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# Evaluation of Historical Simulation Method at Estimating Value at Risk (VaR)

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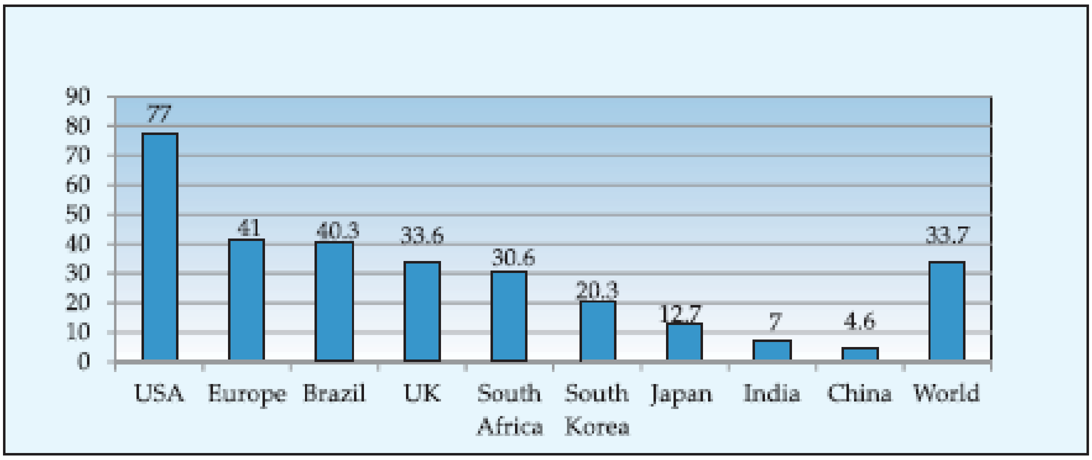
## Introduction

VaR is a popular risk management tool being used by financial professionals in the banking and other related financial industry. International bodies like Basel Committee and Bank for International Settlements recommend adoption of VaR for assessment of capital adequacy ratio in commercial banks. VaR measurement typically requires statisticians that understand the financial markets well, and develop a statistical model that suits to factor in the changes in economic variables and forecast the VaR value as accurately as possible. VaR conveys risk as the likely dollar loss of a portfolio over a time horizon. In India apart from RBI, daily VaR of each stock is reported in the Stock Exchanges. It may be quite popular with the banking sector in India, but, there does not seem to be much work beyond that. Ramaswamy (2011) has attempted to identify potential channels through which risks to financial stability can materialize in the mutual fund sector. The term *Value at Risk* was coined at J. P. Morgan in the late 1980s, by Till Guldimann, who was head of research at the bank. The bank decided to concentrate on 'value risk' rather than 'earnings risk'. Later at a G-30 (group of thirty), the international body's meeting; it was taken up and later included in the G-30 report, published in 1993.

Mutual funds across the world have acquired great significance. In countries like USA, Australia, UK, etc., majority of the retirement funds are handled by these funds. Mutual funds form the major proportion of investments assets in most countries. Figure 1 shows the Asset Under Management-Gross Domestic Product (AUM-GDP) ratio. Excepting India and China, the AUM-GDP ratio is substantially higher. In India, mutual funds are more than five decades old, but still are in the evolving phase. If one has to build a corpus and plan for retirement, investment in mutual funds is an important route. However, India and China lag far behind on this front.




*Source: Investment Company Institute, USA*

**Fig. 2.1:** Asset Under Management-GDP Ratio across Countries

Mutual fund in India is not a recent phenomenon. In 1963 the Unit Trust Act was passed in the Parliament, and the Unit Trust of India (UTI) was formed under the administrative control of Reserve Bank of India (RBI), and the first mutual fund scheme, Unit Scheme 1964, popularly known as US64 was launched. Till the entry of private sector mutual funds in the 1990s, UTI's pioneer scheme of US64 was most popular among Indian public. Some of the insurance companies like Life Insurance Corporation of India (LIC) and General Insurance Corporation of India (GIC); and commercial banks like State Bank of India (SBI), Canara Bank, Punjab National Bank, Indian Bank, Bank of India, Bank of Baroda, etc., made entry into the mutual fund industry with their fund offers. Thus, 1987 marked a new beginning in the Indian mutual fund industry. Thereafter, the Asset Under Management (AUM) started growing more rapidly. The stock market regulator Securities Exchange Board of India (SEBI) was constituted in 1992, followed by SEBI (Mutual Fund) Regulations, 1993, replaced by a stronger SEBI (Mutual Fund) Regulation, 1996. These developments paved way for entry of private sector mutual fund companies in India.

Over the years the SEBI has been making it difficult for the MF companies to fleece the customers. The SEBI's (MF) Regulations have evolved over time. A lot of time and effort has been spent in designing a comprehensive regulatory framework.

Booking of expenses by a mutual fund house has been a contentious issue. It not only erodes the Net Asset Value (NAV) of the fund, but also investors' confidence. SEBI has been very proactive in countering this menace and in streamlining the processes of fund houses. Towards this end SEBI has been coming up with regular amendments in regulations. As per recent amendments, the total expenses of a fund's scheme, including expenses towards advisory charges, administration charges, entry and exit loads, brokerage, other marketing charge, etc., has been capped at 2.50%, calculated on the daily or weekly average NAV of the scheme. To help the mutual funds to penetrate into smaller cities and towns, an additional charge of 0.30% has been allowed.

Though the banking industry and stock markets have adopted VaR as an important tool for measuring risk, the investment industry is yet to adopt such a robust tool for risk reporting purposes. It may be an equally important tool for the Indian mutual fund industry, because VaR measures the downside risk, and may help in predicting their daily/weekly/monthly VaR. It appears from studies in Indian context that very limited work is available in the public domain. These issues were the motivating factors behind pursuing this research on applying different techniques/methods for measuring VaR in the mutual fund industry. A popular non-parametric method, Historical Simulation Model is applied on the daily returns of a sample equity schemes, and is validated using a back testing technique.

## Research Objectives and Methodology

The main objective of this research work is to apply the Historical Simulation method in VaR estimation on data extracted from the equity schemes floated by different mutual fund houses. The findings of the research will be helpful to the fund houses, in evaluating if VaR can be adopted for risk measurement, and further, if Historical Simulation method can be useful in estimating an appropriate VaR. Findings of this research also can be helpful for the individual investors in their assessment of daily expected absolute loss in their portfolio, over the next trading day. The findings of this research will also be helpful to the regulators, especially SEBI and Insurance Regulatory Development Authority (IRDA), in stressing the use of VaR and may be helpful in policy formulation. It may be helpful in assessing the excessive volatility in the markets.

Under the premise stated above, the study aims at using new sets of data, variables and approaches for examining the following aspects:

- To discuss the role of VaR in the Indian financial markets, in general.
- To apply and evaluate the use of Historical Simulation in measuring VaR.

The data was collected from Reports; Journals; and websites of NSE, BSE, AMFI, Mutual Fund Companies, etc. The *Historical Simulation approach* was applied, which is explained below.

Literature Review
Value-at-risk models use the aggregate of several risk factors into a single quantitative figure to estimate the potential loss for a given confidence level over a time horizon. VaR conveys risk associated with a portfolio of assets as an absolute figure in one number (Kiohos & Dimopoulos, 2004). It states in absolute terms the likely dollar loss of a portfolio over the next 'n' days, which enables even a layman to understand and helps him in his decision making with regard to his portfolio (Marshall & Siegel, 1997). In India the VaR of each stock traded on the National Stock Exchange (NSE), is reported on daily basis.

Philippe Jorion, defines it as "*VaR summarises the worst loss over a target horizon that will not be exceeded with a given level of confidence*" (Jorion, 2007). International bodies like Basel Committee, Bank for International Settlements, etc., have advocated financial institutions and the regulators to adopt VaR as a measure for assessment of market risk, and estimate, by how much a bank's portfolio of assets can lose, in a given time horizon. It is a summary of many complex bad outcomes, communicated by a single number. VaR is measured through a challenging set of complex statistical methods that keeps changing with the change in time, change in portfolio structure, change in market conditions, etc., and typically requires statisticians that understand the financial markets well (Damodaran, 2014).

J.P. Morgan developed RiskMetrics, a tool for estimation of VaR, which is now widely accepted as a industry standard. Despite being a popular tool to estimate risk, there exists lot of criticism for VaR. There is scepticism as to the accuracy of VaR estimation. Researchers have however, identified the problems of non-subadditivity, volatility clustering, ignoring the quantum of loss within a given confidence level, etc. Markus Leippold (2004) argues that by defining the best of the five percent worst losses, VaR completely misses the tail distribution, which could prove dangerous for the risk manager, especially if the markets start moving decisively in the negative zone.

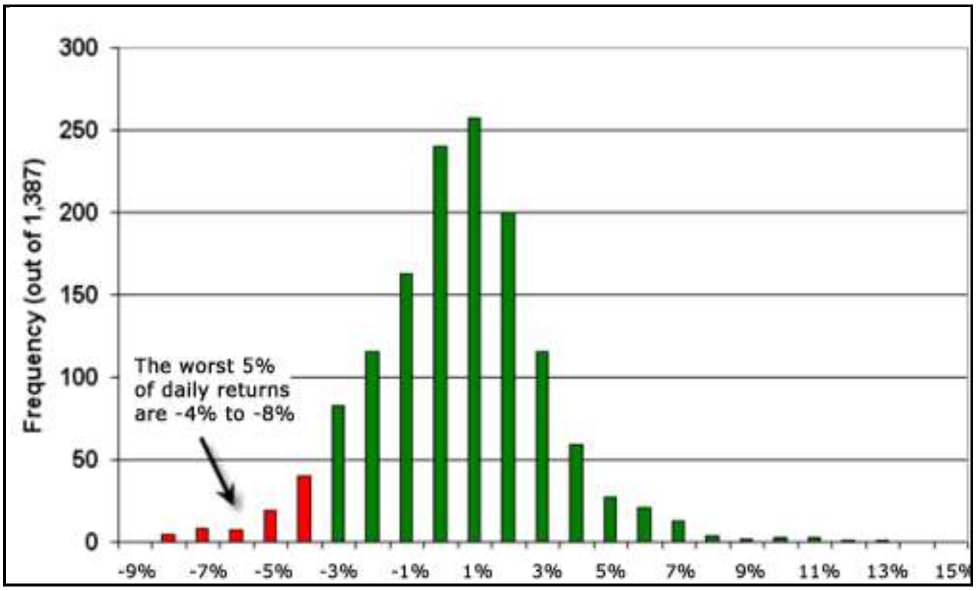



**Fig. 3.1:** Distribution of Daily Returns

VaR as a measure of risk is widely accepted in the banking industry but not that much so as far as the investment industry is concerned. But, it may be equally important for the portfolio managers in the Indian mutual fund industry, because VaR measures the downside risk, and helps in predicting their weekly VaR on rolling basis. Three parametric models and one non-parametric model applied on the weekly returns of sample equity schemes, and two back testing approaches were also applied (Christofferson, Hahn, & Inoue, 2001). The exponential weighted moving average and historical simulation models are free from downward bias (Deb & Banerjee, 2009). Zhao (2004) has shown the application of dynamics of VaR estimation in mutual fund industry, and propagates the idea of designing the dynamic portfolio construction strategies. Five equally weighted moving average approaches, three exponentially weighted moving average approaches, and four historical simulation approaches were applied on 1,000 randomly chosen foreign exchange portfolios over the period 1983-94, but none of the twelve approaches were superior on every count (Leon & Lin, 2004).

VaR models estimate values using normally distributed data, but most economic data do not follow normal distribution on many occasions, and exhibit excess kurtosis and fat tails. To overcome this problem, Principal Component VaR and Monte Carlo VaR, are helpful; even nonlinear extreme value theory has been developed to estimate VaR under such conditions (Fishman, 1996).

## Research Motivation and Objectives

Mutual funds are more than five decades old in India. Investments in capital markets, especially in equities, have proven to provide effective positive returns; and mutual fund route is the best way to get exposed to equities. To garner greater interest, the practitioners in the mutual funds industry, should adopt fair investment practices; and proper risk coverage and risk reporting processes should be in place. Security Exchange Board of India (SEBI) has been, in recent times, been a proactive regulator, and has come up with regulations and policy directions from time to time, to make the environment more and more investor friendly. The risk coding of mutual fund schemes, as advocated by SEBI is a step in the right direction. If, this is combined with daily-VaR reporting, could lead to better communication with the investors. This could help the investor in better financial planning. Despite the apparent advantages, there does not seem to be much work on VaR on the Indian mutual fund sector.

This research work is initiated with the objective of testing the popular Historical Simulation model in estimation of VaR on the Indian mutual fund sector. The research will help in establishing if the method is helpful for risk estimation and risk management in the Indian mutual fund industry. If found to be useful, the fund managers can handle risk associated with mutual fund schemes. Investors can also take well informed decisions. The findings may also be useful to policy makers like Security SEBI, Reserve Bank of India (RBI), Insurance Regulatory Development Authority (IRDA), etc., in formulating better regulatory framework. It may forewarn the policy makers, and help in reduction of excessive volatility in the markets, thus minimizing the chances of economic disasters and help reduce excessive volatility in financial markets, if the finance industry adopts some time tested methods for risk assessment and reporting techniques.

The most widely used *non-parametric* method is historical simulation, which requires no distributional assumptions and estimates the VaR as the quantile of the empirical distribution of historical returns from a moving window of the most recent periods (Berkowitz & O'Brien, 2002). Bhattacharyya (2007) Historical Simulation's assumption of constant volatility is untenable. A study on VaR computation with associated back-testing application on the Indian mutual fund industry data exhibits that the 'moving average' and 'random walk' modes suffer from downward bias; but, EWMA and historical simulations models do not show any such bias, but are conservative in VaR estimation (Deb & Banerjee, 2009).

## Data Collection

The data for analysis was collected from secondary sources. The primary objective of this study is to evaluate the VaR using Historical Simulation method. For analysis daily NAV data and the daily closing prices of all the stocks forming part of the mutual fund schemes that existed between January, 2000 and May, 2016 were chosen. Only the equity schemes with growth option were selected. A total of twenty-two schemes qualified the desired criteria. The list is given in table 1.

The portfolio weights as it existed on 31st December, 2016 were kept constant for reconstruction of NAV behaviour over the year of our study. The historical daily prices of all the stocks forming part of each of the twenty-two mutual fund schemes were downloaded from National Stock Exchange (NSE), Bombay Stock Exchange (BSE), and Yahoofinance website. The NAV data of all mutual fund schemes, from January, 2017 to May, 2017 was used for back-testing purpose.

**Methodology**

VaR estimation has its connection with probability theory. It is the prediction of some future event and about which nothing can be said with certainty. A risk manager or a fund manager may like to issue a statement for its investors that *I am x percent certain that the mutual fund scheme will not lose more than Y-amount over the next trading day.* More formally, assuming that the daily return follows normal distribution, annual VaR is the (1 – α) percentile of the distribution of change in value, over a period of *N*-days; where 'α' is the confidence level. We will use the Historical Simulation, a non-parametric method, for VaR estimation, where no assumptions are made about the shape of distribution of returns. With this background now we can go on to discuss the different methods of computing VaR in the following sections.

In this method, a model time series of returns is reconstructed by running the current market position of each of the assets in the portfolio on the actual historical returns. This approach is based on the premise that history repeats itself, and that the past data reflects full and complete information about the risks involved with an asset or with portfolio. The returns for reconstruction of the portfolio is computed as follows:

$$R_{p,k} = \sum_{i=1}^{N} w_{i,t} R_{i,k} \qquad k = 1, \dots \dots . t \qquad \text{(Eq. 4.17)}$$

where the $w_i$ are kept constant at the current levels, so that the portfolio can be reconstructed based on the historical returns. In this each scenario, *k* is drawn from *t*-historical data points. It uses the history of percentage changes in prices. The method is explained as follows:

- Compute the daily or periodical price changes for each of the assets.
- Apply the historical prices changes computed in the first step above, on the current market value of the asset.
- Sort the series.
- Set the confidence level at *c.*
- The VaR of the portfolio is the computed value that corresponds to the $\alpha = (1 - c)^{th}$ percentile.

The disadvantages of Historical Simulation Method are that the past may not always be reliable, as period selected for model building plays an important role. Supposing, the model were built based the administered prices, and is then applied on the free market regime with excessive volatility, the model would in most likelihood fail to estimate risk. Similarly, assigning equal weights to all the economic variables may not reflect true picture, because, events of recent past would have greater bearing the economic activities of near future, than the remote past events. To overcome this problem, weighted average methods have been introduced, where more weights are assigned to recent data that the older data. Further, new risk due to introduction of new assets in the future would introduce newer risks, which may not be possible to be captured from the past data. Then there is a high chance of sampling error. Despite the disadvantages, there are advantages too. No assumptions need to be made, which may sometimes be unrealistic, about the distribution of returns.

The validity of the model is checked through back-testing process, to ascertain if the assumptions, parameters, modeling techniques, etc., are estimating VaR within the given confidence. It will help in developing a robust model. If $c$ is the confidence level and the fund house sets $p = (1 - c)$ as the probability for exceptions for a total of T-days, and the user counts the exceptions defined by $N$ and the failure rate would be $N/T$. Here our objective is to know if the number of exceptions '$N$' *is* neither too large nor too small. If the exceptions are too small then the VaR level is set too high, and if the exceptions are too large, then the VaR is set too low, and there is a flaw in the model development. This is also called *Bernoulli's Trials* (Hull & Basu, 2010). Under this the number of exceptions in $x$ follows a binomial probability distribution:

$$f(x) = \binom{T}{x} p^x (1-p)^{T-x} \qquad \text{(Eq. 1)}$$

where $x$ has expected value of $E(x) = pT$ with variance $V(x) = p^x (1-p)^{T-x}$. When T becomes large, the sample distribution tends to normality, and we can use central limits theorem, and perform a two-tailed test:

$$z = \frac{x - pT}{\sqrt{p(1-p)T}} \approx N(0,1) \qquad \text{(Eq. 2)}$$

**Value at Risk (VaR) Computation and Model Validation**

VaR was computed using the Historical Simulation Method, on the data from 2007 to 2016. For back-testing data from January, 2016 till May, 2017 was used. Prior to VaR computation, the annual returns and volatility of all the schemes were calculated from the year 2007 till 2016, to observe the market behaviour. Only Franklin India schemes and ICICI Prudential funds had shown fair returns. But volatility in returns was seen across the schemes. Even losses to the investors' principal amount were observed, prime suspect the global recession, since 2008. It was observed from the stocks forming part of the schemes that the most favoured sectors were banking and financial services, IT, pharmaceuticals, FMCG, oil & gas, and automobile, in that order.

In a two-tailed test at 95% confidence levels the calculated z-value should lie between -1.96 and +1.96; and for 99% confidence levels the z-value should lie between -2.58 and +2.58. The portfolio was frozen and weights were assumed to be static over the VaR estimation period. Back-testing was conducted on data beginning from January, 2017 till May, 2017.

**Table 1:** The Mutual Fund Schemes and the Assets Under Management (AUM)

| S.No. | Scheme | Notations used to Describe Schemes | AUM (Rs. in Crores) |
|---|---|---|---|
| 1 | Birla Sun Life India Opportunities Fund-Plan B | BSLIOF | 413.56 |
| 2 | Birla Sun Life MNC Fund | BSLMNCF | 451.10 |
| 3 | DSP BlackRock Technology. com Fund | DSPBRTF | 48.58 |
| 4 | Escorts Tax Plan | ETAX | 207.90 |
| 5 | Franklin India Bluechip Fund | FIBCF | 4644.02 |
| 6 | Franklin India Prima Fund | FIPF | 683.15 |
| 7 | Franklin India Prima Plus | FIPPF | 1971.12 |
| 8 | Franklin India Taxshield | FITAX | 830.18 |
| 9 | Franklin India Infotech Fund | FITECH | 114.40 |
| 10 | ICICI Prudential FMCG Fund - Regular Plan | IPFMCGF | 223.90 |
| 11 | ICICI Prudential Tax Plan - Regular Plan | IPTAX | 1412.60 |
| 12 | ICICI Prudential Technology Fund | IPTECH | 132.38 |
| 13 | ICICI Prudential Top 100 Fund - Regular Plan | IPT100 | 400.84 |
| 14 | ING Core Equity Fund | INGCEF | 58.99 |
| 15 | JM Basic Fund | JMBF | 145.67 |
| 16 | JM Equity Fund | JMEF | 32.07 |
| 17 | Morgan Stanley Growth Fund | MSGF | 121.11 |
| 18 | Principal Growth Fund | PRGF | 231.52 |
| 19 | Principal Tax Savings Fund | PRTAX | 191.55 |
| 20 | Taurus Discovery Fund | TADF | 22.58 |
| 21 | Taurus Starshare | TASTAR | 155.87 |
| 22 | Taurus Tax Shield | TATAX | 88.82 |

**Table 2:** Historical Simulation

| | Scheme | | | Value at Risk (VaR) | | No. Exceptions | | Calculated Z-Value | |
|---|---|---|---|---|---|---|---|---|---|
| **No.** | **Figure No.** | **Name** | **NAV** | **At 95% level** | **At 99% level** | **At 95% level** | **At 99% level** | **At 95% level** | **At 99% level** |
| **1** | **2** | **3** | **4** | **5** | **6** | **7** | **8** | **9** | **10** |
| 1 | 5.2a | BSLIOF | 53.09 | -1.10 | -1.98 | 1 (0.30%) | 0 | -3.95 | -1.84 |
| 2 | 5.2b | BSLMNCF | 267.14 | -4.26 | -8.00 | 4 (1.19%) | 0 | -3.70 | -1.84 |
| 3 | 5.2c | DSPBRTF | 28.90 | -0.83 | -1.43 | 5 (1.49%) | 2 (0.60%) | -2.95 | -0.74 |
| 4 | 5.2d | ETAX | 37.75 | -0.90 | -1.60 | 0 | 0 | -4.26 | -1.84 |
| 5 | 5.2e | FIBCF | 236.67 | -5.70 | -9.70 | 4 (1.19%) | 0 | -3.20 | -1.84 |
| 6 | 5.2f | FIPF | 330.53 | -7.00 | -12.61 | 3 (0.89%) | 0 | -3.45 | -1.84 |
| 7 | 5.2g | FIPPF | 252.34 | -5.52 | -9.48 | 3 (0.89%) | 0 | -3.45 | -1.84 |
| 8 | 5.2h | FITAX | 241.33 | -5.63 | -9.89 | 2 (0.60%) | 0 | -3.70 | -1.84 |
| 9 | 5.2i | FITECH | 61.31 | -1.84 | -3.18 | 10 (2.99%) | 2 (0.60%) | -1.69 | -0.74 |
| 10 | 5.2j | IPFMCGF | 106.34 | -2.44 | -4.34 | 8 (2.38%) | 0 (0%) | -2.20 | -1.84 |
| 11 | 5.2k | IPTAX | 158.07 | -3.85 | -6.48 | 1 (0.30%) | 0 | -3.95 | -1.84 |
| 12 | 5.2l | IPTECH | 19.36 | -0.36 | -0.57 | 13 (3.87%) | 4 (1.20%) | -0.95 | 0.35 |
| 13 | 5.2m | IPT100 | 153.02 | -3.60 | -6.50 | 4 (1.20%) | 0 | -3.20 | -1.84 |
| 14 | 5.2n | INGCEF | 42.38 | -1.18 | -1.95 | 1 (0.30%) | 0 | -3.95 | -1.84 |
| 15 | 5.2o | JMBF | 14.29 | -0.38 | -0.66 | 4 (1.20%) | 0 | -3.20 | -1.84 |
| 16 | 5.2p | JMEF | 35.86 | -0.89 | -1.52 | 5 (1.50%) | 0 | -2.95 | -1.84 |
| 17 | 5.2q | MSGF | 66.41 | -1.45 | -2.70 | 5 (1.50%) | 0 | -2.95 | -1.84 |
| 18 | 5.2r | PRGF | 57.63 | -1.47 | -2.50 | 4 (1.20%) | 0 | -3.20 | -1.84 |
| 19 | 5.2s | PRTAX | 84.83 | -2.17 | -3.70 | 4 (1.20%) | 0 | -3.20 | -1.84 |
| 20 | 5.2t | TADF | 17.48 | -0.38 | -0.71 | 7 (2.08%) | 0 | -2.45 | -1.84 |
| 21 | 5.2u | TASTAR | 63.26 | -1.55 | -2.60 | 5 (1.50%) | 0 | -2.95 | -1.84 |
| 22 | 5.2v | TATAX | 38.25 | -0.96 | -1.67 | 4 (1.20%) | 0 | -3.20 | -1.84 |

Source: Researcher’s Compilation

In the table 2 under calculated z-value column, as can be observed only five out of a total of forty-four cells are shaded. The VaR computation of DSP Black Rock Technology.com at 99% level; and Franklin India Technology fund, and ICICI Prudential Technology fund at both the levels, seem appropriate. As we look at all other schemes, they show a negative z-value. Negative z-value indicates overstatement of one-day expected loss. From January, 2017 till May, 2017, a total of approximately 340 NAV values were available. Accordingly a five percent exception works out to about 17 values beyond the calculated VaR; and at one percent exception about 3 or 4 values can lie beyond calculated VaR. But, as we see there are very few exceptions or expected losses, indicating that the VaR estimation is high, in comparison to actual losses.

The estimated VaR, was expressed as a percentage of NAV for some of the schemes; viz., Birla Sunlife Opportunity fund had an NAV of 53.09 and VaR of Rs. 1.10 and Rs. 1.98 at 95% and 99% respectively. This translates into 2.07% and 3.73% one day loss. Similarly, for Franklin India Prima Fund (FIPF) and Taurus Discovery Fund (TADF), the NAV were Rs. 330.53 and Rs. 17.48 respectively, with one day VaR being Rs. 7 and Rs. 12.61 for FIPF, and Rs. 0.38 and Rs. 0.71 for TADF at 95% and 99% levels respectively. Again it translates into 2.12% and 3.82% for FIPF, and 2.17% and 4.06% for TADF. As the schemes are well-diversified portfolios hence start replicating the market indices. Therefore, a single day movement of 2%, 4% and beyond for an index, is a tectonic shift, that may occur due to some extreme political, economic or natural event.

The frequency plots of the daily changes in Net Asset Value (ΔNAV) showed leptokurtic behaviour, with a number of tall frequency bars around the mean, with a sudden fall in the size of frequency bars near the tails. It looks like a leptokurtic normal distribution curve, with a possible fatter tails; thus indicating higher occurrences of extreme events. But, as we can see from our analysis of the results in the table 2, the extreme events are less frequent, and that there is an overestimation of VaR both at 95% and 99% significance levels. This anomaly could be due to the markets being more volatile and the presence of fat-tails during our analysis phase, i.e., prior to 2016; but subdued or less volatile markets between January, 2017 and May, 2017, i.e., during back-testing period.

## Conclusions and Recommendations

A total of twenty-two schemes offered by ten fund houses were selected for analysis. Overall two out of these ten fund houses, viz., Franklin India schemes and ICICI Prudential funds have given fair returns. The returns given by most schemes were not only flat, but, the annual volatility measured by standard deviation (σ) was also high. Some of the fund houses have even given negative returns, leading to loss of capital for the investors. Many similarities were observed in the stockholding patterns of the fund houses, with fair amount of concentration in large cap stocks. Some of the sectoral funds like IT and FMCG seem to have given good annualized returns.

We observe, VaR has been properly estimated for DSP Black Rock Technology.com only at 99% confidence level; and for Franklin India Technology fund and ICICI Prudential Technology fund at both the levels. Incidentally, all three schemes belong to the technology sector. As the data used at the model building stage pertained to the periods just before and after the global recession of

2008, and technology sector was benefitted due to appreciation in dollar value and increase in outsourcing as a cost cutting measure by many big companies in the United States and Europe.

An analysis of the portfolio of schemes reveals that the majority of the stocks are from banking and financial sector, followed by IT sector. Should it be called herd mentality among the fund managers, or safety first approach by the FMs, is very difficult to predict. It may also be quite possible that the FMs are trying to mimic more successful FMs of other AMCs. Similarly, much of the investment has been into large cap stocks, indicating the risk aversion of fund managers. These may have been some of the causes for very limited returns, especially during most of the volatile times.

Based on our findings from analysis of the data, we may conclude that Historical Simulation may not be the suitable method for computation of VaR in the Indian mutual funds industry. Fest & Sraeel (2009) put it, there is need for developing risk modelling that relies on predictive analytics, providing context and knowledge, including future elements, as well as historical data, to turn unknown-unknowns into risks that can be managed. May be with a larger set of data a more robust model could have been built, with which the VaR estimation would have been better. All said and done, pure reliance on statistical tools will not be recommended as a fool proof risk management system. It has to be complemented with regular qualitative risk assessment as well. The VaR estimation under this method had been too high, leading to too few exceptions.

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