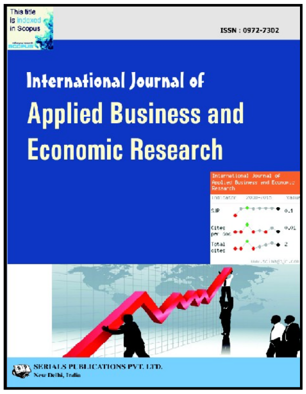

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Estimation of Value at Risk (VaR) in the Indian Mutual Funds Industry A Parametric Approach

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BACKGROUND

The US stock market crash in 1987, wiped out more than $1 trillion of investors' money in a single day, which took the world by surprise, and risk management became the focal point. It was felt necessary to device a measure that can communicate risk in simple and absolute term, which paved the way for the development of Value at Risk (VaR). VaR describes the quantile of the projected distribution of gains & losses over the target horizon (Jorion, 1996); and was popularized in early 1990s, after endorsement by International bodies like G-30, Basel Committee on Banking Supervision, and Bank of International Settlements.

Stocks, bonds, debentures, fixed deposits or for that matter any financial instrument involves risk. Risk is prevalent in all walks of life, and so is the risk in investments in mutual funds. Thus, risk mitigation and not risk avoidance becomes a key challenge for a mutual funds company. High volatility scares the individual investors away from the financial markets, especially from the equities market. Thus the role of mutual fund manager assumes great importance. The corpus vested with the mutual funds is invested in diverse portfolio of securities, after a thorough research based security selection. This helps to build a strong portfolio, with the potential to fetch higher risk-adjusted returns (Huang, Sialm, & Zhang, 2007).

The remaining part of the paper is organised with review of literature in section 2. The research objective, methodology, and data collection methods are discussed in section 3. Section 4 has analysis and discussions of the results. Finally, in section 5 conclusions are drawn based on the research findings.

LITERATURE REVIEW

In the financial markets greed and indiscriminate actions on the part of investors have caused great imbalances in the markets. This induces fear, making the markets very volatile, prompting investors to dump their holding, leading to crashes in financial markets. Indiscriminate action on the part of market participants is human nature, and none has any control over it. Therefore, risk cannot be done away with, but, needs to be managed. Forewarned is forearmed. What cannot be measured cannot be managed. There is an increased interest in quantitative techniques, mathematical and statistical methods, for risk measurement and its management.

One of the most important risk management tools is Value at Risk (VaR). VaR is widely used in the banking and financial sector. It can be described as the quantile of the projected distribution of gains and losses over the target horizon. Philippe Jorion, (2007) who did a pioneering work on VaR, defines it as "*VaR summarises the worst loss over a target horizon that will not be exceeded with a given level of confidence*." Financial institutions and the regulators have adopted VaR as a measure for assessment of market risk. VaR estimates, by how much a bank's portfolio of assets can lose, in a given time horizon. 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).

JP Morgan in 1995, developed RiskMetrics©, a tool for estimation of VaR that uses exponential weighted moving average model (EWMA) to estimate this time-varying conditional volatility, where more weight is assigned to the most recent returns, and less weight on older returns, thus denoting the conditional volatility persistence. Markus Leippold (2004) argues that by defining the best of the five percent worst losses, VaR completely misses the tail distribution, and recommends the use of more coherent risk measures, like expected shortfall (ES). The beauty of VaR is that it does not depict the risk as an abstract figure or as a combination of several risk factors; rather it conveys risk associated with a portfolio of assets as an absolute figure in one number (Kiohos & Dimopoulos, 2004). 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. Glasserman, Heidelberger & Sahabuddin (2002) developed efficient methods for computing portfolio VaR with the associated risk factors having heavy-tailed distribution, using multivariate t-distributions, delta-gamma approximation, and numerical transformation inversion method to approximate the portfolio loss distribution.

As the financial markets become more technology oriented, more and more scientific methods are being adopted for devising business strategies. Business houses have started using data analytics for understanding customer preferences, so as to design their business strategies. Similarly, in financial risk management, understanding the structure of volatility assumes high importance. With the substantial growth in financial markets and increased interest of the participants, risk estimation has become more diverse and complex (Hwang, 2007). Hence, an assessment of trading revenues from such activities, and examination of the statistical accuracy of the VaR forecasts is absolutely essential. Applying different techniques for estimation of VaR forecasts on the profitability of six large commercial banks, the researchers found that the bank VaRs did not adequately reflect changes in P&L volatility, which reflects substantial computational difficulties in constructing large scale structural models that might harm VaR accuracy too (Berkowitz & O'Brien, 2001).

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). Tsai & Shih (2007) discussed the principal components with higher eigenvalues, and the ones with higher correlation with the response variable, and concluded that mean square error matrix of estimators for regression coefficients, and method of ordinary least squares in the multiple regression models, can determine the best regression estimator.

Garcia, Renault, & Tsafack (2007) argued the rationale for decentralized risk management, wherein individual traders possess richer information on their specific market segment to fetch superior returns and for better control over risk. When portfolio responsibility is distributed among several FMs, it would lead to better information assimilation and better fund management; thus, the collective VaR of all FMs would be subadditive. It is thus concluded that lack of coherence of decentralized VaR management, that is VaR non-subadditivity at the richest level of information, should be an exception rather than a rule. Analysing the portfolio selection process, Alexander & Baptista (2004), applied VaR constraint on the single period mean-variance model and compared them with those arising from application of CVaR constraint, and concluded that VaR constrained as a tool to control slightly risk-averse agents, but had perverse effect on highly risk-averse agents, and likely to force them to choose the portfolio with higher risk. Emerging markets have drawn considerable interest in recent years. Fuh & Yang (2007) use bootstrap method for VaR estimation using nine emerging markets stock indices, and compare it with US S&P 500 composite index, and MSCI EM Index; and concluded that VaR estimates computed do not deviate very much from the true VaR. The results also revealed that VaR estimates were relatively low in Turkey, India, Mexico, Russia, and Indonesia.

Ghaoui, Oks, & Oustry (2003) tried to reduce the problem of extreme sensitivity to errors in data posed by the traditional approaches, such as mean-variance or Value-at-Risk (VaR) models, by assuming that the distribution of returns are partially known, defined the worst-case Value-at-Risk as the largest VaR attainable, and have tried to show how to compute an upper bound on the worst-case VaR via semi-definite programming (Krokhmal, Palmquist, & Uryasev, 2002). Existing VaR models are useful in measuring market risk. But concentrating only on VaR and ignoring risks like operational, business, and systemic risks, could make organisations highly sensitive.

The accuracy of VaR in estimating risk was studied, using the daily data of thirty stocks from Indian equity market and two indexes, viz. , BSE-Sensex and NSE-Nifty, by applying portfolio-normal method, and was observed that the VaR predictions were not accurate. The reason for the failure of accurate VaR estimation was attributed to non-normality, leptokurtosis and negative skewness, and problem reduction may be possible, if decaying weights are assigned to the lagged data (Tripathi & Gupta, 2008). Study conducted by Cao, Chang, & Wang, (2008) reveals that there is negative correlation between the intraday inflow of funds in the mutual fund sector and volatility in the market portfolio. It is further revealed that this negative relation between inflow of funds and intraday volatility becomes weaker as the day progresses. American equity mutual funds of varying investment styles investing in Europe was examined, using VaR and expected tail loss (ETL) models developed through three (parametric, nonparametric and style-based approach) techniques, it was found that the least diversified funds that overweight growth and underweight value stocks, the style-based risk model produce significantly lower VaR and ETL estimates than do the other models; whereas, the results for the well-diversified fund show an opposite significance pattern (Papadamou, 2004).

Engle and Manganelli (2004) describe how the VaR literature contains three different categories of methods: parametric, nonparametric, and semi-parametric. *Parametric* approaches involve parameterization of the behaviour of prices. Quantiles are estimated using a volatility forecast with an assumption for the type of the distribution, such as Gaussian (Taylor, 2005). Bhattacharyya (2007) after analysing a few methods of VaR estimation, argues that Variance-Covariance method, often underestimates VaR. 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' models suffer from downward bias (Deb & Banerjee, 2009).

VaR is accepted across the world as an estimator of market risk, and widely used by treasurers in the corporate houses and fund managers. Reserve Bank of India (RBI), India's central banker, has accepted the recommendations of the Basel committee's guidelines, widely circulated by the Bank of International Settlement (BIS); and had mandated that all the commercial banks in India got to do, the VaR measuring and reporting on a regular basis (Hull & Basu, 2010).

OBJECTIVE, METHODOLOGY AND DATA COLLECTION

There are numerous methods of VaR estimation. These can be broadly classified into Parametric, Semi-Parametric, and non-Parametric. Variance-Covariance method, which is also called Delta-Normal method, is a parametric method for VaR estimation. This is one of the most popular parametric methods and has some apparent advantages, which are discussed in the following sections. In this present work, we look at Variance-Covariance method for VaR estimation and risk management. The results would then be validated through back-testing process.

For our analysis we required daily NAV data and the daily closing prices of all the securities forming part of the growth oriented equity schemes of selected mutual fund houses. The schemes that existed on 1st January, 2000, as well as on 31st May, 2014, were chosen for analysis. This data for fifteen years ensured that it had been through multiple up and down-cycles of the market. Even to date, the debt market is not fully developed hence, the debt funds were avoided. A total of twenty-two schemes qualified the desired criteria. The list is given in table 1.

The historical daily closing prices of all the companies forming part of each of the twenty-two mutual fund schemes were downloaded from the websites of NSE, BSE and Yahoofinance. NAV data of all mutual fund schemes, from 1stJanuary, 2013 to May, 2014 were used for back-testing purpose. Adjustments for stock splits, issue of bonus shares, etc., wherever necessary, were carried out.

VARIANCE-COVARIANCE METHOD

This method is implemented by deriving the probability distribution of possible returns, the Variance-Covariance method for computation of Value at Risk can be implemented. For calculating 1-day VaR from annual VaR, we divide annual VaR by $\sqrt{252}$ because, there are approximately 252 trading days in a year. As variances are additive over time i.e., ($\sigma_N^2 = \sigma_1^2 + \sigma_2^2 \ldots = N\sigma^2$), therefore, N-period standard deviation is $\sigma\sqrt{N}$.

Table 1
List of Schemes Included for Analysis and their AUM (as in December, 2013)

	Name of the Schemes	*Asset Under Management (Rs. in Crores)*
1	Birla Sun Life India Opportunities Fund-Plan B	413.56
2	Birla Sun Life MNC Fund-Plan B	451.1
3	DSP BlackRock Technology. com Fund - Regular Plan	48.58
4	Escorts Tax Plan	207.9
5	Franklin India Bluechip Fund	4644.02
6	Franklin India Prima Fund	683.15
7	Franklin India Prima Plus	1971.12
8	Franklin India Taxshield	830.18
9	Franklin Infotech Fund	114.4
10	ICICI Prudential FMCG Fund - Regular Plan	223.9
11	ICICI Prudential Tax Plan - Regular Plan	1412.6
12	ICICI Prudential Technology Fund - Regular Plan	132.38
13	ICICI Prudential Top 100 Fund - Regular Plan	400.84
14	ING Core Equity Fund	58.99
15	JM Basic Fund	145.67
16	JM Equity Fund	32.07
17	Morgan Stanley Growth Fund- Regular Plan	121.11
18	Principal Growth Fund	231.52
19	Principal Tax Savings Fund	191.55
20	Taurus Discovery Fund	22.58
21	Taurus Starshare	155.87
22	Taurus Tax Shield	88.82

Source: Researcher's compilation

For computation of portfolio VaR (VaR_p) consisting of two or more assets, it is assumed that the positions are fixed over time, and portfolio return is computed as a linear combination of the proportion of investment in the asset at the beginning of the investment period, and the rate of return in the asset. This can be formally defined as (Jorion, 2007):

$$R_p = w_1 R_1 + w_2 R_2 + \cdots + w_N R_N = [w_1 w_2 \cdots w_N] \begin{bmatrix} R_1 \\ \vdots \\ R_N \end{bmatrix} = w'R \qquad \text{(Eq. 1)}$$

where we have R_p is the total return on portfolio-p consisting of N assets; $w_1, w_2, \ldots, w_N$ are the proportion of the asset in each asset forming part of the portfolio-p; σ_p^2 is portfolio variance; and $\sigma_{11}, \sigma_{12, \ldots,} \sigma_{NN}$ are the covariance between given two assets. Portfolio variance can be expressed as:

$$\sigma_p^2 = [w_1 w_2 \cdots w_N] \begin{bmatrix} \sigma_1^2 & \cdots & \sigma_{1N} \\ \vdots & \ddots & \vdots \\ \sigma_{N1} & \cdots & \sigma_N^2 \end{bmatrix} \begin{bmatrix} w_1 \\ \vdots \\ w_N \end{bmatrix} = w^T \Sigma w \quad \text{(Eq. 2)}$$

where Σ is the matrix of variance-covariance terms, w is the weights in vector format, and w^T is the transpose of vector matrix w. When we rewrite Eq. 2 to express the portfolio risk in rupee terms, it becomes:

$$\sigma_p^2 V^2 = z^T \Sigma z \quad \text{(Eq. 3)}$$

where V is the market value of the portfolio, 'z' and 'z^T' are the actual exposure to all the assets in the portfolio expressed in rupee terms.

Now, once we have all the terms in place, it is now easier to compute VaR of the portfolio. For calculation of portfolio VaR, under variance-covariance method of VaR calculation, the portfolio returns are assumed to be normally distributed. As all the asset returns are normally distributed random variables, the portfolio returns, being a jointly linear combination of these normally distributed asset returns, are also assumed to be normally distributed. Now, if we define '*c*' as the confidence level at which we calculate the portfolio VaR, then '*α*' can be defined as the standard normal deviate, and observing the value at $-\alpha$, we can determine the portfolio VaR, and can conclude that the probability of portfolio loss, worse than computed VaR is *c*. If we define the initial portfolio value as V, then portfolio value at risk can be calculated as:

$$Portfolio\, VaR = VaR_p = \alpha \sigma_p V = \alpha \sqrt{z^T \Sigma z} \quad \text{(Eq. 4)}$$

and the stand alone VaR_i of asset *i* is given by:

$$VaR_i = \alpha \alpha_i |V_i| = \alpha \sigma_i |w_i| V \quad \text{(Eq. 5)}$$

Only the absolute values for w_i are taken, because, as discussed earlier, the portfolio can have negative weights due to leveraging, whereas, the risk is always positive and irrespective of long or short position in the asset; hence, has to be reported in positive figures.

As we can see from Eq. 4, portfolio VaR is dependent on a number of assets, variance of all the assets, and covariance between assets. We know that variance measures volatility, similarly, covariance is the measure of linear co-movement between any two variables. The degree of covariance depends on the variances of individual variables, and is captured by *correlation coefficient* denoted by ρ, which can be expressed as follows:

$$\rho_{ij} = \sigma_{ij} / (\sigma_i \sigma_j) \quad \text{(Eq. 6)}$$

Similarly, the portfolio variance is defined by:

$$\sigma_p^2 = w_1^2 \sigma_1^2 + w_2^2 \sigma_2^2 + 2\, w_1 w_2\, \rho_{12} \sigma_1 \sigma_2 \quad \text{(Eq. 7)}$$

and the portfolio VaR is given by:

$$VaR_p = \alpha\sigma_p V = \alpha\sqrt{(w_1^2\,\sigma_1^2 + w_2^2\sigma_2^2 + 2\,w_1\,w_2\,\rho_{12}\sigma_1\sigma_2)}\,V \qquad \text{(Eq. 8)}$$

Now, let us look at what happens to portfolio VaR, if there is zero correlation between the two assets. By substituting Eq. 5 in Eq. 8, and setting $\rho = 0$, we get the following:

$$VaR_p = \sqrt{\alpha^2 w_1^2\sigma_1^2\,V^2 + \alpha^2\,w_2^2\sigma_2^2\,V^2} = \sqrt{VaR_1^2 + VaR_2^2} \qquad \text{(Eq. 9)}$$

From Eq. 9 it can be understood that the portfolio VaR_p must be less than the VaRs of the two assets, i.e., ($VaR_p < VaR_1 + VaR_2$). This is the case of portfolio VaR being sub-additive; and proves the benefits of diversification, when the investments and less correlated. However, diversification will not benefit, if there is perfect positive correlation between the assets, i.e., $\rho = 1$. In such a case the VaRs of the two assets are additive.

It is easy to implement as it involves just the matrix multiplication technique. It is computationally quick, very flexible and is very helpful in identifying the specific risk factors to which the portfolio is sensitive. However, it turns a blind eye to the existence of fat tails, as it only captures the data point at the specified confidence level, which may seriously underestimate the underlying risk factor

BACK-TESTING

Back-testing is a reality-check process, where the verification of the actual losses is compared with that of projected losses. In a standardized VaR model, the number of data points falling outside the estimated VaR should be in line with confidence level. The data points that fall outside the estimated VaR are called exceedences or exceptions. If the exceptions are too many then the VaR model underestimates risk, which may lead to serious repercussions. 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. Ideally, with the increase in sample size, N should converge to p. Here our objective is to know if the exceptions N are either too large or too small. If the exceptions are too small then we are overcautious and are operating at sub-optimal level. On the other hand, if the exceptions are too large, then there is a flaw in the VaR estimation, and adjustments are needed to depict reality. Here the tests make no assumptions, and are nonparametric. This is also called *Bernoulli's Trials* (Hull & Basu, 2010). Under this the number of exceptions in x follows a binomial probability distribution:

$$f(x) = \binom{T}{x} p^x (1-p)^{T-x} \qquad \text{(Eq. 10)}$$

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:

$$z = \frac{x = pT}{\sqrt{p(1-p)T}} \approx N(0,1) \qquad \text{(Eq. 11)}$$

Based on our results we ascertain the number of exceptions by verifying with the historical returns; apply the two-tailed *t*-test, evaluate if our model provides unbiased estimation of VaR, and draw our conclusions accordingly.

ANALYSIS AND DISCUSSIONS

The closing prices of all stocks downloaded from NSE, BSE, and YahooFinance websites, were adjusted for corporate actions like bonus issue and stock splits. After making adjustments, the daily log returns for each company stock were calculated; and from the daily returns the variance covariance matrices were generated. These values are not shown in this paper due to lack of space.

The variance-covariance terms and stock weights in the scheme were used for calculating portfolio variance; which was then combined with NAV of the scheme as on 31st December, 2012 to obtain one day VaR at 95% and 99% confidence levels. This one day VaR at both the levels were then back-tested by computing the daily change in NAV from January, 2013 till May, 2014. Based on exceptions obtained from the above process, z-values were computed, for ascertaining the validity of the method on all twenty-two schemes.

Table 2
The Returns and Volatility of Mutual Fund Schemes Included in the Study

S.No.	*Scheme*	*Notations used to Describe Schemes*	*NAV[1]*	
			Annual Returns	*Annual Volatility (σ)*
1	Birla Sun Life India Opportunities Fund-Plan B	BSLIOF	22.30%	14.98%
2	Birla Sun Life MNC Fund	BSLMNCF	5.86%	21.66%
3	DSP BlackRock Technology. com Fund	DSPBRTF	0.74%	41.22%
4	Escorts Tax Plan	ETAX	1.07%	23.92%
5	Franklin India Bluechip Fund	FIBCF	6.40%	23.22%
6	Franklin India Prima Fund	FIPF	9.30%	22.05%
7	Franklin India Prima Plus	FIPPF	10.10%	21.88%
8	Franklin India Taxshield	FITAX	7.54%	22.74%
9	Franklin India Infotech Fund	FITECH	12.74%	27.72%
10	ICICI Prudential FMCG Fund - Regular Plan	IPFMCGF	13.76%	18.14%
11	ICICI Prudential Tax Plan - Regular Plan	IPTAX	9.29%	21.73%
12	ICICI Prudential Technology Fund	IPTECH	11.85%	18.26%
13	ICICI Prudential Top 100 Fund - Regular Plan	IPT100	6.37%	24.48%
14	ING Core Equity Fund	INGCEF	3.49%	24.83%
15	JM Basic Fund	JMBF	4.50%	30.00%
16	JM Equity Fund	JMEF	-1.05%	27.19%
17	Morgan Stanley Growth Fund	MSGF	5.92%	24.31%
18	Principal Growth Fund	PRGF	2.30%	23.55%
19	Principal Tax Savings Fund	PRTAX	2.30%	23.55%
20	Taurus Discovery Fund	TADF	-8.07%	25.14%
21	Taurus Starshare	TASTAR	8.82%	17.40%
22	Taurus Tax Shield	TATAX	2.45%	23.70%

Source: Researcher's compilation

From table 3, it could be observed that the cells containing calculated z-values falling within the acceptable range of -1.96 and +1.96 for 95% confidence levels, and -2.58 and +2.58 for 99% confidence levels, have been shaded, indicating the proper estimation of VaR for the scheme, at the given confidence level. It reveals very few shaded cells. At 95% confidence level we can observe only two shaded cells for Franklin India Technology Fund and ICICI Prudential Technology fund. Similarly, we can observe 5 shaded cells at 99% level, for schemes like DSP Black Rock Technology.Com, Franklin India Blue Chip Fund, Franklin India Technology Fund, ICICI Prudential FMCG Fund and Morgan Stanley Growth Fund. Almost all other cells show negative calculated z-values. It means the one-day VaR is being over-estimated for all the remaining schemes, leading to very few cases of outliers/exceptions. Based on z-values it can only be said that the estimated VaR is high. But it may not be possible to comment on the magnitude of over-estimation of VaR, because VaR methods do not measure the magnitude. Further the z-score of -1.84 is within the range for both the confidence levels, yet we do not accept it as a valid score for the above reason. We have considered cases that have at least one exception.

FINDINGS AND CONCLUSIONS

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 gave good returns. Volatility in all the schemes were found to be high. Investment in the schemes of some of the fund houses has even caused capital loss for the investors. The main concentration of investments seems to be in large cap stocks. Some of the sectoral funds like IT and FMCG funds have given excellent annualized returns. 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.

For back-testing, data from January, 2013 till May, 2014 were downloaded from the respective website of mutual fund companies. A total of approximately 340 daily NAV values were available for each scheme. During back-testing, as we know, if the calculated z-value is zero then the exceedences are exactly, what was expected. If the exceptions are on the negative side beyond the desired range, then the VaR method is overstating risk, and if the calculated z-values are on the positive side beyond the desired range, then there is under-estimation of VaR.

In a tow-tailed test z-values should lie between -1.96 and +1.96 for 95% confidence levels; and between -2.58 and +2.58 for 99% confidence levels. VaR of all twenty-two schemes were calculated, it was observed that only two schemes, viz., Franklin India Technology Fund and ICICI Prudential Technology fund have properly estimated VaR at both the confidence intervals. Apart from that, we can observe that four schemes, i.e., DSP Black Rock Technology.Com, Franklin India Blue Chip Fund, Franklin India Technology Fund, ICICI Prudential FMCG Fund and Morgan Stanley Growth Fund, have estimated VaR accurately at 99% level. Almost in all other cases, there is an overestimation of VaR under this method.

Based on our findings from analysis of the data, we may conclude that Variance-Covariance method may not be the suitable method for computation of VaR in the Indian mutual funds industry. Fest & Sraeel (2009) put it that 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,

Table 3
Monte Carlo Simulation Results

Equation No.	*Figure No.*	*Scheme*	*Equation for Estimation of NAV*	R^2	*NAV*	*VaR (in rupees)*		*No. of Exceptions*		*Calculated Z-Value*	
						At 95%	*At 99%*	*At 95%*	*At 99%*	*At 95%*	*At 99%*
1	*2*	*3*	*4*	*5*	*6*	*7*	*8*	*9*	*10*	*11*	*12*
5.1	5.3a	BSLIOF	$Ln(BSLIOF) = 2.46 + 0.00062 \times \Delta T - 0.00274\, \varepsilon \sqrt{(\Delta T)}$ (88.56) (-0.46)	0.72	294.26	-0.56	-1.10	20	1	0.80	-1.29
5.2	5.3b	BSLMNCF	$Ln(BSLMNCF) = 3.21 + 0.00083 \times \Delta T - 0.00275\, \varepsilon \sqrt{(\Delta T)}$ (-196.95) (-0.64)	0.92	66.29	-2.46	-5.74	21	1	1.05	-1.29
5.3	5.3c	DSPBRTF	$Ln(DSPBRTF) = 1.48 + 0.00076 \times \Delta T - 0.00387\, \varepsilon \sqrt{(\Delta T)}$ (-122.48) (0.63)	0.82	28.90	-0.54	-1.18	20	2	0.80	-0.75
5.4	5.3d	ETAX	$Ln(ETAX) = 2.33 + 0.00064 \times \Delta T - 0.00236\, \varepsilon \sqrt{(\Delta T)}$ (82.86) (-0.36)	0.70	37.75	-0.42	-0.85	22	1	1.18	-1.32
5.5	5.3e	FIBCF	$Ln(FIBCF) = 3.01 + 0.00095 \times \Delta T - 0.00268\, \varepsilon \sqrt{(\Delta T)}$ (160.64) (-0.54)	0.90	236.67	-3.32	-7.70	23	1	1.55	-1.29
5.6	5.3f	FIPF	$Ln(FIPF) = 3.29 + 0.00097 \times \Delta T - 0.00237\, \varepsilon \sqrt{(\Delta T)}$ (110.36) (-0.32)	0.80	355.00	-4.02	-9.97	20	0	0.80	-1.84
5.7	5.3g	FIPPF	$Ln(FIPPF) = 3.01 + 0.00097 \times \Delta T + 0.00167\, \varepsilon \sqrt{(\Delta T)}$ (161.84) (0.34)	0.90	266.34	-1.73	-4.53	51	6	8.56	1.45
5.8	5.3h	FITAX	$Ln(FITAX) = 3.09 + 0.00091 \times \Delta T - 0.00199\, \varepsilon \sqrt{(\Delta T)}$ (157.69) (-0.41)	0.89	241.32	-2.07	-5.19	37	4	5.05	0.35
5.9	5.3i	FITECH	$Ln(FITECH) = 2.56 + 0.00059 \times \Delta T - 0.00505\, \varepsilon \sqrt{(\Delta T)}$ (116.14) (-1.07)	0.81	94.01	-1.09	-2.16	21	7	1.07	2.00
5.10	5.3j	IPFMCGF	$Ln(IPFMCGF) = 1.95 + 0.00093 \times \Delta T - 0.0037\, \varepsilon \sqrt{(\Delta T)}$ (177.35) (-0.85)	0.91	116.20	-1.52	-3.65	23	2	1.55	-0.75
5.11	5.3k	IPTAX	$Ln(IPTAX) = 2.59 + 0.00092 \times \Delta T - 0.00253\, \varepsilon \sqrt{(\Delta T)}$ (131.86) (0.40)	0.84	174.12	-1.79	-4.23	27	1	2.55	-1.29
5.12	5.3l	IPTECH	$Ln(IPTECH) = 1.12 + 0.00068 \times \Delta T + 0.00389\, \varepsilon \sqrt{(\Delta T)}$ (118.59) (0.74)	0.81	31.47	-0.27	-0.57	23	4	1.55	0.35

contd. table 3

1	2	3	4	5	6	7	8	9	10	11	12
5.13	5.3m	IPT100	Ln(IPT100) = 2.93 + 0.00077 x ΔT - 0.00324 ε √(ΔT) (153.33) (-0.68)	0.88	170.43	-1.91	-4.15	23	2	1.55	-1.29
5.14	5.3n	INGCEF	Ln(INGCEF) = 1.92 + 0.00065 x ΔT - 0.00469 ε √(ΔT) (121.86) (-0.92)	0.82	42.81	-0.64	-1.29	15	1	-0.45	-1.29
5.15	5.3o	JMBF	Ln(JMBF) = 2.53 + 0.00008 x Δ T + 0.00722 ε √(ΔT) (12.75) (1.24)	0.05	13.19	-0.27	-0.39	22	4	1.30	0.35
5.16	5.3p	JMEF	Ln(JMEF) = 2.05 + 0.00058 x Δ T - 0.00402 ε √(ΔT) (92.35) (0.64)	0.72	36.47	-0.51	-0.94	24	4	1.80	0.35
5.17	5.3q	MSGF	Ln(MSGF) = 2.74 + 0.00059 x Δ T - 0.00532 ε √(ΔT) (96.31) (0.61)	0.76	69.43	-.0.82	-1.61	23	3	1.55	-0.20
5.18	5.3r	PRGF	Ln(PFGF) = 2.39 + 0.00063 x ΔT + 0.00438 ε √(ΔT) (94.27) (0.71)	0.74	62.42	-0.92	-1.85	23	1	1.55	-1.29
5.19	5.3s	PRTAX	Ln(PRTAX) = 2.77 + 0.00065 x ΔT - 0.00369 ε √(ΔT) (85.52) (-0.53)	0.70	92.08	-1.21	-2.31	29	3	3.05	-0.20
5.20	5.3t	TADF	Ln(TADF) = 1.51 + 0.00052 x ΔT - 0.00503 ε √(ΔT) (64.54) (0.736)	0.58	17.64	-0.29	-0.54	19	0	0.55	-1.84
5.21	5.3u	TASTAR	Ln(TASTAR) = 1.74 + 0.00094 x ΔT - 0.00293 ε √(ΔT) (122.18) (0.43)	0.83	64.79	-0.94	-2.18	20	0	0.80	-1.84
5.22	5.3v	TATAX	Ln(TATAX) = 1.99 + 0.00058 x ΔT - 0.00498 ε √(ΔT) (145.79) (-1.37)	0.87	38.43	-0.59	-1.12	22	1	1.30	-1.29

Source: Researcher's Compilation

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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