at 95%, 97.5% and 99% significance level.

Table 4.18: Normal & Student-t ES (Parametric Estimation).

	ES 95%		**ES@97.5%**		**ES@99%**	
	NORM	**T-DIST**	**NORM**	**T-DIST**	**NORM**	**T-DIST**
ABL	-0.04327	-0.0433	-0.0491	-0.0642	-0.05591	-0.0996
AKBL	-0.05246	-0.0523	-0.0594	-0.0808	-0.06778	-0.1311
BAFL	-0.04963	-0.0457	-0.0563	0.0659	-0.06413	0.0992
BAHL	-0.04783	-0.0451	-0.0542	-0.0713	-0.0618	-0.1192
BOK	-0.09043	-0.0689	-0.1025	-0.1071	-0.11685	-0.1746
BOP	-0.07273	-0.0784	-0.0824	-0.1216	-0.09398	-0.1991
BIPL	-0.06409	-0.0725	-0.0726	-0.0469	-0.08281	-0.1777
FABL	-0.05672	-0.0568	-0.0643	-0.0843	-0.07329	-0.1310
HBL	-0.14246	-0.0477	-0.1615	-0.0748	-0.18407	-0.1231

	ES 95%		**ES@97.5%**		**ES@99%**	
	NORM	**T-DIST**	**NORM**	**T-DIST**	**NORM**	**T-DIST**
HMB	-0.05074	-0.0621	-0.0575	-0.1013	-0.06556	-0.177
JSBL	-0.07399	-0.0721	-0.0838	-0.1049	-0.09561	-0.1598
MCB	-0.05243	-0.0515	-0.0594	-0.0754	-0.06774	-0.1156
MEBL	-0.04765	-0.0471	-0.0541	-0.0697	-0.06156	-0.1083
NBP	-0.05272	-0.0523	-0.0597	-0.0808	-0.06812	-0.1311
SBL	-0.08274	-0.0881	-0.0937	-0.1328	-0.10691	-0.2104
SILK	-0.07607	-0.0817	-0.0862	-0.1291	-0.09829	-0.2174
SNBL	-0.05607	-0.0581	-0.0635	-0.0893	-0.07245	-0.1446
SCBPL	-0.05181	-0.0533	-0.0587	-0.0789	-0.06692	-0.1224
SMBL	-0.08022	-0.0832	-0.0909	-0.1238	-0.10365	-0.1940
UBL	-0.08411	-0.0427	-0.0952	-0.0420	-0.10853	-0.0946

At 95% confidence level, Normal distribution method reports that there are 95% chances that the loss will not exceed from 14.3% in HBL. It means that there is the maximum potential for loss is 14.3%. Normal distribution method reports that ABL has the lowest risk of 4.3%. The potential loss for one day to the investor is lower in this stock. It means that HBL is the riskiest bank in the portfolio and ABL is the least risky bank. At the 95% significance level, student t model reports the SBL, the riskiest bank with a maximum value of 8.8% and UBL, the least risky bank with minimum risk of 4.2%.

At 97.5% confidence level, Normal distribution method reports the highest risk of 16.14% at HBL. It means that there are 2.5% chances that the loss will exceed 16.14%. Normal distribution method reports that ABL has the lowest risk of 4.9%. The potential loss for one day to the investor is lower in this stock. It means that BOP is the riskiest bank in the portfolio and ABL is the least risky bank. Student-t model reports the SBL, the riskiest bank with a maximum value of risk of 13.3% and UBL, the least risky bank with minimum risk of 4.2% at the 97.5% confidence level.

At 99% confidence level, Normal distribution method reports the highest risk of 18.4% at HBL. It means that there are 1% chances that the loss will exceed 18.4%. Normal distribution method reports that ABL has the lowest risk of 5.6%. The potential loss for one day to the investor is lower in this stock. It means that HBL is the riskiest bank in the portfolio and ABL is the least risky bank. Student t model reports the SBL, the riskiest bank with a maximum risk of 21% and UBL, the least risky bank with minimum risk of 9.4% at the 99% significance level.

Table 4.19 expected shortfall under EWMA and GARCH model at 95%, 97.5%, and 99% significance level.

TABLE 4.19: ES under EWMA & GARCH.

EWMA & GARCH						
	ES 95%		**ES@97.5%**		**ES@99%**	
	EWMA	**GARCH**	**EWMA**	**GARCH**	**EWMA**	**GARCH**
ABL	-0.03124	-0.03973	-0.03541	-0.04503	-0.04037	-0.05134
AKBL	-0.03735	-0.04771	-0.04233	-0.05407	-0.04826	-0.06164
BAFL	-0.03192	-0.03948	-0.03618	-0.04475	-0.04124	-0.05102
BAHL	-0.03808	-0.07521	-0.04315	-0.08524	-0.0492	-0.09718
BOK	-0.07204	-0.08091	-0.08165	-0.09171	-0.09309	-0.10454
BOP	-0.03812	-0.04952	-0.04321	-0.05613	-0.04926	-0.06399
BIPL	-0.04139	-0.06845	-0.04691	-0.07758	-0.05347	-0.08844
FABL	-0.08118	-0.10526	-0.09201	-0.11931	-0.10491	-0.13611
HBL	-0.03529	-0.07769	-0.04213	-0.08805	-0.04561	-0.10038
HMB	-0.04381	-0.04613	-0.04965	-0.05228	-0.05661	-0.05961
JSBL	-0.04111	-0.04865	-0.04534	-0.05513	-0.05169	-0.06286
MCB	-0.03374	-0.04292	-0.03824	-0.04865	-0.04361	-0.05546
MEBL	-0.03191	-0.03871	-0.03617	-0.04386	-0.04123	-0.05321
NBP	-0.02998	-0.05281	-0.03398	-0.05984	-0.03873	-0.06822
SBL	-0.12087	-0.10391	-0.13699	-0.11776	-0.15617	-0.13426
SILK	-0.03178	-0.04555	-0.03602	-0.04328	-0.04106	-0.05885
SNBL	-0.03726	-0.05779	-0.04223	-0.06551	-0.04814	-0.07467
SCBPL	-0.03911	-0.04784	-0.04432	-0.05421	-0.05053	-0.06181
SMBL	-0.04059	-0.05572	-0.04601	-0.06315	-0.05245	-0.07212
UBL	-0.03709	-0.04213	-0.04203	-0.05144	-0.04792	0.06111

At 95% confidence level, EWMA method reports that there are 95% chances that the loss will not exceed from 8.1% in FABL. It means that there is the maximum potential for loss is 8.1%. EWMA method reports that NBP has the lowest risk of 2.9%. The potential loss for one day to the investor is lower in this stock. It means that FABL is the riskiest bank in the portfolio and NBP is the least risky bank. At the 95% significance level, GARCH model reports the FABL, the riskiest bank with a maximum risk of 10.5% and MEBL, the least risky bank with minimum risk of 3.8%.

At 97.5% confidence level, EWMA method reports the highest risk of 9.2% in FABL. It means that there are 2.5% chances that the loss will exceed 9.2%. EWMA method reports that NBP has the lowest risk of 3.39%. The potential loss for one day to the investor is lower in this stock. It means that FABL is the riskiest bank in the portfolio and NBP is the least risky bank. GARCH model reports the FABL, the riskiest bank with a maximum value of risk of 11.9% and MEBL, the least risky bank with minimum risk of 4.38% at the 97.5% confidence level.

At 99% confidence level, EWMA method reports the highest risk of 10.4% at FABL. It means that there are 1% chances that the loss will exceed 10.4%. EWMA method reports that NBP has the lowest risk of 3.87%. The potential loss for one day to the investor is lower in this stock. It means that FABL is the riskiest bank in the portfolio and NBP is the least risky bank. GARCH model reports the FABL, the riskiest bank with a maximum risk of 13.6% and MEBL, the least risky bank with minimum risk of 5.3% at the 99% significance level.

Summary

VaR is the famous tool of risk measurement proposed by the regulatory authorities but from the last few years, risk professionals are thinking to replace the VaR with ES due to the drawbacks of VaR models. Such as, the issue of subadditivity, lack of coherent risk measure and is not sensible for the tail risk assessment. Conversely, ES is a coherent risk measure and captures the tail loss distribution. It has been estimated in that one out of five models underestimate the risk in banks, the overestimation of risk is a problem. Backtesting is a technique that helps the financial institutions to reject the model that over/underestimate the risk. The results of Christoffersen test reveals that GARCH is the best model and Kupiec test reveals that Historical simulation model performs better than the other model. The model that performs worst is the normal distribution model.

4.5 Extreme Value Theory

The use of Extreme Value approach is used to compute the VaR at tail distributions. In this, the confidence level of 95%, 97.5%, and 99% was used. The Extreme value theory is getting popularity due to its focus on the empirical tail distribution data for prediction of extreme events. In this study, the POT and BMM methods are used to model the tail risk behavior associated with the occurrence of the extreme events in the Pakistani banking stocks. The VaR modeling using the POT and BMM method is considered as a static model due to the assumption of stationarity in the raw data.

4.5.1 Generalized Pareto Distribution Parameters and VaR Estimation

The table 4.20 provides the results of GPD parameters and standard error estimates of the left tail of the return distributions. The test is conducted on three different quantiles $q = (0.95, 0.975, \text{ and } 0.99)$. The estimation of parameters is done by the Maximum Likelihood estimation method. The estimates for the shape and scale parameters are shown in the table with the standard error of shape and scale parameters. The shape parameter ε is greater than zero indicating heavy-tailed data. The threshold is chosen to be 95% of the empirical distribution.

Table 4.20 Parametric estimation of POT with Threshold μ, Number of exceedances, Negative log likelihood estimates, Maximum Likelihood Estimates of shape and scale with Standard error.

Table 4.20: GPD Parametric estimation under MLE.

Parametric Estimation Of POT Shape and Scale parameters							
	Quantile 95%						
	threshold	**nexc**	**Nllh**	**MLE**		**S. E**	
	μ			**Shape** ε	**Scale** β	**Shape** ε	**Scale** β
ABL	0.0336	156	-478	0.0156	0.0991	0.0016	0.0623
AKBL	0.0376	244	-706	0.0149	0.3139	0.0013	0.0654
BAFL	0.0397	170	-533	0.0125	0.2426	0.0012	0.0682
BAHL	0.0268	244	-680	0.0124	0.6002	0.0013	0.0969
BOK	0.0476	149	-404	0.0158	0.4367	0.0022	0.1174
BOP	0.051	244	-647	0.0123	0.9577	0.0021	0.2055
BIPL	0.0476	148	-437	0.0189	0.0118	0.0023	0.0894
FABL	0.0438	244	-725	0.0141	0.2986	0.0013	0.0757
HBL	0.0312	131	-384	0.0175	0.1117	0.0019	0.0686
HMB	0.033	244	-677	0.0156	0.3867	0.0015	0.0741
JSBL	0.0511	137	-376	0.0212	0.1657	0.0026	0.1004
MCB	0.0445	244	-778	0.0104	0.3793	0.001	0.0821
MEBL	0.035	198	-607	0.0143	0.1805	0.0014	0.0699
NBP	0.0417	200	-633	0.0111	0.3399	0.0011	0.0671
SBL	0.0611	173	-447	0.0284	-0.0231	0.0032	0.0819
SILK	0.048	204	-571	0.0145	0.4336	0.0017	0.0966
SNBL	0.0385	244	-61	0.0161	0.3435	0.0015	0.0733
SCBPL	0.0444	136	-455	0.0101	0.2474	0.0014	0.1113
SMBL	0.0545	125	-335	0.0209	0.1884	0.0031	0.1148
UBL	0.0362	154	-500	0.0118	0.1963	0.0012	0.0627

The R project, *ismev* package is used to run the results in the project R. At the threshold level of 0.05, the shape parameter estimated by the Maximum Likelihood Estimates is the fatter tail in JSBL, SBL and SMBL stock and remaining stocks have a thin tail. The maximum number of exceedances diagnosis in the stocks of (AKBL, BAHL, BOP, FABL, HMB, MCB, and SNBL) is 244. The positive shape parameter is an indication that the empirical distribution (left and/ or right) has a fatter tail than that of the normal distribution, which can lead to the occurrence of extreme losses.

Table 4.21 Maximum Likelihood estimates of shape and scale parameters with a standard error at 97.5% confidence level.

At the 97.5% confidence level, the shape parameters of MLE are in the range of 0.01-0.02 with lower standard error estimates. The scale parameter is related to the volatility and maximum volatility predicted by the model is 0.96 for BOP.

TABLE 4.21: MLE at 97.5% confidence level.

Parametric Estimation Of POT shape and scale parameters							
	Quantile 97.5%						
	threshold	**Nexce**	**Nllh**	**MLE**		**S.E**	
	μ			**Shape** ε	**Scale** β	**Shape** ε	**Scale** β
ABL	0.0509	78	-452	0.0003	1.3443	0.0000	0.2138
AKBL	0.0510	122	-414	0.0013	2.2769	0.0000	0.2841
BAFL	0.0510	85	-366	0.0004	2.4102	0.0000	0.3349
BAHL	0.0390	122	-307	0.0126	0.8573	0.0021	0.1605
BOK	0.0612	75	-182	0.0217	0.4050	0.0038	0.1392
BOP	0.0646	122	-265	0.0310	0.2985	0.0046	0.1195
BIPL	0.0604	74	-217	0.0194	0.0065	0.0035	0.1419
FABL	0.0513	130	-351	0.0160	0.4004	0.0025	0.1354
HBL	0.0499	66	-290	0.0017	0.9567	0.0000	0.1860
HMB	0.0485	122	-373	0.0053	1.1753	0.0009	0.1821
JSBL	0.0652	69	-179	0.0252	0.0926	0.0040	0.1058
MCB	0.0512	122	-483	0.0001	4.3645	0.0000	0.4563
MEBL	0.0471	99	-311	0.0103	0.4275	0.0016	0.1320
NBP	0.0512	100	-575	0.0001	2.6264	0.0000	0.3253
SBL	0.0815	87	-228	0.0275	-0.0275	0.0044	0.1179
SILK	0.0595	102	-256	0.0181	0.5009	0.0031	0.1510
SNBL	0.0510	122	-332	0.0109	0.8002	0.0021	0.1843
SCBPL	0.0510	68	-213	0.0121	0.2848	0.0030	0.2261
SMBL	0.0698	63	-160	0.0251	0.1469	0.0053	0.1696
UBL	0.0490	77	-331	0.0025	0.6842	0.0003	0.1392

Table 4.22 shows the Maximum Likelihood estimates of shape and scale parameters with a standard error at 99% confidence level is given below.

At the 99% confidence level, the shape parameters of MLE are in the range of 0.01-0.04 with lower standard error estimates. The scale parameter is related to the volatility and maximum volatility is in the stock of NBP that is 6.31.

TABLE 4.22: MLE at 99% confidence level.

Parametric Estimation Of POT shape and scale parameters							
	Quantile 99%						
	Threshold	**Nexc**	**Nllh**	**MLE**		**S.E**	
	μ			**Shape** ε	**Scale** β	**Shape** ε	**Scale** β
ABL	0.0512	32	-183	0.0000	3.3854	0.0000	0.7141
AKBL	0.0596	49	-106	0.0178	0.8642	0.0052	0.2859
BAFL	0.0547	34	-83	0.0184	0.5628	0.0053	0.2549
BAHL	0.0511	49	-79	0.0215	1.2263	0.0175	0.8253
BOK	0.0843	30	-63	0.0256	0.5600	0.0074	0.2474
BOP	0.0955	49	-91	0.0468	0.2127	0.0114	0.1995
BIPL	0.0775	30	-87	0.0237	-0.1519	0.0077	0.2712
FABL	0.0684	49	-111	0.0359	0.0580	0.0097	0.2406
HBL	0.0513	27	-146	0.0000	4.2644	0.0000	0.9449
HMB	0.0541	49	-87	0.0364	0.5353	0.0104	0.2610
JSBL	0.0885	28	-73	0.0196	0.3221	0.0060	0.2519
MCB	0.0692	49	-176	0.0278	0.0000	0.0001	0.0002
MEBL	0.0587	40	-112	0.0112	0.6875	0.0035	0.2937
NBP	0.0513	40	-140	0.0000	6.3167	0.0000	1.1060
SBL	0.1031	35	-89	0.0351	-0.1970	0.0091	0.2014
SILK	0.0804	41	-83	0.0318	0.4163	0.0081	0.2103
SNBL	0.0660	49	-99	0.0270	0.5841	0.0075	0.2546
SCBPL	0.0616	28	-81	0.0391	-0.6585	0.0000	0.0398
SMBL	0.0958	26	-64	0.0229	0.2885	0.0103	0.4101
UBL	0.0513	31	-197	0.0000	3.2125	0.0000	0.6899

4.5.2 Generalized Extreme Value (BMM) Parameters and VaR Estimation

The parameters of the extreme distribution are based on the assumption that the extreme observations follow the extreme values distribution. For the parametric estimation of GEV distribution, Maximum likelihood estimation method is used to measure the three parameters like shape ε, scale σ, and location μ parameters.

In the block maxima method, return distribution is divided into small blocks of m = 30 day length and calculate the maximum likelihood of ε, σ, μ with standard error estimates. The theoretical number of exceedances of a VaR 95%, 97.5%, and 99% are given in the table.

Table 4.23 Maximum Likelihood estimates of shape, scale and location parameters with a standard error at 95% confidence level.

Location μ represents the average of the extremes; scale σ represents the deviation and shape ε called the tail index. In this case, all the stocks have a positive shape parameter instead of SBL stock means that it has a thin tail while remaining stocks have fatter tails. The location parameter μ is very small for each of the stock.

Table 4.23: MLE under BMM method.

Maximum likelihood estimate of Block Maxima							
		MLE			**S.E**		
	Nllh	**location μ**	**scale σ**	**shape ε**	**location μ**	**scale σ**	**shape ε**
ABL	-270.381	0.0294	0.0130	0.2766	0.0014	0.0011	0.0691
AKBL	-348.887	0.0328	0.0203	0.3063	0.0017	0.0014	0.0542
BAFL	-259.079	0.0339	0.0199	0.1387	0.0020	0.0014	0.0456
BAHL	-338.54	0.0284	0.0196	0.4487	0.0016	0.0015	0.0567
BOK	-207.437	0.0471	0.0218	0.3112	0.0025	0.0020	0.0798
BOP	-302.121	0.0468	0.0279	0.2521	0.0024	0.0019	0.0552
BIPL	-232.575	0.0446	0.0192	0.0450	0.0022	0.0016	0.0742
FABL	-351.435	0.0407	0.0214	0.1844	0.0018	0.0014	0.0498
HBL	-191.617	0.0271	0.0238	0.0159	0.0027	0.0018	0.0380
HMB	-352.431	0.0326	0.0181	0.4700	0.0016	0.0015	0.0741
JSBL	-194.358	0.0497	0.0248	0.0369	0.0028	0.0019	0.0486

		MLE			S.E		
	Nllh	**location** μ	**scale** σ	**shape** ε	**location** μ	**scale** σ	**shape** ε
MCB	-367.558	0.0370	0.0203	0.1100	0.0018	0.0013	0.0585
MEBL	-331.742	0.0358	0.0153	0.1597	0.0014	0.0010	0.0442
NBP	-290.54	0.0321	0.0196	0.2850	0.0019	0.0015	0.0579
SBL	-231.428	0.0652	0.0295	-0.1015	0.0030	0.0020	0.0469
SILK	-261.508	0.0439	0.0277	0.1617	0.0026	0.0019	0.0475
SNBL	-331.999	0.0396	0.0231	0.2618	0.0020	0.0016	0.0511
SCBPL	-224.956	0.0405	0.0186	-0.0998	0.0021	0.0014	0.0567
SMBL	-178.696	0.0517	0.0214	0.2406	0.0027	0.0022	0.1026
UBL	-261.299	0.0315	0.0141	0.2653	0.0016	0.0012	0.0774

For the EVT analysis, Various *R* packages are used like fExtremes, evir, and ismev. The VaR modeling using the POT and BMM method is static, due to the assumption of stationarity in the data.

TABLE 4.24: Value at Risk under GPD and GEV assumptions.

VaR of Banking stock computed by using the Extreme Value Method						
		GPD			**GEV**	
	VaR=95%	**VaR=97.5%**	**VaR=99%**	**VaR=95%**	**VaR=97.5%**	**VaR=99%**
ABL	0.0000	0.0039	0.0040	-0.0121	-0.0115	-0.0110
AKBL	0.0000	0.0042	0.0042	-0.0218	-0.0207	-0.0196
BAFL	0.0000	0.0050	0.0050	-0.0903	-0.0883	-0.0861
BAHL	0.0000	0.0018	0.0018	-0.0082	-0.0076	-0.0070
BOK	0.0001	0.0059	0.0060	-0.0149	-0.0142	-0.0134
BOP	0.0049	0.1500	0.2471	-0.0450	-0.0432	-0.0413
BIPL	-0.0094	-0.0038	-0.0023	-0.3588	-0.3562	-0.3534
FABL	0.0000	0.0262	0.0263	-0.0585	-0.0568	-0.0549
HBL	0.0001	0.0106	0.0109	-1.4334	-1.4298	-1.4257
HMB	0.0000	0.0014	0.0015	-0.0031	-0.0028	-0.0026
JSBL	0.0000	0.0009	0.0009	-0.5908	-0.5874	-0.5835
MCB	0.0000	0.0072	0.0072	-0.1266	-0.1244	-0.1220
MEBL	0.0000	0.0003	0.0003	-0.0480	-0.0468	-0.0454
NBP	0.0000	0.0118	0.0119	-0.0247	-0.0236	-0.0225
SBL	0.0001	-0.0002	-0.0003	0.4098	0.4166	0.4242
SILK	0.0060	0.2060	0.3115	-0.1019	-0.0993	-0.0965
SNBL	0.0029	0.1469	0.1771	-0.0338	-0.0324	-0.0309
SCBPL	0.0008	0.0233	0.0260	0.2605	0.2647	0.2695
SMBL	-0.0139	-0.0971	-0.0519	-0.0268	-0.0258	-0.0247
UBL	-0.0002	-0.0110	-0.0109	-0.0150	-0.0143	-0.0137

At the 95% confidence level, the VaR under the POT Method is much lower than the BMM method. POT method reports the highest risk of 1.3% in SMBL. It means that there are 5% chances that the loss will exceed 1.3%. Most of the stocks have a minimum risk of 0% diagnosed by the POT Method. While in the BMM method, maximum risk is 143% in the HBL stock while the minimum risk measured by the model is in the HMB stock is 0.3%.

At the 97.5% confidence level, The POT model considers the SILK as the riskiest bank at 20.6% and least risky bank diagnosed by the model is SBL at 0.02%. The maximum risk diagnosed by the BMM model is 20.6% of SILK and minimum risk calculated by the model is 4% of BAHL. At the 99% confidence level, the maximum risk diagnosis by the model is 142% of HBL and minimum risk calculated by the model is 0.28% in HMB.

At the 99% confidence level, The POT model considers the SILK as the riskiest bank at 31% and least risky bank diagnosed by the model is SBL at 0.03%. The maximum risk diagnosis by the BMM model is 20.6% of SILK and minimum risk calculated by the model is 4% of BAHL. At the 99% confidence level, the maximum risk diagnosed by the model is 142% of HBL and minimum risk calculated by the model is 0.26% in HMB.

While evaluating these results, the BMM method diagnoses the maximum risk of 143% at the HBL stock, that is the reason, the BMM method is considered as the weaker method than the POT. POT method is considered an efficient method of VaR calculation in case of limiting data (Gilli, 2006). The other reason is that the POT method uses the data that exceeds from the threshold level, while the BMM method uses the maximum from the block length from distribution estimation.

Table 4.25: Violation ratio of POT method.

Backtesting of Pareto Distribution			
	VR=95%	**VR=97.5%**	**VR=99%**
ABL	1.00289296	1.002893	1.0286082
AKBL	1.00184767	1.001848	1.0059536
BAFL	1.00206307	1.002063	1.0020631

	VR=95%	VR=97.5%	VR=99%
BAHL	1.00205339	1.002053	1.0061602
BOK	1.00777815	1.014542	1.0145418
BOP	1.64088769	1.640888	1.6476126
BIPL	0.60680607	0.606806	0.6150062
FABL	1.00164204	1.067323	1.0057471
HBL	1.00344696	1.011107	1.0340866
HMB	1.00123102	1.001231	1.0053344
JSBL	1.00219459	1.00951	1.0241405
MCB	1.00164204	1.001642	1.0057471
MEBL	1.00075815	1.000758	1.0108668
NBP	1.00452034	1.00452	1.0045203
SBL	1.00406268	1.009867	1.0156703
SILK	1.50497971	1.50498	1.5123571
SNBL	1.20108294	1.201083	1.2060054
SCBPL	1.08496211	1.084962	1.1168728
SMBL	0.51324163	0.517348	0.5337713
UBL	0.98402556	0.984026	0.9904153

The violation ratio of Pareto distribution model at 95%, 97.5%, and 99% level indicate that BOP and SILK stock returns are underestimated by the model. So, the GPD model is not reliable for the BOP, and SILK at all confidence levels. Overall, the performance of the POT method is good as compared to the parametric and non-parametric models.

Table 4.26 Violation Ratio of BMM at the 95%, 97.5% and 99% confidence levels.

Table 4.26: Violation ratio of BMM method.

Backtesting of Block Maxima			
	VR-95%	VR-97.5%	VR-99%
ABL	3.99	8.27	21.63
AKBL	2.11	4.47	12.30
BAFL	0.02	0.04	0.09
BAHL	4.59	9.54	25.05
BOK	5.02	10.34	26.95
BOP	1.26	2.64	7.18
BIPL	0.00	0.00	0.00
FABL	0.31	0.69	1.83
HBL	0.00	0.00	0.00
HMB	7.25	14.66	37.51
JSBL	8.51	17.21	43.78
MCB	0.01	0.03	0.07
MEBL	0.50	1.04	2.78
NBP	1.82	3.90	10.29
SBL	0.00	0.00	0.00
SILK	0.11	0.21	0.53
SNBL	1.19	2.61	7.30
SCBPL	0.00	0.00	0.00
SMBL	3.99	8.27	21.63
UBL	2.11	4.47	12.30

BMM method is considered as a weak method because the violation ratio at three confidence level is higher than the 1. Most of the violations occur and method underestimates the most of the stocks. The other reason is that Block Maxima only models the largest observations in the data. So, it is not a reliable method for risk assessment of Pakistani banking stocks under extreme tail behavior.

4.6 VaR Under Dynamic EVT

McNeil and Frey (2000) considered the dynamic EVT into account for the calculation of Volatility of returns. In this study, the approach of McNeil and Frey (2000) is used to calculate the Volatility by using the GARCH (1,1) to capture the current market fluctuations and market risk. GARCH model forecast the current market volatility and provide dynamic one day ahead forecast of VaR for financial time series data.

It is not necessary that data is always normal, there is some movement found in the data by Various scholars Kratz, Lok, and McNeil (2018). To estimate this model, fExtreme and fGarch packages were used to estimate the model at 5%, 2.5%, and 1% confidence level. In the table below, the VaR results show that it adjusts itself with changing volatility.

Table 4.27 VaR under Dynamic POT method at 95%, 97.5% and 99% confidence level.

Table 4.27: VAR under EVT GARCH(1,1).

	VaR=95%	**VaR=97.5%**	**VaR=99%**
ABL	-0.0008	-0.0007	-0.0006
AKBL	0.0008	0.0009	0.0010
BAFL	0.0002	0.0003	0.0004
BAHL	0.0001	0.0003	0.0004
BOK	0.0016	0.0018	0.0021
BOP	0.0005	0.0006	0.0011
BIPL	0.0010	0.0012	0.0014
FABL	0.0009	0.0010	0.0011
HBL	0.0004	0.0005	0.0006
HMB	0.0008	0.0009	0.0011
JSBL	0.0016	0.0019	0.0024
MCB	0.0001	0.0002	0.0005
MEBL	0.0006	0.0007	0.0008
NBP	0.0007	0.0008	0.0011

	VaR=95%	**VaR=97.5%**	**VaR=99%**
SBL	0.0020	0.0026	0.0037
SILK	0.0006	0.0010	0.0016
SNBL	0.0002	0.0004	0.0011
SCBPL	0.0006	0.0007	0.0010
SMBL	0.0015	0.0018	0.0024
UBL	0.0002	0.0003	0.0004

The results of Dynamic GPD are quite interesting as compared to the static VaR results. The model has a diagnosis of the minimum risk in all of the stocks as compared to the other models.

Table 4.28: Violation Ratio of EVT GARCH(1,1).

	Dynamic POT		
	VR=95%	VR=97.5%	VR=99%
ABL	10.70	21.68	54.87
AKBL	4.25	22.76	59.26
BAFL	11.37	22.98	58.37
BAHL	10.42	21.40	55.80
BOK	12.02	24.45	63.19
BOP	11.52	23.52	60.92
BIPL	12.12	24.67	62.69
FABL	11.05	22.40	57.01
HBL	10.17	20.05	51.55
HMB	11.48	23.41	59.85
JSBL	11.37	23.47	60.12
MCB	10.83	21.96	55.87
MEBL	11.28	22.72	57.94
NBP	11.57	23.60	59.70
SBL	12.44	25.24	64.41
SILK	12.10	24.47	62.58
SNBL	11.35	23.09	59.36

	VR=95%	VR=97.5%	VR=99%
SCBPL	11.62	23.42	59.25
SMBL	11.73	23.72	60.17
UBL	10.68	21.58	54.68

As the confidence level increased, the number of violations increased. At the 99% confidence level, more violations occurred as compared to the 95% and 97.5% level. In this case, the violation ratio is greater than 1, that POT model under-forecast the risk. The results of the violation ratio clearly indicate that the model is weak and not reliable.

Table 4.29 Dynamic POT volatility at 95%, 97.5% and 99% confidence level.

Table 4.29: Volatility ratio of EVT GARCH (1,1).

	Dynamic GPD Volatility		
	VOL=95%	VOL=97.5%	VOL=99%
ABL	0.001	0.001	0.001
AKBL	0.016	0.002	0.025
BAFL	0.001	0.001	0.001
BAHL	0.002	0.002	0.002
BOK	0.001	0.002	0.004
BOP	0.002	0.002	0.003
BIPL	0.001	0.001	0.001
FABL	0.001	0.002	0.002
HBL	0.001	0.001	0.017
HMB	0.002	0.002	0.002
JSBL	0.001	0.001	0.001
MCB	0.002	0.002	0.002
MEBL	0.001	0.001	0.001
NBP	0.001	0.001	0.002
SBL	0.001	0.001	0.002
SILK	0.002	0.002	0.003
SNBL	0.001	0.001	0.002
SCBPL	0.001	0.001	0.001

The model with lower volatility will be preferred. In this case, the volatility is lower of each stock at three confidence levels except the volatility of HBL is higher at 99% confidence level.

4.7 Backtesting Static GPD

Table 4.30 Static Generalized Pareto Distribution Backtesting by using the Kupiec and Christoffersen test.

TABLE 4.30: Backtesting static GPD model.

	Kupiec Test			**Christoffersen test**		
P-Value	**.05**	**.025**	**.01**	**.05**	**.025**	**.01**
Chi-square	**(3.84)**	**(5.02)**	**(6.63)**	**(3.84)**	**(5.02)**	**(6.63)**
ABL	0	0	0	0	0	0
AKBL	0	0	0	0	0	0
BAFL	0	0	0	0	0	0
BAHL	0	0	0	0	0	0
BOK	0	0	0	0	0	0
BOP	0	47.8	20.5	0	7.06	10.8
BIPL	0	0	0	0	0	0
FABL	0	0	0	0	0	0
HBL	0	20.8	102.6	0	0	0
HMB	0	0	0	0	0	0
JSBL	0	0	0	0	0	0
MCB	0	0	0	0	0	0
MEBL	0	0	0	0	0	0
NBP	0	0	0	0	0	0
SBL	0	0	0	0	0	0
SILK	0	124.4	50.6	0	8.9	12.4
SNBL	0	130.2	0	0	5.17	0
SCBPL	0	0	0	0	2.20	1.27
SMBL	0	0	0	0	0	0
UBL	0	0	0	0	0	0

The violation ratios of BOP, HBL, SILK, SNBL, and SCBPL are quite high as compared to the other stocks. The ratios forecasted by the Kupiec test are very high as compared to the Christoffersen test. Christoffersen provides the better forecast than the Kupiec test. Both tests accept the hypothesis at 95% confidence level but reject some stocks at 97.5% confidence level.

Static POT fails the Kupiec test for BOP, HBL, and SILK at the 97.5% and 99% confidence level while fails the SNBL stock at the 97.5%. While the Christoffersen test fails the BOP, SILK, SCBPL at the 97.5% and 99% confidence level while the SNBL stock at the 97.5% level. The unusual behavior of the model also confirms the weak model. The result is consistent with the study of (Vee & Gonpot, 2014).

4.8 Backtesting Static BMM

Table 4.31 Static BMM Backtesting by using the Kupiec and Christoffersen test.

TABLE 4.31: Backtesting static BMM.

	Kupiec Test			**Christoffersen test**		
P-Value	**.05**	**.025**	**.01**	**.05**	**.025**	**.01**
Chi-square	**(3.84)**	**(5.02)**	**(6.63)**	**(3.84)**	**(5.02)**	**(6.63)**
ABL	0.11	0.17	0.00	0.00	0.00	0.00
AKBL	0.00	0.00	0.00	0.00	0.00	0.00
BAFL	210.10	91.43	25.75	0.00	7.57	7.57
BAHL	0.00	0.00	0.00	0.00	0.00	0.00
BOK	0.00	0.00	0.00	0.00	0.00	0.00
BOP	0.00	0.00	0.00	0.00	0.00	0.00
BIPL	0.00	0.00	0.00	0.00	0.00	0.00
FABL	122.1	9.1	24.3	85.3	85.63	94.04
HBL	0.00	0.00	0.00	0.00	0.00	0.00
HMB	0.00	0.00	0.00	0.00	0.00	0.00
JSBL	0.00	0.00	0.00	0.00	0.00	0.00
MCB	328.44	153.85	53.27	0.00	0.00	0.00

	Kupiec Test			Christoffersen test		
P-Value	**.05**	**.025**	**.01**	**.05**	**.025**	**.01**
Chi-square	**(3.84)**	**(5.02)**	**(6.63)**	**(3.84)**	**(5.02)**	**(6.63)**
MEBL	25.93	2.04	76.78	56.30	54.06	56.99
NBP	0.00	0.00	0.00	0.00	0.00	0.00
SBL	0.00	0.00	0.00	0.00	0.00	0.00
SILK	194.25	65.03	6.38	15.80	3.42	3.42
SNBL	0.00	0.00	0.00	0.00	0.00	0.00
SCBPL	0.00	0.00	0.00	0.00	0.00	0.00
SMBL	0.00	0.00	0.00	0.00	0.00	0.00
UBL	0.00	0.00	0.00	0.00	0.00	0.00

The Backtesting results of static BMM method are different from the static GPD results. The violation ratio is very high as compared to the GPD. Kupiec test is significant at 95%, 97.5% and 99% level for all stocks except (BAFL, FABL, MCB, MEBL, and SILK). Christoffersen test also rejects the BMM model for FABL at 97.5% and 99% level. The model is not reliable for BAFL, FABL, MEBL, and SILK. The results are applied by the results of the convergence test.

4.9 Backtesting Dynamic GPD

The Backtesting results of Dynamic GPD indicate that Kupiec and Christoffersen tests at 95%, 97.5%, and 99% confidence level pass the test. It means that dynamic GPD is not best model of risk assessment for the Pakistani banking stock in the volatile market.

Table 4.32 Dynamic Generalized Pareto Distribution Backtesting by using the Kupiec and Christoffersen test.

Table 4.32: Backtesting dynamic GPD method.

	Kupiec Test			**Christoffersen test**		
P-Value	**.05**	**.025**	**.01**	**.05**	**.025**	**.01**
Chi-square	**(3.84)**	**(5.02)**	**(6.63)**	**(3.84)**	**(5.02)**	**(6.63)**
ABL	0	0	0	0	0	0
AKBL	0	0	0	0	0	0
BAFL	0	0	0	0	0	0
BAHL	0	0	0	0	0	0
BOK	0	0	0	0	0	0
BOP	0	0	0	0	0	0
BIPL	0	0	0	0	0	0
FABL	0	0	0	0	0	0
HBL	0	0	0	0	0	0
HMB	0	0	0	0	0	0
JSBL	0	0	0	0	0	0
MCB	0	0	0	0	0	0
MEBL	0	0	0	0	0	0
NBP	0	0	0	0	0	0
SBL	0	0	0	0	0	0
SILK	0	0	0	0	0	0
SNBL	0	0	0	0	0	0
SCBPL	0	0	0	0	0	0
SMBL	0	0	0	0	0	0
UBL	0	0	0	0	0	0

This section develops a static and dynamic extreme value approach to financial risk measurement. The new methods based on EVT (GPD, BMM) provide a robust and accurate forecast of daily VaR The sample performance results show that the statistical theory of extreme and implied tail estimation produce more accurate results of VaR as compared to the traditional assumption of VaR calculations. The results are in line with the previous outcome and provide that dynamic model should not be used.

Chapter 5

Conclusion and Recommendations

5.1 Conclusion

The objective of the study was to perform the statistical risk assessment of Pakistani banking stocks under extreme value theory 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 parametric (Historical simulation model) and non-parametric (EWMA, Normal, Student t and GARCH) models. The validation of the models is done by the Backtesting technique by using the Kupiec and Christoffersen test. Kupiec POF test reveals that Historical simulation performs better than the other models at 95%, 97.5%, and 99% confidence level. Christoffersen independent test results are quite different from the Kupiec test. At the 95% confidence level, all of the models pass the Christoffersen test, while, at 97.5% and 99%, GARCH model passes the test and considered as the reliable method of risk forecasting.

In the second part, the Expected shortfall has been analyzed by using the parametric (Historical simulation model) and non- parametric (EWMA, Normal, Student t and GARCH) models. Most of the professionals argued that the non-elicitable function of the Expected shortfall is non-testable. That is the reason, different

Backtesting techniques used by a number of scholars but not yet found to be appropriate. That is the reason, Banking Regulation does not rely on the ES results, but the comparison of VaR and ES is used by the banks.

The third section contains the analysis of extreme value theory namely, the Generalized extreme value also known as Block Maxima method and Generalized Pareto distribution, also known as Peak over Threshold Method of tail estimation. In this, the maximum likelihood approach is used to estimate the parameters of the POT and BMM. The Backtesting result suggests that POT is better than the BMM method and out of POT method, Dynamic POT method provides the weak results that are confirmed by the Backtesting.

5.2 Recommendations

Based on the findings and analysis, it is recommended that Historical Simulation is still the better method of risk estimation as compared to the Normal, student t, methods for risk assessment. While considering the volatility models from EWMA and GARCH, GARCH is recommended as the best model for risk estimation. This study used the static and Dynamic Extreme Value theory under the POT and BMM method. It is recommended that dynamic EVT is not a reliable method of tail estimation of extreme events. While comparing the results of Static and Dynamic EVT, Static is considered a better model for risk assessment of extreme events. Historical simulation is a popular method for VAR calculation in the banking industry and it is confirmed by this study that Historical simulation is best in modeling Value at risk.

5.3 Future Research

The Backtesting of the Expected shortfall is questionable but the Emmer, Kratz, and Tasche (2015), and Acerbi and Szekely (2014) perform the Backtesting of Expected shortfall and methods do not exploit the property of elicitability. It is a future direction for the scholars to perform the Backtesting of the Expected shortfall and enrich the literature. It will help to compare the VaR and ES models and to recommend the best model for the Pakistani banking stocks. Secondly, Monte Carlo simulation, Variance, and covariance methods for VaR and the Expected shortfall can be used to assess the risk. Thirdly, the other sample of the data like the index returns of Pakistan stock exchange in comparison with other stock markets of the world can be used.

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