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Portfolio Construction by Using Different Risk Models: A Comparison among Diverse Economic Scenarios

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Abstract: We aim to construct portfolios by employing different risk models and compare their performance in order to understand their appropriateness for effective portfolio management for investors. Mean variance (MV), semi variance (SV), mean absolute deviation (MaD) and conditional value at risk (CVaR) are considered as risk measures. The price data were extracted from the Pakistan stock exchange, Bombay stock exchange and Dhaka stock exchange under diverse economic conditions such as crisis, recovery and growth. We take the average of GDP of the selected period of each country as a cut-off point to make three economic scenarios. We use 40 stocks from the Pakistan stock exchange, 92 stocks from the Bombay stock exchange and 30 stocks from the Dhaka stock exchange. We compute optimal weights using global minimum variance portfolio (GMVP) for all stocks to construct optimal portfolios and analyze the data by using MV, SV, MaD and CVaR models for each subperiod. We find that CVaR (95%) gives better results in each scenario for all three countries and performance of portfolios is inconsistent in different scenarios.

Keywords: mean variance; semi variance; mean absolute deviations; conditional value at risk; stock market; portfolio construction

1. Introduction

Portfolio construction is considered to be one of the main concerns in securities investment as the future returns are uncertain. Portfolio selection is an ex-ant decision procedure. Despite the fact that risk is inevitable in every aspect of life, undertaking strategies to minimize risk has become an essential part of life. In finance, the risk is the possibility of deviation identified with the inconstancy of future returns (Artzner et al. 1999). The role of proper risk management of a portfolio of financial assets or securities has been recognized in the literature. Thus, the concerns relate back to the era of Markowitz's (1959) portfolio selection model which is the foundational framework of portfolio selection with optimal risk-return trade-off. In the last decade, the development of trading activities has provided new methods of underscoring the necessity for market participants to manage the risk.

Markowitz (1952) establishes a quantitative paradigm, leading to the first ever mean risk models to incorporate different classes of assets into a portfolio. He further suggests historical variance as

a measure of risk. Moreover, Markowitz utilizes this in a more computational model by measuring portfolio risk by the covariance framework identified with the individual asset returns. On occasion, variance is criticized as a measure of risk, most commonly for its deliberate nature and for the irregularity with aphoristic models for decision (semi variance, mean absolute deviation and stochastic predominance). This motivates the development of alternative risk measures, and Markowitz's mean variance (MV) model worked as the premise for numerous other models which utilize its essential assumptions (Bodie et al. 2011; Elton et al. 2007).

Efficient risk measurement strategies punish attractive (upside) deviations from the mean same way as they punish undesirable (drawback) deviations. Owing to this criticism, Markowitz (1959) proposes the semi variance as a risk estimation method. The semi variance gives a measure of the variance of the returns that remains below the normal return. As such, rational investors seem more responsive towards downside deviations in relation to upside deviations. Hence, SV is a preferred risk indicator (Chow and Denning 1994; Grootveld and Hallerbach 1999; Markowitz et al. 1993). Konno and Yamazaki (1991) recommend the mean absolute deviation (MaD) model as another risk evaluation measure. Unlike, the mean variance (MV) model, which is a quadratic model, the MaD model is a linear programming model that generally can handle portfolios of fewer assets, and it gives more efficient results than the MV model (Liu and Gao 2006). The conditional value at risk (CVaR) model (also identifies as a mean excess loss, tail VAR) was proposed by Rockafellar and Uryasev (2000). It can be described as the conditional loss estimation over that sum α at a predefined likelihood level β (Lim et al. 2011). This technique fulfills all premises of coherent risk.

The approaches adopted by portfolio managers for optimizing portfolios can be classified into two broad groups. First, managers opted for an active strategy attempt to outperform the market by generating portfolios that are designed in a more unique manner than the index. The goal is to achieve a higher return whilst assuming lower or same risk as that of market, or to assume lower risk of the higher or same returns as that of the market. However, index tracking is a passive management strategy. Tracking an index of the stock market involves generating a portfolio that simulates the index's performance. The portfolio generated is referred to as a tracking portfolio, and the tracked index is sometimes referred to as a benchmark (García et al. 2018). However, passive managers tacitly presume that it is not possible to outperform the risk–return combo of the market. The solution to the issue is therefore distinct from that applied by Markowitz's MV model, where the construction of the portfolio is determined by an optimization model method. However, managers using passive strategies tend to lower the level of adjustments to their portfolios and perform tasks only to redesign them in order to comply with the index's composition. Portfolios created using the MV model or index tracking vary considerably. The global portfolio risk is mitigated in the mean variance model, while only the unsystematic risk portion is mitigated in the index tracking method.

A well-developed stock market ensures a strong economy. Stock markets are volatile in nature and highly affected by the cost of borrowing. As the cost of borrowing rises, businesses become unstable and incapable of investing funds further, which in turn has a direct impact on their profit margins. The decline in the level of profit also causes decline in stock prices, making it difficult for investors to find attractive investments in a risky stock market environment. The stock market comes as a medium to facilitate the investors and borrowers by providing a platform to exchange and mobilize funds to different economic sectors (Jaaman et al. 2013). This study examines the performance of the above-mentioned portfolios covering the stock markets of three fast-growing emerging markets of South Asia i.e., Pakistan, India and Bangladesh.

Byrne and Lee (2004) carried out research to affirm the validity of different risk measures in portfolio construction and made a comparison of parameters. They propose that all risk measures perform in a diversified manner and have their own merits and demerits. So, the model selection depends not on the model's theoretical merits over the other but on the attitude of individual towards risk. This may be the reason for not using alternative risk measures frequently. The mean variance that is used in portfolio optimization models may be due to the difficulty in deciding the appropriate

risk measure and continuous comparison of different risks measures until a common risk measure is brought into action. To outsource this, comparing the portfolio holdings generated by diverse risk measures, instead of the risk return trade-off, is utilized. The results show that the portfolio structures generated by diverse risk measures vary from one another. They propose that choosing a model depends highly on the risk attitude rather than the merits of the model. Having multiple risk modeling alternatives in portfolio optimization, causes various concerns to arise about their legitimacy, utilization and applicability. Specifically, a question arises regarding the barriers of the alternative models with respect to the basic presumption of [Markowitz and Todd's \(1987\)](#) classical model. Comparatively an analysis is made among the classic Markowitz's model and other models that employ [Markowitz and Todd's \(1987\)](#) classic model formulation. There are plenty of unresolved questions related to the selection of different risk models by different investors for risk and return estimation. Do each of these models perform equally well in each different economic scenario? If one model yields better in growth days, does it yield the same results in declining days?

Stock market crises cause investors to be unable to recover their original investments in the stock market, real estate business, and gold and currency market. Government and private sector investment schemes dictate their own behaviors. Moreover, inconsistent policies and strict regulations add fuel to fire. Later on, in money-related crisis, investors have taken a couple of fundamental measures in order to achieve maximum possible return. These measures have driven theorists to give cautious to managing the risk. With these necessities it has become a need of every investor to assess the performance of portfolios under different risk models in different economic scenarios. South Asian emerging markets are an important region to study. For instance, [Hunjra et al. \(2020\)](#) studied profitability of momentum and contrarian tactics incorporating sample of South Asian countries. Given the economic and financial growth in the region over the last two decades ([South Asian Financial Market Review 2010](#)), it is an important topic for research. It is of great significance for investors in emerging South Asian countries (Pakistan, Bangladesh and India) to make suitable investment decisions on the performance of portfolios. In this study, analysis of efficient portfolios is conducted by utilizing four different risk measures; the mean variance (MV), semi variance (SV), mean absolute deviation (MaD) and conditional value at risk (CVaR), under three different scenarios of the economy (crisis, recovery, growth). Further comparison of results is performed to understand their relative performance as effective portfolio management technique.

To the best of our knowledge, this study is the first in the context of emerging South Asian countries which compares the portfolio performance constructed by using various risk measures under three different economic scenarios (crises, recovery and growth). The contribution of the paper is two-fold. (i) The outcome of the current study helps to identify if the same risk assessment is applicable in all three substituents or a different risk measure is required for a different sub period. (ii) It provides insights on asset choice, management and the use of an optimal risk model to estimate expected risk and return. The implications of our findings may be beneficial for the investors, investment decision makers and policy makers not only in Pakistan, Bangladesh and India but also those in other emerging economies.

The remainder of the paper is organized as follows. Section 2 offers past studies findings and hypotheses development; Section 3 presents the data, variables and methodology used for the empirical analysis. Section 4 shows the empirical results. Section 5 provides recommendations and concludes the paper.

2. Literature Review

Portfolio optimization is a key idea in valuation theories. [Markowitz \(1952\)](#) started additional work for building up a scientific way to deal with multi asset portfolios. [Markowitz's \(1952\)](#) classical model utilizes the relationship of mean and variance of the returns. [Markowitz's \(1952\)](#) expected variance of returns (EV) rule inferred an adequate diversification which relies upon the quantity and diversification of securities crosswise over assets with a specific end goal to reduce variance. Generally,

firms in a similar industry, as a rule, demonstrate high covariance among themselves as they respond like economic occasions which prompt to a higher risk presentation. Thus, an investor prefers a MV effective portfolio when a given risk level gives the maximum expected return (Campbell et al. 1997). With a specific end goal to decrease or to eradicate the unsystematic risk, the equity allocation must demonstrate an optimal allocation of uncorrelated stocks.

Artzner et al. (1999) introduce the idea of a coherence asset of desired properties for risk measures associated with the tail of distribution. CVaR is the coherent risk indicator, also called expected shortfall by few authors (Konno et al. 2002; Rockafellar and Uryasev 2000). Despite the amount of studies on risk measures and average risk models, there is still controversy as to which risk measure is the most suitable one. In addition, it continued to challenge the theoretical validity of the mean risk models. Regardless of the number of studies on risk indicators, the topic of which risk measure performs well is still questionable. The Markowitz efficient frontiers (Markowitz 1952) explain how investors select their portfolios maximizing return for a specified amount of risk as measured by the return's variance. A key understanding of this work is that assets should not be chosen exclusively in light of only their exceptional attributes of return and variance. Market specialists need to consider the connection of the portfolio having the same return with lower risk than a portfolio that overlooked these connections (Elton et al. 1997).

Since the early work by Markowitz (1952), optimization models aimed at managing the exchange between risk and return in finance have been studied extensively. According to Filippi et al. (2020), shortfall and quantile risk measures are receiving increasing attention where CVaR is probably the most common of such indicators. Ogryczak and Sliwinski's (2010) study on CVaR finds that the classical Markowitz's model utilizes the variance as the risk measures by providing solution to quadratic optimization issue. Some other studies presented a few option risks measures which are computationally alluring (for discrete random factors) for better understanding of straight programming (SP) issues (Konno and Yamazaki 1991; Rockafellar and Uryasev 2000). The SP reasonability is essential for applications to genuine financial choices where well-developed portfolios need to meet various limitations and consider exchange costs. A range of SP-utilizable risk measures have been introduced in the portfolio construction, albeit the vast majority of them are identified with the outright Lorenz bend and accordingly, the CVaR measures. Ogryczak and Sliwinski (2010) demonstrate that all risk measures are utilized as a part of the SP feasible portfolio improvement models can be taken from the setback criteria. Gluzicka (2010) conducts a research on CVaR and Gini's Mean Difference (GMD) models. GMD is analyzed for different measures of risk such as: variance, semi variance, VaR or CVaR. Different measures of risk are centered on different properties of distribution of returns. For example, the variance measures the deviation of return and the VaR or CVaR measures the possible loss. Gluzicka (2010) studies risk models with two measures (mean and variance) applied for different risk portfolios. He finds that the CVaR and SV models provide better estimates than MV model. When making comparisons of outcomes from all models it can be mentioned that the models with two measures of risk most often provide better outcomes than the models with only one risk measure (Gluzicka 2010).

Vidovic (2011) conducts a study by characterizing various risk indicators in portfolio composition on seven European stock markets. He identifies that extreme kurtosis and skewness exist in stock returns. Consequently, portfolios employed stocks with high kurtosis and stocks with depreciative skewness. Banihashemi and Navidi (2017) employee CVaR as a risk measure using various confidence level. They compare two measures of risk such as VaR and CVaR to identify the best one for portfolio optimization. They reveal that CVaR is more accurate than VaR. Further, they indicate that high confidence levels are more accurate than low levels. Jaaman et al. (2013) conducted a study and compared the portfolio construction and performance based on different risk measures using Malaysian Stock returns data in three diverse economic criterions. The study shows multiple optimal portfolios' construction and performances for the three subperiods. However, among the risk models studied, CVaR model gave the peak portfolio skewness and is the most optimal portfolio optimization model.

Based on the above discussion, it can be said that CVaR model significantly impacts the portfolio performance and this performance is consistent in all scenarios. We can hypothesize it as:

Hypothesis 1 (H1). *Conditional value at risk (CVAR) is significantly related to portfolio performance.*

Hypothesis 2 (H2). *Performance of conditional value at risk (CVAR) is consistent in each economic scenario.*

It is evident from the literature that portfolios have different risk criteria so they cannot be easily compared. The reason behind this is that portfolios have different construction, so their performance is also different from one another. This fact has also been proved by [Moazeni et al. \(2014\)](#). All portfolios have different risk criteria, construction and also performance. [Soleimani and Govindan \(2014\)](#) identify that supply chain risk shows better presentations with mean-CVaR models. [Baghdadabad \(2015\)](#) conducts a study to assess the risk accustomed performance of global mutual assets utilizing the risk measurement created by the mean absolute deviation (MaD).

[Henriques and Neves \(2019\)](#) present portfolio optimization framework that considers investment decision under various assumptions of risk. Their findings reflect the risk and return trade-off. In addition, they argue that investors who are less sensitive to risk find the formulation based on mean absolute deviation (MaD) more attractive as it generally offers lower returns variance. According to the study of [Baghdadabad \(2015\)](#), MaD is one of the important determinants to evaluate the portfolio performance. Moreover, portfolio managers can use the results anywhere in the global stock market. Based on their findings, we hypothesize as follows:

Hypothesis 3 (H3). *Mean absolute deviation (MaD) is significantly related to portfolio performance.*

Hypothesis 4 (H4). *Performance of mean absolute deviation (MaD) is consistent in each economic scenario.*

As discussed in the literature, different risk measures have different structures, so their performance also differs from each other. In order to test the performance of different risk measures with the objective of increasing the returns while limiting risk, [Gökgöz and Atmaca \(2017\)](#) examine the different risk measures including mean-variance and semi variance for development in power sectors. According to them, these two models could be associated with all sectors to make efficient points of confinement, diversified portfolios and utility limits. They find that different optimal portfolios offer different return levels to investors with different risk avoidance levels. Recent studies have seen a growing use of the portfolio optimization approach centered on risk/diversification. Mean-diversification efficient frontiers are taken for different diversification measures and portfolios are identified that optimize the risk and return trade-off ([Oyenubi 2020](#)). [Oyenubi \(2020\)](#) further claims that these portfolios are better options than the portfolio that is designed to be optimal for mean variance, as they are sensitive to returns. Various measures support the returns while limiting the related market risks. We develop the following hypotheses for our study.

Hypothesis 5 (H5). *Mean variance (MV) is significantly related to portfolio performance.*

Hypothesis 6 (H6). *Semi variance (SV) is significantly related to portfolio performance.*

Hypothesis 7 (H7). *Performance of mean variance (MV) is consistent in each economic scenario.*

Hypothesis 8 (H8). *Performance of semi variance (SV) is consistent in each economic scenario.*

3. Methodology

Our sample included 40 stocks from Pakistan stock exchange, 92 Stocks from Bombay stock exchange and 30 stocks from Dhaka stock exchange. Summary statistics of all stocks of Pakistan, Bombay and Dhaka stock exchange is given in Tables A1–A3. Based on the availability of complete data, the sample period of our study was from 2003 to 2015. Further, the study period was also of particular significance as it covers before, during and after the financial crisis 2008–09. The global financial tsunami of 2008 has been recognized as one of the century's greatest catastrophes. It has posed many challenges to world social and economic development. However, studies revealed mixed outcomes in terms of impact of GFC on South Asian stock markets (Long et al. 2012; Rastogi 2014). Thus, we are also interested in knowing how the emerging South Asian stock markets performs before, during and after the crisis. The data were comprised of monthly closing prices for every security from January 2003 to the end of December 2015. Only those stocks that were indexed before 2003 and whose complete data were accessible were included. Stocks were extracted from the national stock index which incorporates top performing stocks. Then, we computed a natural logarithm of monthly returns for every stock an individual considered. We employed the global minimum variance portfolio (GMVP) method for optimal portfolio composition (Engle and Kelly 2012). We computed the global minimum variance portfolio weights by computing covariance matrix of return series. We calculated optimal weights for all our stocks under each scenario for Pakistan stock exchange, Dhaka stock exchange and Bombay stock exchange. We analyzed the data by using MV, SV, MaD and CVaR models for each subperiod.

We collected data of the annual GDP from the World Development Indicator (WDI) of selected countries from 2003 to 2015. Annual GDP was converted into monthly GDP by using Eviews. Conversion of annual data is widely accepted and has been applied in large number of studies such as Tang and Chua (2012) and Shahbaz et al. (2014). Following Jaaman et al. (2013), for each country, average of GDP for the selected period was calculated and taken as the cut-off point to make three scenarios; crisis, recovery and growth. The crisis, recovery and growth periods were different for different countries as GDP varied significantly, depending on a variety of factors such as the scale of the economy, the degree of trade openness and the potential for countercyclical policies (Keat 2009). For Pakistan, data from 2003 to 2005 were used as crisis, 2006 to 2011 as recovery and 2012 to 2015 as growth period. For Bangladesh, data from 2006 to 2009 were used as decline, 2010 to 2013 as recovery and 2014 to 2015 as growth period. For India, data from 2004 to 2007 were used as decline, 2008 to 2011 as recovery and 2012 to 2015 as growth period. Each risk measure was applied on a selected country under three different economic scenarios (crises, recovery and growth). As the studies completed in various time periods probably offer various compositions of optimal portfolios (Prakash et al. 2003). The result for each case is presented below in next section.

The models used for estimation are as follows:

The MV model calculates the variation below and above the mean. It not only penalizes the downward deviations but upstream deviations too (Markowitz 1952).

$$V = \sum_{i=1}^n \sum_{j=1}^n \sigma_{ij} x_i x_j \quad (1)$$

where σ_{ij} is the covariance between assets i and j , x_j is the amount invested in asset j .

Markowitz (1959) proposes semi variance (SV) which centers only on the deviations below the mean. This model penalizes only the downstream deviations not the upward deviations. The semi variance model is presented as:

$$SV = \frac{1}{T} \sum_{i=1}^T (\max[0, E(R) - R_{pt}])^2, \quad (2)$$

where t is used as the number of periods, R_{pt} is the portfolio return at period t , $E(R_{pt})$ is the mean return.

The mean absolute deviation (MaD) model is proposed by Konno and Yamazaki (1991). In this model absolute deviation is used as risk measure to replace variance.

$$y_t + \sum_{j=1}^n (r_{jt} - r_j)x_j \geq 0, \quad t = 1, \dots, T \quad (3)$$

$$y_t - \sum_{j=1}^n (jt - r_j)x_j \geq 0, \quad t = 1, \dots, T \quad (4)$$

where y_t is the continuous variable that represents the deviations among the mean return of the portfolio as well as return of portfolio at time t , T is the number of period, r_{jt} is the realization of random variable r_j during period t , r_j is the expected return of asset j per period, ρ is a parameter indicating the minimal rate of return required by an investor and x_j is the amount invested in asset j .

The conditional value at risk (CVaR) model is presented by Rockafellar and Uryasev (2000) and is also called the mean excess loss, mean shortfall or tail VaR. The CVaR is defined as the conditional expectation of loss beyond that amount α at a given probability level β (Lim et al. 2011).

$$\text{CVaR} = \alpha + \frac{1}{T(1-\beta)} \sum_{t=1}^T z_t, \quad (5)$$

where α is the minimal amount of loss, β is the probability that the loss will not surpass α , T is the number of period, z_t is the variable, r_{jt} is the realization of random variable R_j during period t , x_j is the amount invested in asset j and r_j is the expected return of asset j . In this study, we followed this framework with the selected risk confidence levels $\beta = 0.99$ and $\beta = 0.95$. Investors seldom experience a loss exceeding VaR(X) when β is 0.99 as compared with 0.95. CVaR (0.99) means investors have higher downstream risk aversion than CVaR (0.95).

4. Results

Tables 1–9 report optimal portfolio compositions for Pakistan (Tables 1–3), Bangladesh (Tables 4–6) and India (Tables 7–9) under economic status of crisis, recovery and growth.

Table 1. Optimal portfolio compositions for economic crisis period (2003–2005).

	MV	SV	MaD	CVaR95%	CVaR99%
DG KCCL	0.2313	0.1546	0.0965	0.2661	−0.0135
DHCL	0.3527	0.3586	0.1799	0.4029	0.0887
NISHAT PCL	0.2993	0.2370	0.1512	0.2953	0.0492
MARI PCL	0.0886	0.0148	0.0060	0.1841	−6.3591
NESTLE	0.1210	0.0745	0.0101	0.2085	−4.6033
MCB	0.3641	0.3679	0.2217	0.4060	0.0989

Note: Pakistan stock exchange, MV = mean variance, SV = semi variance, MaD = mean absolute deviation, CVaR95% = conditional value at risk with risk confidence levels $\beta = 0.95$ and CVaR99% = conditional value at risk with risk confidence levels $\beta = 0.99$.

Table 2. Optimal portfolio compositions for economic recovery period (2006–2011).

	MV	SV	MaD	CVaR95%	CVaR99%
SHELL	0.0738	0.0302	0.1446	0.0639	0.0483
DHCL	0.0206	−0.0301	0.0859	0.0141	−0.0683
PPL	0.2049	0.0514	0.2095	0.2527	0.1381
FFCL	0.0302	0.0050	0.1043	0.0243	0.0063
KOT ADDU PCL	0.0349	0.0056	0.1136	0.0269	0.0078

Note: Pakistan stock exchange, MV = mean variance, SV = semi variance, MaD = mean absolute deviation, CVaR95% = conditional value at risk with risk confidence levels $\beta = 0.95$ and CVaR99% = conditional value at risk with risk confidence levels $\beta = 0.99$.

Table 3. Optimal portfolio compositions for economic growth period (2012–2015).

	MV	SV	MaD	CVaR95%	CVaR99%
DHCL	0.0141	0.0059	0.0740	0.2021	−0.4015
NESTLE	0.0042	0.0019	0.0447	0.0767	−0.8124
MBL	0.0032	0.0007	0.0362	−0.1710	−2.8366
NFL	0.0182	0.0063	0.0783	0.2239	−0.3625
STD CHARTER	0.0258	0.0091	0.1086	0.2960	−0.2859
NISHAT PCL	0.0067	0.0036	0.0541	0.1351	−0.4979
LCL	0.0044	0.0021	0.0466	0.1077	−0.7360
ABL	0.0037	0.0012	0.0433	0.0613	−0.8711
APL	0.0145	0.0060	0.0759	0.2164	−0.3715
FFBQL	0.0061	0.0026	0.0509	0.1286	−0.5753
OGDCL	0.0822	0.0668	0.1221	0.6752	0.1201
FFCL	0.0065	0.0029	0.0530	0.1350	−0.5269
KOT ADDU PCL	0.0070	0.0037	0.0585	0.1361	−0.4847

Note: Pakistan stock exchange, MV = mean variance, SV = semi variance, MaD = mean absolute deviation, CVaR95% = conditional value at risk with risk confidence levels $\beta = 0.95$ and CVaR99% = conditional value at risk with risk confidence levels $\beta = 0.99$.

Table 4. Optimal portfolio compositions for economic crisis period (2006–2009).

	MV	SV	MaD	CVaR95%	CVaR99%
Square Limited	0.3961	0.1123	0.2115	0.0159	0.0413
RAK Ceramics Ltd.	0.0447	0.0173	0.2180	−0.3741	−0.9856
Grameenphone.	0.0002	0.0304	0.1973	0.0037	0.0109
Titas and Dist. Co., Ltd.	0.4565	0.1795	0.2192	0.0325	0.0603
Meghna Ltd.	0.2701	0.0708	0.2045	0.0082	0.0284
Heidelberg Cement Ltd.	0.0211	0.0088	0.2108	−0.2329	−0.6032
IDLC Finance Limited	0.1514	0.0402	0.1975	0.0050	0.0148

Note: Dhaka stock exchange, MV = mean variance, SV = semi variance, MaD = mean absolute deviation, CVaR95% = conditional value at risk with risk confidence levels $\beta = 0.95$ and CVaR99% = conditional value at risk with risk confidence levels $\beta = 0.99$.

Table 5. Optimal portfolio compositions for economic recovery period (2010–2013).

	MV	SV	MaD	CVaR95%	99%
BDCOM	0.0144	0.0033	0.8399	0.1650	−0.5225
BA Tobacco	0.0108	0.0034	0.8315	−0.1430	−0.3846
Lafarge Cement Ltd.	0.0151	0.0040	0.8471	0.1870	−0.5138
NBL	0.0122	0.0046	0.8319	0.1669	−0.4614
Titans and Dist. Co., Ltd.	0.0314	0.0067	0.8323	−0.2143	−0.5662
IDLC Finance Limited	0.0232	0.0107	0.8537	−0.2473	−0.6281
ACI Limited	0.0231	0.0108	0.8428	−0.3010	−0.8151
Pharmaceuticals Ltd.	0.0454	0.0154	0.8638	0.1926	−0.5335
Islamic Bank Bed Ltd.	0.0118	0.0067	0.8279	0.1816	−0.4809
Meghna Ltd.	0.0074	0.0031	0.8546	−0.1456	−0.4405
Padma Co.	0.0095	0.0047	0.8351	0.1835	−0.4706
BA Tobacco Bang	0.0092	0.0041	0.8373	−0.1803	−0.6226
BRAC Bank Ltd.	0.0122	0.0043	0.8359	0.1612	−0.4084
Grameenphone.	0.0077	0.0056	0.8567	−0.1993	−0.6386
Heidelberg Cement Ltd.	0.0083	0.0049	0.8540	−0.2079	−0.5615
Square Limited	0.0171	0.0104	0.8258	−0.3007	−0.8510
BATL	0.0075	0.0035	0.8545	0.1537	−0.4132
Delta Insurance	0.0079	0.0044	0.8465	−0.1800	−0.4963

Note: Dhaka stock exchange, MV = mean variance, SV = semi variance, MaD = mean absolute deviation, CVaR95% = conditional value at risk with risk confidence levels $\beta = 0.95$ and CVaR99% = conditional value at risk with risk confidence levels $\beta = 0.99$.

Table 6. Optimal portfolio compositions for economic growth period (2014–2015).

	MV	SV	MaD	CVaR95%	CVaR99%
Aftab Automobiles	0.0612	0.0053	0.4048	0.2520	0.0450
Padma Co.	0.0513	0.0026	0.3920	0.2042	0.0463
Olympic Ltd.	0.0532	0.0030	0.3946	0.2328	0.0460
Jamuna Oil Com. Ltd.	0.0982	0.4532	0.4565	0.4114	−6.0997
RAK Ceramics Ltd.	0.0441	0.0023	0.3891	0.1948	0.0493
Delta Insurance	0.0912	0.0208	0.4089	0.3201	0.0261
BSRM Steels	0.0920	0.0678	0.4144	0.3409	0.0174
Pubali Bank	0.1793	0.4921	0.4506	2.1221	0.0498
Heidelberg Cement Ltd.	0.0734	0.0150	0.4069	0.3129	0.0314
Summit Power Ltd.	0.0244	0.0018	0.3823	−0.1868	−0.0727
Titans and Dist. Co., Ltd.	0.0223	0.0017	0.3798	−0.1816	−0.0951
NBL	0.0545	0.0031	0.3969	0.2365	0.0459
Beximco Pharma	0.0131	0.0012	0.3763	−0.0898	−0.1242
BDCOM	0.0081	0.0026	0.4068	−0.2547	−0.6520
Pharmaceuticals Ltd.	0.0272	0.0020	0.3841	0.1934	0.0385
Lafarge Cement Ltd.	0.0599	0.0041	0.4039	0.2399	0.0452
Meghna Ltd.	0.0572	0.0039	0.3971	0.2378	0.0455
Square Limited	0.0062	0.0150	0.4044	−0.3673	−1.4223
BRAC Bank Ltd.	0.0823	0.0167	0.4077	0.3145	0.0282
Grameenphone.	0.0962	0.3485	0.4321	0.3950	−0.6841
BDFINANCE	0.0044	0.0027	0.3969	−0.2408	−0.7403
IDLC Finance Ltd.	0.0632	0.0059	0.4062	0.2737	0.0421
UCBL	0.0176	0.0015	0.3774	−0.1651	−0.1191
BATL	0.0323	0.0015	0.3797	−0.1934	−0.5952

Note: Dhaka stock exchange, MV = mean variance, SV = semi variance, MaD = mean absolute deviation, CVaR95% = conditional value at risk with risk confidence levels $\beta = 0.95$ and CVaR99% = conditional value at risk with risk confidence levels $\beta = 0.99$.

Table 7. Optimal portfolio compositions for economic crisis period (2004–2007).

	MV	SV	MaD	CVaR95%	CVaR99%
NTPC Ltd.	0.2324	0.2098	0.2453	0.331	0.0223
Bosch Ltd.	0.0722	0.0217	0.1438	0.0422	0.0004
Maruti Suzuki India Ltd.	0.2251	0.1872	0.2355	0.3235	0.0094
Eicher Motors Ltd.	0.1006	0.0456	0.1558	0.1121	0.0005
ONGC Ltd.	0.2422	0.2164	0.2526	0.3323	0.0332
Dabur India Ltd.	0.0919	0.0410	0.1547	0.0534	0.0005
Mahindra & Mahindra Ltd.	0.2224	0.1844	0.2329	0.3234	0.0087
Canara Bank	0.0752	0.0230	0.1476	0.0432	0.0004
ABB India Ltd.	0.1037	0.1752	0.1728	−1.1277	−2.9871
Asian Paints Ltd.	0.1440	0.3302	0.1438	−1.1062	−5.0733
Godrej Consumer Ltd.	0.1225	0.0681	0.1655	0.1222	0.0007
Exide Industries Ltd.	0.1037	0.0539	0.1571	0.1122	0.0005
Sun Pharmaceutical Ltd.	0.1340	0.1306	0.1490	−1.0832	−2.9161
Bharat Heavy Electricals Ltd.	0.0678	0.0203	0.1386	0.0344	0.0003
Infosys Ltd.	0.1674	0.1360	0.2108	0.2423	0.0035
HDFC Ltd.	0.1332	0.0811	0.1728	0.1323	0.0007
GMR Infrastructure Ltd.	0.1120	0.0611	0.1617	0.1213	0.0006
Colgate-Palmolive Ltd.	0.0845	0.0253	0.1490	0.0443	0.0004
Hero MotoCorp Ltd.	0.1340	0.0857	0.1767	0.2121	0.0007
ITC Ltd.	0.3007	0.5054	0.2540	−1.9406	−4.9598
Punjab National Bank	0.2685	0.2420	0.2540	0.3333	0.0343
Lupin Ltd.	0.2123	0.1752	0.2259	0.3232	0.0076
Titan Company Ltd.	0.4523	0.4644	0.3579	0.5232	0.0080
HDFC Bank Ltd.	0.1340	0.0823	0.1759	0.1324	0.0907
ACC Ltd.	0.1662	0.0062	0.1271	−0.2256	−0.7054
Bharti Airtel Ltd.	0.0707	0.0213	0.1417	0.0422	0.0004

Note: Bombay stock exchange, MV = mean variance, SV = semi variance, MaD = mean absolute deviation, CVaR95% = conditional value at risk with risk confidence levels $\beta = 0.95$ and CVaR99% = conditional value at risk with risk confidence levels $\beta = 0.99$.

Table 8. Optimal portfolio compositions for economic recovery (2008–2011).

	MV	SV	MaD	CVaR95%	CVaR99%
NMDC Ltd.	0.0316	0.0218	0.1147	0.4523	0.0087
Infosys Ltd.	0.0248	0.0162	0.1095	0.3453	0.0035
Sun Pharmaceutical Ltd.	0.0637	0.1203	0.1421	0.5345	0.0563
Lupin Ltd.	0.0281	0.0202	0.1133	0.4342	0.0065
Bharat Electricals Ltd.	0.0111	0.0051	0.0777	0.0452	0.0003
Titan Company Ltd.	0.1247	0.2642	0.1722	0.5634	0.0908
Tata Global Beverages Ltd.	0.2044	0.4486	0.1964	0.6453	0.1323
Cipla Ltd.	0.0138	0.0066	0.0851	0.1233	0.0004
Dabur India Ltd.	0.0155	0.0075	0.0908	0.2234	0.0005
Nestle India Ltd.	0.0331	0.0228	0.1162	0.4534	0.0097
Tata Consultancy Ltd.	0.0175	0.0172	0.0850	−0.3327	−1.2194
Godrej Consumer Ltd.	0.0177	0.0098	0.0968	0.2352	0.0007
Bharti Airtel Ltd.	0.0132	0.0058	0.0810	0.0535	0.0043
Hindustan Unilever Ltd.	0.0054	0.0023	0.0578	−0.1173	−0.2943
Colgate-Palmolive Ltd.	0.0042	0.0018	0.0459	−0.1147	−0.3271

Note: Bombay stock exchange, MV = mean variance, SV = semi variance, MaD = mean absolute deviation, CVaR95% = conditional value at risk with risk confidence levels $\beta = 0.95$ and CVaR99% = conditional value at risk with risk confidence levels $\beta = 0.99$.

Table 9. Optimal portfolio compositions for economic growth period (2012–2015).

	MV	SV	MaD	CVaR95%	CVaR99%
State Bank of India	0.0185	0.2063	0.1685	0.6403	0.2232
Infosys Ltd.	0.0148	0.0334	0.1204	0.5345	0.0563
Dabur India Ltd.	0.0069	0.0049	0.0636	0.2342	0.0007
NTPC Ltd.	0.0196	0.0016	0.0482	0.0245	0.0002
Nestle India Ltd.	0.0202	0.0033	0.0587	0.1344	0.0005
Axis Bank Ltd.	0.1143	0.1853	0.1789	−1.1342	−3.3683
Asian Paints Ltd.	0.1165	0.3855	0.1884	−1.1382	−4.7054
HCL Technologies Ltd.	0.0041	0.0014	0.0500	−0.0953	−0.2664
Dr. Reddy's Lab. Ltd.	0.0039	0.0023	0.0482	−0.1292	−0.3482
United Breweries Ltd.	0.0942	0.0061	0.0681	0.3233	0.0009
Hindustan Unilever Ltd.	0.0105	0.0044	0.0605	0.2324	0.0006
Glenmark Pharma Ltd.	0.0071	0.0051	0.0581	−0.1811	−0.6612
Jindal Steel Ltd.	0.0153	0.0049	0.0633	0.2332	0.0006
Idea Cellular Ltd.	0.0025	0.0012	0.0386	0.0095	0.0067
Wipro Ltd.	0.0057	0.0031	0.0536	−0.1655	−0.4858
Divi's Laboratories Ltd.	0.0701	0.0025	0.0509	0.0453	0.0043
Tata Consultancy Ltd.	0.0311	0.0014	0.0432	0.0232	0.0002
ITC Ltd.	0.0134	0.0012	0.0386	0.0132	0.0005
Cairn India Ltd.	0.0056	0.0013	0.0534	−0.1050	−0.3090

Note: Bombay stock exchange, MV = mean variance, SV = semi variance, MaD = mean absolute deviation, CVaR95% = conditional value at risk with risk confidence levels $\beta = 0.95$ and CVaR99% = conditional value at risk with risk confidence levels $\beta = 0.99$.

Markowitz (1952) describes that finding the right mix of stocks (risky assets) in terms of expected return and variance of return, that is, an optimal portfolio in terms of yield and risk, is the greatest challenge for an investor. A simple principle for the optimal stock composition is that the highest returning portfolio is not automatically the lowest risk (variance) portfolio. We use four risk measures in every scenario and their results are quite different from each other. These models are utilized to develop ideal portfolio from 40 accessible firms listed on the Pakistani stock exchange.

Choosing a model depends highly on the risk attitude of an investor. However, rather than being risk averse or a risk taker, he/she may choose an optimal portfolio with low risk and high returns. Table 1, presenting optimal portfolio composition for economic crises, explains that MCB make up the maximum percentage in optimal portfolios respectively for all four measures. Furthermore, it explains that MCB invested the most where investors invest 36.41% of funds in MCB if he/she chooses to employ the MV model, 36.79% funds are invested for SV model, 22.17% if MaD model is used, 40.60% of funds are used for employing CVaR (95%) and 9.89% of funds are invested when using CVaR (99%) model.

According to Pakistan's annual GDP recovery rate, this scenario is built where four risk models yields distinctive optimal portfolios for economic period of recovery. It is found that when investors are willing to take more risk, either the expected return of a portfolio increases, or a risk averse investor is able to decrease the variance in trade for a lower expected return. From Table 2 it is assumed that during economic recovery, PPL makes up the highest proportion of optimal portfolio. If an investor opts for an MV model, he/she invests up to 20.49% in aforesaid security. He/she invests 5.14% of funds when using an SV model, 20.95% for MaD, 25.27% for CVaR (95%) and 13.81% of investment for the CVaR (99%) model.

It is implied that ample diversification is based on the quantity of shares, and volatility is minimized by diversification across sectors and industries. Companies in the same sector typically display high covariance between themselves in general as they respond similarly to economic events that lead to greater risk exposure. Consequently, when a prescribed level of risk earns the maximum possible expected return, an investor carries an MV-efficient portfolio (Campbell et al. 1997). A financial specialist can decrease the risk of his investment by diversifying it over various stocks. From Table 3, it is examined that during the economic growth period, OGDCL invested the most where it is deduced

that an investor puts 8.22% of funds in OGDCL if he/she chooses to opt for the MV model, 6.68% if SV model is employed, 12.21% for MaD model, 67.52% if CVaR (95%) model is chosen and 12.01% for CVaR (99%). It can also be examined that CVaR (99%) provides negative returns for all securities except OGDCL during this period.

If we summarize the results for the Pakistan stock exchange during the periods of crises, recovery and growth, it can be said that MCB made the highest proportion in optimal portfolio in the crisis period and in the case of recovery and growth, the highest proportion lies with PPL and OGDCL, respectively. The results are similar for all types of risk measures. It shows that these securities are able to attract more investment in any scenario.

Literature states that portfolio theory affects the management of money and other assets worldwide. From Table 4, it is concluded that during economic crises in Dhaka Stock Exchange, Titas and Dist. Co., Ltd. remains the riskiest security in the optimal portfolio for all risk measures. It makes up the highest proportion in optimal portfolio. Investors invest 45.65% of funds in Titas and Dist. Co., Ltd. if they opt for the MV model, 17.95% investments when using the SV model, 21.92% for employing the MaD Model, 3.25% funds are invested in the case of CVaR (95%) and 6.03% funds are invested if investors choose the CVaR (99%) model.

By analyzing all the optimal portfolios from Table 5, it is stated that during the time of economic recovery, Pharmaceuticals Ltd. comprises the highest risk. By considering the fact that high risk leads to high return, investors tend to invest 4.54% of their funds into this particular security while they choose the MV risk model. This proportion is 1.54% for using the SV model, 86.36% for the MaD model and 19.26% for CVaR (95%). It can also be examined that CVaR (99%) provides negative returns for all securities during this period.

This research reveals that the multiperiod issue can be resolved as a series of single-period issues under many sets of rational assumptions. However, if only one period is analyzed, the optimal portfolio will be different from that which is chosen. The distinction occurs because in the multiperiod case, the relevant utility function is a derived that takes multiple periods into account. Independence of returns between periods is one principle behind multiperiod portfolio research. In the last decade, there has been considerable research showing that mean returns and variances are correlated over time and are components of variables that are easily noticeable (Fama and French 1989; Campbell and Shiller 1988).

In Table 6, optimal portfolios are created for economic period of growth for Bangladesh market. This table shows that Pubali Bank comprises the highest risk. In order to receive high returns, investors are willing to invest in risky securities. It can be deduced that investors tend to invest 17.93% of their funds into this particular security while they choose the MV risk model. This proportion is 49.21% for using the SV model, 212% for employing the CVaR (95%) model and 4.96% funds are invested if investors opt for the CVaR (99%) model for optimal portfolio selection. However, if they choose the MaD model, the highest proportion is made by Jamuna Oil Com. Ltd.

From the above discussion, it can be concluded that for each of the scenario, top risky securities continue to change. Investors choose securities for investment by keeping the nature of economic condition in mind. They also choose securities depending on their investing attitude. Risk averse investors choose less risky securities and hence get low profits/returns. Whereas, risk takers invest in risky securities to get high returns. They prefer high returns, so they are more likely to choose the optimal portfolio. Diversification can keep them safe from risks so they may choose different securities in single scenario.

Table 7 presents results for the Bombay stock exchange about portfolio composition in the time of economic crises. The results reveal that investors invest 45.23% of their funds in Titan Company Ltd. if they choose the MV model, 46.44% if they choose the SV model, 35.79% investment is for the MaD model and this percentage is about 52.32% in the case of choosing CVaR (95%). However, if they choose CVaR (99%), they invest 9.07% of their funds in HDFC Bank Ltd.

The four risk models build distinctive ideal portfolio creations for the economic period of recovery. From Table 8 it is deduced that during the time of economic recovery, Tata Global Beverages Ltd. gives up the highest risk level in the optimal portfolios for all risk indicators. This particular security is the riskiest so the returns for investing in this security under different risk measures are also high. In order to receive high returns, investors invest 20.44% of their funds in Tata Global Beverages Ltd. if they choose the MV model, 44.86% is invested for the SV model, 19.64% for using the MaD model, 64.53% of funds are allocated if the CVaR (95%) model is selected and 13.23% for CVaR (99%).

For Bombay stock exchange, these four risk measures again give distinctive portfolios creations for each of the scenario. From Table 9 it is deduced that during the time of economic growth, Asian Paints Ltd. remains the riskiest security in the optimal portfolios for all risk measures except when the CVaR (95%) and CVaR (99%) models are employed. For these two models, the riskiest security is State Bank of India. From the above results, it is concluded that with the change of economic conditions, investor's investment decisions also change. In the decline, recovery and growth phase, their motive is to invest in those securities which generate more returns. They also prefer to invest in more than one security for minimizing risks. For this purpose, they are more inclined towards choosing the optimal portfolio.

From the above tables, it is evident that the top risky securities, in different scenarios, keeps on changing. It is not necessary that a security which is risky in the period of crisis stays risky in recovery and growth period. So, it totally depends on the investor's attitude, portfolio type and nature of economy (or economic scenario) that which the security (or group of securities) is to be selected for the portfolio. The risks associated with security also impact the decision. Similarly, risk measures also have direct influence on choosing the optimal structure as each model does not perform equally well in each economic scenario. In addition, a model performing better in crises phases does not necessarily yield the same results in recovery or growth period.

The summary statistics of the optimal portfolios in three different economic sub periods of Pakistan, Bangladesh and India are shown in Appendix A. For Pakistan, the average rate of return calculated for the period is 9.31%, which is the average risk-free rate from the period 2003 to 2015. This average rate of return is not achieved for all models in each scenario. This implies all portfolios developed are not ready to produce returns at any rate identical to the risk-free return. CVaR (95%) gives the best results for all optimal portfolios in each scenario of Pakistan. The results about mean returns are highest during the growth time period (2012–2015) for portfolios created by the CVaR (95%), MV, MaD and SV models. However, CVaR (99%) yields low or negative returns. From risk perspectives, as appeared by the portfolios' variance and skewness during the economic crisis investors bring more risk. Model CVaR (95%) provides the highest portfolio skewness during recovery period. Positive skewness is desirable as it decreases the probability of getting extreme negative returns. Results are consistent with each scenario. Hence, the CVaR (95%) is the most appropriate risk measure to control downside risk. Comparison of CVaR (95%) and CVaR (99%) is also shown in Appendix B.

For Bangladesh, the average required rate of return calculated for the period is 5.75%. Again, this average rate of return is not achieved for all models in each scenario. During the recovery period (2010–2013), mean returns are highest for all portfolios created by each of these four risk models. However, the portfolios developed by the CVaR (95%) model provides the maximum returns. Results with respect to skewness indicates that the CVaR (95%) model provides the highest skewness during the economic growth period. Results are consistent as model CVaR (95%) yields outstanding results in each scenario for the Dhaka stock exchange. These findings suggest that the MV, SV and MAD models are unable to develop optimal portfolios with maximum returns in each scenario. Thus, The CVaR (95%) model is the most suitable portfolio optimization model for all three economic scenarios.

For India, the minimum required rate of return for the period is 7.89%, which is the average risk-free rate from the period 2004 to 2015. Again, this average rate of return is not achieved for all models, but crisis and growth periods yield return more than their average in specific scenario. Results of the Bombay stock exchange show that mean returns are highest during the crises time

period (2004–2007) for all portfolios produced by these four risk models. Portfolios that are built by utilizing CVaR (95%) demonstrate the highest returns. From risk perspectives, as appeared by the portfolios' variances and skewness during the economic crisis' economic specialists bring about more risks. Portfolios that are built by utilizing the CVaR (95%) model also gives the highest skewness during periods of economic crisis. For the Indian market the results are also consistent because CVaR (95%) gives outstanding results in each economic scenario but the trend is different from the country perspective. Similar to the other two countries, CVaR (99%) does not perform likewise for this market but CVaR (95%) yields outstanding results.

The merits and demerits of each risk measure are evident by the results. H1, H3, H5 and H6 are accepted because each of the risk measure has its impact on the portfolio performance. However, their performance is not consistent in each period, so H4, H7 and H8 are not supported. H2 is also supported because the performance of CVaR is consistent in each scenario for all three countries. This study is evident the prior studies done by [Jaaman et al. \(2013\)](#) that variance is not a proper risk measure for all markets and for all economic scenarios. The CVaR is fundamentally the downward risk that particularly concentrates on the descending deviations under the mean return. CVaR is a superior coordinating choice for economic specialist's recognition that is risk averse.

5. Conclusions

This study concludes that for Pakistan, all risk measures perform better in the growth phase, for Bangladesh they perform better in the recovery phase and for India they show better performance in the crises phase. We found that the CVaR model gave a better result in each scenario. Thereby, investors are recommended to use this model for their portfolio construction. Public and private investors are required to re-evaluate their investment portfolio to improve their investment skills. The contribution of the paper is two-fold. (i) The outcome of the current study helps to identify if the same risk assessment is applicable in all three substituent or different risk measure is required for a different sub period. (ii) It provides an insight on asset choice, management and the use of an optimal risk model to estimate expected risk and return. The implications of our findings would be beneficial for the investors, investment decision makers and policy makers not only in Pakistan, Bangladesh and India, but also those in other developing countries. Our study has some limitations. Firstly, it only covered three developing countries. It will be of great importance to conduct a study to make a comparison between developing and developed economies so that it can further validate the consistencies of these risk models. Secondly, this study focuses on four models (MV, SV, MaD, CVaR), future studies may test the applicability of other risk models such as the mean Gini (MG) model, second degree stochastic dominance (SSD) and other quadratic models. Furthermore, future research may back-test risk measures such as CVaR as conducted by [Amendola and Candila \(2017\)](#). Moreover, our study only considered GDP to identify different economic scenarios, and therefore some other criteria may be used to identify the economic scenario. Researchers can use other macroeconomic indicators such as interest rates, inflation, gross national product (GNP) and foreign direct investment (FDI) instead of GDP as criteria to identify different economic scenario.

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Appendix A

Table A1. Summary Statistics of Optimal Portfolios.

	Crisis			Recovery			Growth		
Pakistan									
Risk Measures	Mean	Variance	Skewness	Mean	Variance	Skewness	Mean	Variance	Skewness
MV	0.1428	0.0137	-0.4075	0.0729	0.0059	1.8830	0.1551	0.0005	1.0215
SV	0.1012	0.0214	-0.0043	0.0124	0.0009	-0.1855	0.1087	0.0003	1.4904
MaD	0.1109	0.0080	-0.1789	0.0765	0.0023	1.2953	0.1651	0.0007	1.2168
CVaR95%	0.1938	0.0089	0.2662	0.1316	0.0101	2.0513	0.2710	0.0353	1.3053
CVaR99%	-1.7899	8.4855	-1.1224	0.0264	0.0057	0.5249	-0.6648	0.4900	-2.7662
Bangladesh									
Risk Measures	Mean	Variance	Skewness	Mean	Variance	Skewness	Mean	Variance	Skewness
MV	0.1914	0.0345	0.4557	0.0152	0.0001	1.9847	0.0547	0.0016	1.2360
SV	0.0656	0.0038	1.2322	0.0061	0.0000	1.5331	0.0614	0.0211	2.4846
MaD	0.2084	0.0001	-0.1733	0.8429	0.0001	0.2067	0.4021	0.0004	1.2387
CVaR95%	0.0774	0.0256	1.4813	0.8612	0.0384	2.3499	0.5918	0.2278	2.8992
CVaR99%	0.2047	0.1747	1.5100	-0.5449	0.0166	-1.1988	-0.4187	1.6037	-4.2728
India									
Risk Measures	Mean	Variance	Skewness	Mean	Variance	Skewness	Mean	Variance	Skewness
MV	1.1605	0.0278	-0.6841	0.0406	0.0369	-0.2957	0.0302	0.0015	0.3029
SV	1.1382	0.0150	-0.1429	0.0647	0.0105	-1.1429	0.0450	0.0105	0.1294
MaD	1.1886	0.1299	0.3402	0.1056	0.2082	0.2957	0.0765	0.0024	0.4278
CVaR95%	0.3224	-0.3071	0.6235	0.8597	-0.0385	-0.2345	0.6123	-0.2584	0.4624
CVaR99%	0.2162	-5.8917	0.4424	0.6343	-0.1861	-0.2345	0.5166	-0.9606	0.2324

Note: MV = mean variance, SV = semi variance, MaD = mean absolute deviation, CVaR95% = conditional value at risk with risk confidence levels $\beta = 0.95$ and CVaR99% = conditional value at risk with risk confidence levels $\beta = 0.99$.

Table A2. Summary Statistics of Pakistan Stock Exchange.

Summary Statistics Pakistan Stock Exchange					
S. No.	Stocks	Mean	Standard Deviation	Skewness	Count
1.	Oil and Gas Development Co. Limited	0.001021	0.221281	-1.50018	156
2.	Pakistan Petroleum Limited	0.001086	0.22892	0.276563	156
3.	Pakistan Oilfields Limited	0.000733	0.3062	-0.26124	156
4.	Mari Petroleum Company Limited	0.007585	0.278518	-0.50018	156
5.	Standard Chartered Bank Limited	0.001315	0.272276	1.111712	156
6.	National Bank of Pakistan	0.001448	0.482104	2.418173	156
7.	Bank Al-Falah Limited	0.001051	0.513031	0.976922	156
8.	Bank of Punjab Limited	-0.002	0.595658	2.099947	156
9.	Habib Bank Limited	0.002073	0.308275	0.327552	156
10.	Askari Bank Limited	0.005141	0.413128	3.213836	156
11.	United Bank Limited	0.002536	0.333472	0.083406	156
12.	Faysal Bank Limited	0.005985	0.697984	0.817687	156
13.	MCB Bank Limited	0.001059	0.180457	0.212136	156
14.	Bank Al-Habib Limited	0.00193	0.433875	-1.41979	156
15.	Soneri Bank Limited	0.003921	0.862424	1.055569	156
16.	Habib Metropolitan Bank Limited	0.004279	0.313162	2.762352	156
17.	Meezan Bank Limited	0.002111	0.387592	0.046732	156
18.	Pakistan Telecommunication Co. Limited	0.000105	0.332074	-0.0121	156
19.	TRG Pakistan Limited	0.002827	0.70609	-1.1057	156
20.	K-Electric Limited	0.003277	0.540738	-1.62602	156
21.	Hub Power Company Limited	0.001326	0.302786	0.795003	156
22.	Kot Addu Power Company Limited	0.001105	0.273556	-1.44901	156
23.	Nishat Power Limited	0.003869	0.45398	0.37976	156
24.	Fauji Fertilizer Company Limited	0.001028	0.283348	-1.87297	156
25.	Fauji Fertilizer Bin Qasim Limited	0.001746	0.475096	0.87015	156
26.	Engro Corporation Limited	0.003254	0.523509	-0.17939	156
27.	Dawood Hercules Corporation Limited	0.00338	0.349771	1.057867	156
28.	Fauji Cement Company Limited	0.009017	0.498798	-0.42289	156
29.	Maple Leaf Cement Factory Limited	0.004824	0.576098	-1.94281	156
30.	D.G. Khan Cement Company Limited	0.001742	0.397196	0.113583	156
31.	Lucky Cement Limited	0.005225	0.283228	-0.03627	156
32.	Pioneer Cement Limited	0.009626	0.542533	-0.57855	156
33.	Cherat Cement Company Limited	0.003574	0.60806	-2.53044	156
34.	Kohat Cement Limited	0.004201	0.559042	-0.82246	156
35.	Pakistan State Oil Company Limited	0.002733	0.228718	-3.55791	156
36.	Shell Pakistan Limited	0.004873	0.352169	2.257017	156
37.	Attock Petroleum Limited	0.001572	0.298047	0.166549	156
38.	National Foods Limited	0.002727	0.390825	-1.2129	156
39.	Nestle Pakistan Limited	0.002127	0.363435	-0.33565	156
40.	Murree Brewery Company Limited	0.007543	0.318573	1.216602	156

Table A3. Summary Statistics of Bombay Stock Exchange.

Summary Statistics Bombay Stock Exchange					
S. No.	Stocks	Mean	Standard Deviation	Skewness	Count
1.	ABB India Ltd.	-0.00157	0.233363	-2.25599	156
2.	ACC Ltd.	-0.00084	0.145414	-1.94626	156
3.	Aditya Birla Nuvo Ltd.	-0.00124	0.37893	0.014707	156
4.	Ambuja Cements Ltd.	-0.00099	0.23382	-1.16542	156
5.	Ashok Leyland Ltd.	-0.0027	0.217722	-1.68763	156
6.	Asian Paints Ltd.	-0.00132	0.310585	-4.627	156
7.	Aurobindo Pharma Ltd.	-0.00211	0.274632	-3.12489	156
8.	Axis Bank Ltd.	0.003356	0.296079	-2.22231	156
9.	Bank of Baroda	-0.00181	0.333875	-1.46145	156
10.	Bank of India	-0.00142	0.227189	-0.72262	156
11.	Bharat Forge Ltd.	-0.00235	0.302002	-0.34207	156
12.	Bharat Heavy Electricals Ltd.	-0.00127	0.325302	-0.02748	156
13.	Bharat Petroleum Corporation Ltd.	-0.00154	0.170063	-1.18159	156
14.	Bharti Airtel Ltd.	-0.00049	0.375371	-0.19651	156
15.	Bosch Ltd.	0.012793	0.733424	-0.75958	156
16.	Cairn India Ltd.	0.001032	0.145309	1.230483	156
17.	Canara Bank	-0.0019	0.182741	-0.41748	156
18.	Cipla Ltd.	-0.00129	0.17321	-2.20387	156
19.	Colgate-Palmolive (India) Ltd.	-0.00092	0.240767	-2.92544	156
20.	Crompton Greaves Ltd.	-0.00123	0.252653	0.227359	156
21.	Cummins India Ltd.	-0.00168	0.226236	-3.16762	156
22.	DLF Ltd.	4.42×10^{-5}	0.235311	2.332312	156
23.	Dabur India Ltd.	-0.0009	0.401805	-0.82827	156
24.	Divi's Laboratories Ltd.	-0.00069	0.204466	-4.24654	156
25.	Dr. Reddy's Laboratories Ltd.	-0.0005	0.38532	-0.91409	156
26.	Eicher Motors Ltd.	-0.00265	0.66675	-1.98111	156
27.	Exide Industries Ltd.	-0.00145	0.244269	-4.96028	156
28.	Federal Bank Ltd.	-0.00178	0.22905	-0.23047	156
29.	GAIL (India) Ltd.	-0.00061	0.178616	-1.02371	156
30.	GMR Infrastructure Ltd.	0.000612	0.494066	1.842718	156
31.	Glenmark Pharmaceuticals Ltd.	-0.00092	0.204925	-2.17214	156
32.	Godrej Consumer Products Ltd.	-0.0007	0.305101	0.141337	156
33.	Grasim Industries Ltd.	-0.00084	0.328513	-0.29509	156
34.	HCL Technologies Ltd.	-0.00015	0.211023	0.315107	156

Table A3. Cont.

Summary Statistics Bombay Stock Exchange					
S. No.	Stocks	Mean	Standard Deviation	Skewness	Count
35.	HDF Corporation Ltd.	-0.00098	0.179843	-4.33258	156
36.	HDFC Bank Ltd.	-0.00111	0.177979	-4.51155	156
37.	Hero MotoCorp Ltd.	-0.0013	0.330888	-0.92848	156
38.	Hindustan Petroleum Corporation Ltd.	-0.002	0.210976	-0.52083	156
39.	Hindustan Zinc Ltd.	-0.00096	0.266736	-3.54545	156
40.	Hindalco Industries Ltd.	-0.00112	0.17116	0.462405	156
41.	Hindustan Unilever Ltd.	-0.0009	0.197239	-4.04114	156
42.	ICICI Bank Ltd.	0.004245	0.473254	-0.51326	156
43.	IDBI Bank Ltd.	-0.00081	0.164191	0.421009	156
44.	IDFC Ltd.	-0.00146	0.205183	0.863535	156
45.	ITC Ltd.	0.007871	0.128682	-1.42025	156
46.	Idea Cellular Ltd.	0.010322	0.234203	1.782345	156
47.	Indian Oil Corporation Ltd.	-0.00088	0.355123	1.689711	156
48.	IndusInd Bank Ltd.	-0.0019	0.505213	-2.24344	156
49.	Infosys Ltd.	0.002398	0.384179	-0.95713	156
50.	JSW Steel Ltd.	-0.00048	0.283034	-0.32537	156
51.	Jaiprakash Associates Ltd.	0.001771	0.635872	1.911416	156
52.	Jindal Steel & Power Ltd.	0.001708	0.416398	0.519836	156
53.	Kotak Mahindra Bank Ltd.	-0.00172	0.331907	-1.33099	156
54.	Larsen & Toubro Ltd.	-0.00104	0.396199	0.722518	156
55.	LIC Housing Finance Ltd.	-0.00201	0.298472	-1.41351	156
56.	Lupin Ltd.	-0.00121	0.294502	-1.55839	156
57.	M & M Financial Services Ltd.	-0.00087	0.233975	-3.35674	156
58.	Mahindra & Mahindra Ltd.	-0.00084	0.162597	-0.35194	156
59.	Maruti Suzuki India Ltd.	-0.00191	0.217107	-2.38063	156
60.	NMDC Ltd.	-0.0002	0.433197	0.760369	156
61.	NTPC Ltd.	-0.00057	0.348464	-0.4629	156
62.	Nestle India Ltd.	-0.00076	0.281296	-2.53393	156
63.	Oil and Natural Gas Corporation Ltd.	-0.00057	0.316139	2.333243	156
64.	Power Finance Corporation Ltd.	-0.00184	0.233618	-1.39979	156
65.	Punjab National Bank	0.003609	0.221933	-1.80743	156
66.	Reliance Capital Ltd.	-0.00128	0.266942	1.017342	156
67.	Reliance Industries Ltd.	-0.00028	0.176676	2.922033	156
68.	Reliance Infrastructure Ltd.	-0.00097	0.209109	1.035737	156
69.	Reliance Communications Ltd.	0.001353	0.376787	1.878953	156

Table A3. Cont.

Summary Statistics Bombay Stock Exchange					
S. No.	Stocks	Mean	Standard Deviation	Skewness	Count
70.	State Bank of India	0.006937	0.547412	-1.00748	156
71.	Shriram Transport Finance Co., Ltd.	-0.00164	0.420911	-1.88917	156
71.	Siemens Ltd.	-0.00125	0.50214	1.433028	156
73.	Steel Authority of India (SAIL) Ltd.	-0.00095	0.449804	-0.40762	156
74.	Sun Pharmaceutical Industries Ltd.	-0.00087	0.253425	-2.09883	156
75.	Tata Chemicals Ltd.	-0.00139	0.309131	-0.33424	156
76.	Tata Consultancy Services Ltd.	-0.00039	0.212023	0.66793	156
77.	Tata Global Beverages Ltd.	-0.00022	0.356531	-0.47745	156
78.	Tata Motors Ltd.	-0.00077	0.200697	-3.33218	156
79.	Tata Power Company Ltd.	-0.00023	0.399376	-1.04622	156
80.	Tata Steel Ltd.	-0.00041	0.206793	-1.74184	156
81.	Tech Mahindra Ltd.	-0.00102	0.268141	-1.61563	156
82.	Titan Company Ltd.	-0.0014	0.30896	-6.30429	156
83.	UPL Ltd.	-0.00169	0.247734	-1.23392	156
84.	UltraTech Cement Ltd.	-0.00118	0.484679	-1.1287	156
85.	Union Bank of India	-0.0021	0.568566	-2.31036	156
86.	Unitech Ltd.	-0.00095	0.832437	0.732133	156
87.	United Breweries Ltd.	-6.8×10^{-5}	0.315536	-1.69065	156
88.	United Spirits Ltd.	-0.00042	0.265947	-1.52575	156
89.	Vedanta Ltd.	-0.00048	0.427308	-4.16601	156
90.	Wipro Ltd.	0.000183	0.279398	-1.0839	156
91.	YES Bank Ltd.	-0.0023	0.350807	-1.20037	156
92.	Zee Entertainment Enterprises Ltd.	0.003819	0.124231	-0.9429	156

Table A4. Summary Statistics of Dhaka Stock Exchange.

Summary Statistics Dhaka Stock Exchange					
S. No.	Stocks	Mean	Standard Deviation	Skewness	Count
1.	ACI Limited	0.004334	0.350274	1.663434	156
2.	Aftab Automobiles	0.006824	0.437234	1.119555	156
3.	Aftab Autos	0.004728	0.371382	-2.16318	156
4.	BA Tobacco	0.003842	0.33855	-0.48418	156
5.	BA Tobacco Bang	0.006408	0.56416	-0.00198	156
6.	BATL	0.010952	0.367048	1.758986	156
7.	BDCOM	0.004365	0.35258	-3.14547	156
8.	BDFINANCE	0.001898	0.400461	1.024068	156
9.	Beximco Pharma	0.008049	0.356722	-1.40479	156
10.	BRAC Bank Ltd.	0.001536	0.491285	-2.03121	156
11.	BSRM Limited	0.010723	0.460103	-1.64063	156
12.	BSRM Steels	0.007602	0.324726	0.372816	156
13.	Delta Insurance	0.006416	0.384159	0.57767	156
14.	Grameenphone.	0.003052	0.264329	-1.21256	156
15.	Heidelberg Cement Ltd.	0.000443	0.237939	0.824452	156
16.	IDLC Finance Limited	-0.00175	0.4041	0.328328	156
17.	Islamic Bank Bed Ltd.	0.002342	0.393956	0.787155	156
18.	Jamuna Oil Com. Ltd.	0.006292	0.35112	-2.80508	156
19.	Lafarge Cement Ltd.	0.000457	0.284184	-1.34556	156
20.	Meghna Ltd.	-6×10^{-5}	0.337869	0.677172	156
21.	NBL	0.006128	0.744517	-0.65584	156
22.	Olympic Ltd.	0.005392	0.276331	1.910264	156
23.	Padma Co.	0.004012	0.409943	0.098543	156
24.	Pharmaceuticals Ltd.	0.00664	0.413572	-0.16638	156
25.	Pubali Bank	0.005005	0.367949	-0.37062	156
26.	RAK Ceramics Ltd.	0.001145	0.518974	0.768791	156
27.	Square Limited	-0.00049	0.339855	1.707854	156
28.	Summit Power Ltd.	0.007812	0.405936	0.743032	156
29.	Titas & Dist. Co., Ltd.	0.004302	0.27178	-0.86032	156
30.	UCBL	0.000642	0.590343	-1.70207	156

Appendix B

Table A5. Comparison of CVaR (95%) and CVaR (99%).

	Crisis		Recovery		Growth	
Pakistan Stock Exchange						
	CVaR (95%)	CVaR (99%)	CVaR (95%)	CVaR (99%)	CVaR (95%)	CVaR (99%)
Mean	-2.1823	-3.9703	-0.6261	-1.5016	-0.1858	-0.5816
Variance	0.9630	3.2236	0.0764	0.9194	0.0110	0.1895
<i>t</i> -Stat	11.5461		7.8080		7.4820	
<i>p</i> -value	0.0000		0.0000		0.0000	
	Crisis		Recovery		Growth	
Dhaka Stock Exchange						
	CVaR (95%)	CVaR (99%)	CVaR (95%)	CVaR (99%)	CVaR (95%)	CVaR (99%)
Mean	-0.6784	-2.2771	-0.5086	-0.6971	-0.3541	-1.3358
Variance	0.0770	1.4085	0.3079	0.5785	0.2486	5.7294
<i>t</i> -Stat	9.4964		5.0201		2.8327	
<i>p</i> -value	0.0000		0.0000		0.0083	
	Crisis		Recovery		Growth	
Bombay Stock Exchange						
	CVaR (95%)	CVaR (99%)	CVaR (95%)	CVaR (99%)	CVaR (95%)	CVaR (99%)
Mean	-1.1096	-3.2941	-0.4432	-1.5000	-0.3238	-1.1248
Variance	0.5368	3.9344	0.0956	1.7517	0.0616	0.8113
<i>t</i> -Stat	16.2525		9.8578		11.5921	
<i>p</i> -value	0.0000		0.0000		0.0000	

Appendix B presents the comparison of CVaR (95%) and CVaR (99%) by providing values of mean, variance, *t*-stat and *p*-values. CVaR (95%) has higher mean and smaller variances as compared to CVaR (99%) for all three stock exchanges under each scenario. The values of *t*-stat are significant for the Pakistan stock exchange, Dhaka stock exchange and Bombay stock exchange under each scenario. However, values of *t*-stat are slightly higher in crisis period for all three stock exchanges as compared to recovery and growth period. Results indicates that CVaR (95%) is a better measure of risk as compared to CVaR (99%).

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