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A Review of Backtesting Methods for Evaluating Value-at-Risk

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Value at Risk (VaR) measures the lower tail of the distribution and maximum portfolio loss that could occur for a given holding period with a given confidence level. VaR models are based on number of assumptions and accuracy of VaR depends on these assumptions. Backtesting is a process to evaluate the accuracy of VaR. Hence, to check the accuracy of VaR models, Backtesting methods are popular tool among researchers and professionals. Expectations from Backtesting methods are high in terms of differentiating good VaR model from bad VaR model. In this paper we have critically examined assumptions and features of various Backtesting methods and assessed their accuracy in Indian capital market. We calculated the VaR for Nifty Fifty securities on daily adjusted closing price for the period 2007-08 and Backtested the results for the period 2004-06 assuming log normal distribution.

JEL Codes: C52, D81 and G32

1. Introduction

Value-at-Risk (henceforth VaR) is an important risk measurement tool for practitioners because of its wide implications on firm's losses and regulatory capital requirement. VaR measures the lower tail of the distribution and maximum portfolio loss that could occur for a given holding period with a given confidence level. Three important components of VaR are confidence level, period and potential loss in value. *Confidence level* refers to probability of the expected minimum loss. *Period* refers to the reference period and the holding period, where Reference period captures the extent of information captured in VaR measure i.e. length of historical data used. Holding period is a function of turnover of the instrument composing a portfolio, like daily VaR is calculated for commercial banks for trading activity and monthly or quarterly VaR is calculated for pension fund reports. Broadly, there are three methods of calculating VaR in existing literature: Variance-Covariance, Historical Simulation and the Monte Carlo Simulation. These VaR models are based on number of assumptions like distribution assumption, and assumptions regarding confidence level, holding period, reference period etc. As the number of assumptions increases, the accuracy of VaR tends to decrease. Variance-Covariance method assumes normal distribution for financial returns but in reality return distribution may have fatter tails and greater number of observation in the center. Historical Simulation doesn't make any assumption about distribution rather it uses actual historical record of financial data. Each observation is weighted equally in this method so it ignores the dynamic ordering of observation. Historical Simulation is based on the assumption that history repeats itself, which may not be true. This method is simple to calculate as compared to other VaR models. Monte Carlo Simulation method is flexible as compared to other two methods but more computer

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programming intensive. Monte Carlo Simulation method uses stochastic approach to generate series of random path from historical distributions of the risk factor returns (Konatantinos *et al.*, 2007; Valerie Louisy-Louis, 1998; Hendricks, 1996). It is worth to mention that VaR is not a coherent measure of risk because it discourages diversification and is not sub additive. VaR provides a probability of loss at particular confidence level but does not tell the loss or magnitude of loss in remaining percentage of occasions.

The importance of VaR as a technique for risk measurement raised the necessity of evaluating the accuracy of VaR (Blanco and Oks, 2004). Hence, to address these concerns Backtesting is a popular tool among researchers and professionals. Backtesting is a process to evaluate the accuracy of VaR. This paper emphasized that there is need to assess the accuracy of Backtesting methods itself because a VaR model is as effective as its Backtest models are. This paper broadly looks few important Backtesting methods normally used by researcher as well as practitioners and critically evaluates their efficiency as a reliable tool for decision making in the context of Indian capital markets.

The following section discusses the existing literature on VaR and application of Backtesting methods. Literature review is followed by methodology and empirical results respectively. Methodology part discusses the Backtesting methods and parameters used to measure them. After this we analyzed the empirical findings thoroughly. Finally, we concluded that existing methods are not consistent, there is a need for consistent methods and this might have policy implications for regulators in developing countries.

2. A Review of Past Research

Backtesting methods can be unconditional and conditional. Unconditional methods count the number of exceptions and compare them with confidence level. If the exceptions are within statistical limits, model is accepted otherwise rejected. In contrast, conditional methods test whether the exceptions are independent of each other and there are joint test also which combines the conditional and unconditional methods. An accurate VaR model should satisfy the unconditional coverage and independence properties of the hit sequence (Christoffersen, 1998). Lopez (1999) discussed binomial method, Interval forecast method, and proposed an evaluation method that uses standard forecast evaluation techniques. Lopez (1999) considered three loss function for his method: the *Binomial loss function* that assigns a numeric score of 1 when a VaR estimate is exceeded by its corresponding portfolio loss, the *Zone loss function* based on the adjustments to the multiplication factor used in market risk amendment, and the *Magnitude loss function* that assigns a quadratic numerical score when a VaR estimate is exceeded by its corresponding portfolio loss. So this method not only incorporates VaR violation but also magnitude of the loss. Since 1996 Basel Accord prescribed Value-at-Risk based on 1% quantile of the profit and loss account for risk measurement. Blanco and Oks (2004) raised concerns regarding the necessity of evaluating the accuracy of VaR not only for the importance of VaR techniques for risk measurement purpose but also as an effective risk management tool. The simplest Backtest consists of counting the number of exceptions for a given period and comparing to the expected number for the chosen confidence interval. Blanco and Oks (2004) gave an overview of qualitative and quantitative tools for Backtesting. Haas (2001) also emphasized the importance of Backtesting from regulatory point of view for banks and summarized existing methods like Kupiec's POF test, Kupiec's TUFF test, Point estimator for p, Lopez' Magnitude loss function, Crnkovic and Drachman models etc. Haas (2001) discussed improved Backtesting methods also like Scaled CD model, Mixed Kupiec-Test etc. Haas (2001) suggested some improvements in existing methods and tried to find out optimal Backtesting strategy.

Regulated banks are required to keep some minimum capital to protect them against adverse market condition and prevent them from taking extraordinary risk. Capital requirements depend on the risk measurement method and multiplication factor. The decision about multiplication factor is made by regulators on the basis of back testing results. Since 1996 Basel Accord prescribed VaR based on 1% quantile of the profit and loss account for risk measurement. It discussed various risk measures like quantiles, VaR, expected shortfall and suggest a scheme for determining multiplication factor. A study by Kerkhof and Melenberg (2003) showed that this scheme results in less severe penalties for the back test based on expected shortfall compared to back tests on VaR.

Another study by Compbell (2005) reviewed both conditional and unconditional back testing methods and their suitability. On the basis of simulation experiments Compbell (2005) suggested that tests that examine several quartiles are most successful in identifying inaccurate VaR models. Lehikoinen (2007) introduced a framework for the improvement of the Backtesting process by empirically studying the real profit and loss data of bank portfolio against corresponding simulated data from the VaR model. Lehikoinen (2007) formulated a detailed framework for sustainable development and improvement of the back testing and of the VaR model.

A recent study by Nieppola (2009) tried to evaluate the accuracy of the VaR estimation in the context of Finnish institutional investor. He applied and analysed different methods of Backtesting on daily VaR estimates for three investment portfolios at three confidence levels, i.e. 90%, 95% and 99% for one year time period. Nieppola (2009) explored the accuracy and power of the Backtest and most importantly, which tests are suitable for forthcoming model validation process in the company. Nieppola (2009) found that because of the normality assumption of VaR there are problems in the evaluation of Backtesting outcomes. The empirical evidence showed that VaR measures underestimated the risk, especially for equities and equities option.

In brief decision about VaR model depends on its Backtest result. There are basically two types of Backtest methods used i.e. unconditional and conditional. Unconditional methods count the number of exceptions and compare them with confidence level. If the exceptions are within statistical limits, model is accepted otherwise rejected. Conditional methods test whether the exceptions are independent of each other and there are joint test also which combines the conditional and unconditional methods.

Indian Context: A study in the context of Government of India bonds and representative portfolios of Government of India for banks by Samanta and Nath (2003) found that normal methods generally under-estimate VaR, whereas tail index method is good but slightly conservative and loss functions & tail index method give the least amount of excess loss. Nath and Reddy (2003) also explored the VaR model on daily exchange rate (from March 1 to October 8, 2003) in Indian context. They found that models are not providing accurate VaR and full sample data is over estimating risk. Similarly Tripathi and Gupta (2008) tried to find out the accuracy of Value at Risk model in measuring equity investment in India. They assumed normal distribution on returns of assets and used portfolio- normal method. The analysis is performed on individual 30 securities of Bombay Stock Exchange (BSE) Sensex and two stock indices- BSE Sensex and National Stock Exchange (NSE) Nifty for the period from January 2006 to February 2007. Deb and Banerjee (2009) applied three parametric models and one nonparametric model on weekly returns of a sample of equity mutual fund schemes in India. Backtesting results showed that random walk and the moving average models suffer from downward bias and Exponentially Weighted Moving Average (EWMA) and Historical simulation models are free from that bias.

3. Methodology

In this study we estimated VaR by using variance covariance approach at 95% confidence level on Nifty 50 Securities for the period 2006-07. Results are back tested on data from 2004-05. To measure the accuracy of VaR model, back testing methods[i] used are Kupiec's POF Test (Proportion Of Failure), Kupiec's TUFF Test (Time Until First Failure), Christoffersen's Interval Forecast Test and Joint test.

3.1 Kupiec's Proportion of Failure (POF) Test

Kupiec's POF Test is based on null hypothesis that empirically determined probability matches the given probability i.e.

$$H_0 : p = \hat{p} = \frac{x}{T} \qquad \text{… (1)}$$

Here T is the number of observation, x is number of exceptions, c is confidence level and p is failure rate (1-c). The null hypothesis is that observed failure rate $\hat{p}$ is equal to the failure rate suggested by the confidence level. Where x represents the number of exceptions and n represents the number of back testing points. The Likelihood ratio test statistic is:

$$LR_{POF} = -2\ln\left(\frac{(1-p)^{T-x}\, p^{x}}{\left[1-\frac{x}{T}\right]^{T-x}\left(\frac{x}{T}\right)^{x}}\right) \qquad \text{… (2)}$$

Kupiec's POF test is statistically weak for sample size consistent with current regulatory framework (Nieppola, 2009).

3.2 Kupiec's Time Until First Failure (TUFF) Test

This test is based on similar assumptions as the previous POF test. If we take the exceptions to be binomially distributed, then the probability of an exception is again the inverse probability of the VaR confidence level. For VaR calculated at 99% confidence interval, exceptions can be expected every hundred days. Null hypothesis for this test will be:

$$H_0 : p = \hat{p} = 1/v = 0.01 \quad \dots (3)$$

Where v is the time until first exception occur in sample. The test statistic is a likelihood ratio:

$$LR_{TUFF} = -2\ln\left(\frac{p(1-p)^{v-1}}{\left(\frac{1}{v}\right)\left(1-\frac{1}{v}\right)^{v-1}}\right) \quad \dots (4)$$

Both LR_{POF} Ratio and LR_{TUFF} Ratio is asymptotically Chi-squared distributed with one degree of freedom. If the value of LR_{POF} or LR_{TUFF} statistics exceeds the critical value of the Chi-square distribution for given confidence level, the null hypothesis is rejected.

The Kupiec's tests measures only the number of exceptions but ignores the time dynamics of exceptions. A good Backtesting model should not only satisfy the independence property but also the unconditional coverage property.

3.3 Christoffersen's Interval Forecast Test

Christoffersen's interval forecast test is a conditional test. This test not only covers the violation rate but the independence of exception also. If the model is accurate, then an exception today should not depend on whether or not an exception occurred on the previous day. The test statistic for independence of exception is likelihood–ratio:

$$LR_{ind} = -2\ln\left(\frac{(1-\Pi)^{n_{00}+n_{10}}\,\Pi^{n_{01}+n_{11}}}{(1-\Pi_0)^{n_{00}}\,\Pi_0^{\,n_{01}}(1-\Pi_1)^{n_{10}}\,\Pi_1^{\,n_{11}}}\right) \quad \dots (5)$$

Where, $\Pi_0 = \dfrac{n_{01}}{n_{00}+n_{01}}, \Pi_1 = \dfrac{n_{11}}{n_{10}+n_{11}}\, and, \Pi = \dfrac{n_{01}+n_{11}}{n_{00}+n_{01}+n_{10}+n_{11}}$

Then n_{ij} is defined as the number of days when condition j occurred assuming that condition i occurred on the previous day. The outcome is displayed in 2X2 contingency table as follows:

	$I_{t-1} = 0$	$I_{t-1} = 1$	
$I_t = 0$	n_{00}	n_{10}	$n_{00} + n_{10}$
$I_t = 1$	n_{01}	n_{11}	$n_{01} + n_{11}$
	$n_{00} + n_{01}$	$n_{10} + n_{11}$	N

Where,

n(00) is no VaR violation at time I and on I-1 day.

n(10) is no VaR violation at time I but there is VaR violation on I-1 day

n(01) is VaR violation on time I but no VaR violation at time I-1 day

n(11) is VaR violation at time I followed at other VaR violation at time I-1 day

Then π_i represents the probability of observing an exception conditional on state i on the previous day

Where, $I_t = \begin{Bmatrix} 1 \\ 0 \end{Bmatrix}$ *1 If violation occurs*

0 If no violation occurs

Christoffersen interval forecast test measure the dependence of VaR exceptions also i.e. if model is accurate, then a VaR exception today should not depend on whether or not an exception occurred on previous day. This test doesn't measure all kind of dependence. It just measures the dependence between two exceptions only.

3.4 Joint Test

By combining this independence statistic with Kupiec's POF- test, joint test is estimated that not only measure the correct failure rate but independent of exception also i.e. mixed Kupiec POF-test

$LR_{mix} = LR_{POF} + LR_{ind}$ … (6)

Where

LR_{mix} = Likelihood ratio for mixed Kupiec's POF test

LR_{POF} = Likelihood ratio for Probability of failure

LR_{ind} = Likelihood ratio for Independence of exception

LR_{mix} statistic is Chi-square distributed with n+1 degree of freedom.

3.5 The Basel Framework for Backtesting

Current Basel accord requires bank to calculate VaR for a 10-day time window at 99% confidence level. For Backtesting comparison of last 250 daily 99% VaR estimate is made with corresponding daily trading outcomes (Nieppola, O. 2009). If the bank's VaR model generate zero to four exceptions, it comes under Green Zone;

if five to nine, it is in Yellow Zone; and if there are more than ten exceptions, it is in the Red Zone (Jackson, Maude and David 1998).

4. Empirical Findings

We found that for lognormal distribution VaR calculated at 95% confidence level overestimated the risk except in the case of Punjab National Bank (Refer Table 1). Backtest results showed that Kupiec's POF and TUFF test have rejected the model for 100% of securities evaluated which means number of exception are less than as prescribed by VaR limit. Christoffersen's interval forecast test accepted that in 61% of cases observed, exceptions are occurring independent of each other. Christoffersen's Joint test rejected the lognormal distribution for VaR, showing the exceptions are neither independent of each other nor they are within confidence level used.

Table 1: VaR Statistics at 95% Confidence Level for Log-Normal Distribution

VaR Data = 2007-08 Backtest Data = 2004-06	VaR Figure	Number of observation (T)	Confidence Interval (P= 1-C)	VaR limits	VaR exceptions	Failure Rate
ABB Ltd.	-0.16	773	5%	38.65	00	0.00
ACC Ltd.	-0.05	773	5%	38.65	17	0.02
Ambuja Cements Ltd.	-0.05	773	5%	38.65	18	0.02
Axis Bank Ltd.	-0.07	773	5%	38.65	08	0.01
Bharat Heavy Electricals Ltd.	-0.09	773	5%	38.65	03	0.00
Bharat Petroleum Corporation Ltd.	-0.05	773	5%	38.65	15	0.01
Bharti Airtel Ltd.	-0.05	773	5%	38.65	22	0.02
GAIL (India) Ltd.	-0.07	773	5%	38.65	11	0.01
Grasim Industries Ltd.	-0.05	773	5%	38.65	16	0.02
HCL Technologies Ltd.	-0.09	773	5%	38.65	16	0.02
HDFC Bank Ltd.	-0.05	773	5%	38.65	05	0.00
Hero Honda Motors Ltd.	-0.04	773	5%	38.65	25	0.03
HDFC	-0.06	773	5%	38.65	08	0.01
Hindalco Industries Ltd.	-0.07	773	5%	38.65	20	0.02
I T C Ltd.	-0.04	773	5%	38.65	18	0.02
ICICI Bank Ltd.	-0.07	773	5%	38.65	04	0.00
Infosys Technologies Ltd.	-0.04	773	5%	38.65	15	0.01
Mahindra & Mahindra Ltd.	-0.07	773	5%	38.65	00	0.00
Maruti Suzuki India Ltd.	-0.05	773	5%	38.65	27	0.03
National Aluminium Co. Ltd.	-0.07	773	5%	38.65	11	0.01
Oil & Natural Gas Corporation Ltd.	-0.05	773	5%	38.65	15	0.01
Punjab National Bank	-0.05	773	5%	38.65	43	0.05
Reliance Capital Ltd.	-0.08	773	5%	38.65	09	0.01
Reliance Industries Ltd.	-0.05	773	5%	38.65	09	0.01
Reliance Infrastructure Ltd.	-0.07	773	5%	38.65	10	0.01
State Bank of India	-0.06	773	5%	38.65	08	0.01
Steel Authority of India Ltd	-0.07	773	5%	38.65	20	0.02
Sun Pharmaceutical Industries Ltd.	-0.04	773	5%	38.65	23	0.03
Tata Consultancy Services Ltd.	-0.05	773	5%	38.65	13	0.01
Tata Motors Ltd.	-0.06	773	5%	38.65	15	0.01
Tata Power Co. Ltd.	-0.06	773	5%	38.65	11	0.01
Tata Steel Ltd.	-0.07	773	5%	38.65	12	0.01
Wipro Ltd.	-0.06	773	5%	38.65	08	0.01
L&T	-0.09	773	5%	38.65	05	0.00
Cipla	-0.04	773	5%	38.65	24	0.03
NTPC	-0.05	551	5%	27.55	05	0.00

Table 2: Input data for Backtesting Independence Test at 95% Confidence Level for Log- Normal Distribution

Company	n(00)	n(10)	n(01)	n(11)	π0	π1	Π
ABB Ltd.	n/a	n/a	n/a	n/a	n/a	n/a	n/a
ACC Ltd.	741	15	15	2	0.020	0.118	0.022
Ambuja Cements Ltd.	737	18	18	0	0.024	0.000	0.023
Axis Bank Ltd.	758	07	07	1	0.009	0.125	0.010
Bharat Heavy Electricals Ltd.	768	02	02	1	0.003	0.333	0.004
Bharat Petroleum Corporation Ltd.	744	14	14	1	0.018	0.067	0.019
Bharti Airtel Ltd.	730	21	21	1	0.028	0.045	0.028
GAIL (India) Ltd.	752	10	10	1	0.013	0.091	0.014
Grasim Industries Ltd.	742	15	15	1	0.020	0.063	0.021
HCL Technologies Ltd.	741	16	16	0	0.021	0.000	0.021
HDFC Bank Ltd.	763	05	05	0	0.007	0.000	0.006
Hero Honda Motors Ltd.	725	23	23	2	0.031	0.080	0.032
HDFC	759	06	06	2	0.008	0.250	0.010
Hindalco Industries Ltd.	733	20	20	0	0.027	0.000	0.026
I T C Ltd.	739	16	16	2	0.021	0.111	0.023
ICICI Bank Ltd.	766	03	03	1	0.004	0.250	0.005
Infosys Technologies Ltd.	744	14	14	1	0.018	0.067	0.019
Mahindra & Mahindra Ltd.	773	00	00	0	0.000	0.000	0.000
Maruti Suzuki India Ltd.	720	26	26	1	0.035	0.037	0.035
National Aluminium Co. Ltd.	753	09	09	2	0.012	0.182	0.014
Oil & Natural Gas Corporation Ltd.	744	14	14	1	0.018	0.067	0.019
Punjab National Bank	694	36	36	7	0.049	0.163	0.056
Reliance Capital Ltd.	757	07	07	2	0.009	0.222	0.012
Reliance Industries Ltd.	756	08	08	1	0.010	0.111	0.012
Reliance Infrastructure Ltd.	753	10	10	0	0.013	0.000	0.013
State Bank of India	758	07	07	1	0.009	0.125	0.010
Steel Authority of India Ltd	737	16	16	4	0.021	0.200	0.026
Sun Pharmaceutical Industries Ltd.	730	20	20	3	0.027	0.130	0.030
Tata Consultancy Services Ltd.	750	10	10	3	0.013	0.231	0.017
Tata Motors Ltd.	745	13	13	2	0.017	0.133	0.019
Tata Power Co. Ltd.	752	10	10	1	0.013	0.091	0.014
Tata Steel Ltd.	751	10	10	2	0.013	0.167	0.016
Wipro Ltd.	757	08	08	0	0.010	0.000	0.010
L&T	763	05	05	0	0.007	0.000	0.006
Cipla	729	20	20	4	0.027	0.167	0.031
NTPC	543	05	05	0	0.009	0.000	0.009

Table 3: Backtesting Results for Lognormal Distribution at 95% Confidence Level

	Unconditional Coverage				Conditional Coverage			
Company	**Kupiec's POF Test**	**Critical value = 3.84**	**Kupiec's TUFF Test**	**Critical value = 3.84**	**Christoffersen's Interval Forecast Test** LR(ind)	**Critical value = 3.84**	LR(cc) = LR(pof)+LR(ind)	**Critical value = 5.99**
ABB Ltd.	n/a	n/a	n/a		n/a		n/a	n/a
ACC Ltd.	16.00	Reject	6.77	Reject	3.78	**Accept**	19.79	Reject
Ambuja Cements Ltd.	14.36	Reject	7.15	Reject	n/a	n/a	n/a	n/a
Axis Bank Ltd.	37.36	Reject	8.18	Reject	3.37	**Accept**	40.73	Reject
Bharat Heavy Electricals	57.66	Reject	15.79	Reject	7.67	Reject	65.33	Reject
BPCL	19.65	Reject	8.18	Reject	1.12	Accept	20.77	Reject
Bharti Airtel Ltd.	8.88	Reject	7.73	Reject	0.20	**Accept**	9.08	Reject
GAIL (India) Ltd.	28.68	Reject	6.17	Reject	2.15	**Accept**	30.84	Reject
Grasim Industries Ltd.	17.76	Reject	14.87	Reject	0.93	**Accept**	18.7	Reject
HCL Technologies Ltd.	17.76	Reject	7.50	Reject	n/a	n/a	n/a	n/a
HDFC Bank Ltd.	48.36	Reject	17.85	Reject	n/a	n/a	n/a	n/a
Hero Honda Motors Ltd.	5.76	Reject	6.63	Reject	1.36	**Accept**	7.13	Reject
HDFC	37.36	Reject	15.48	Reject	9.92	Reject	47.28	Reject
Hindalco Industries Ltd.	11.41	Reject	7.50	Reject	n/a	n/a	n/a	n/a
I T C Ltd.	14.36	Reject	7.39	Reject	3.38	**Accept**	17.75	Reject
ICICI Bank Ltd.	52.76	Reject	8.83	Reject	6.32	Reject	59.08	Reject
Infosys Technologies Ltd.	19.65	Reject	7.27	Reject	1.12	**Accept**	20.77	Reject
Mahindra & Mahindra Ltd.	n/a	n/a	n/a	n/a	n/a	n/a	n/a	n/a
Maruti Suzuki India Ltd.	4.11	Reject	6.77	Reject	0.00	**Accept**	4.11	Reject
National Aluminium Co.	28.68	Reject	15.79	Reject	7.17	Reject	35.85	Reject
Oil & Natural Gas Corp	19.65	Reject	5.14	Reject	1.12	**Accept**	20.77	Reject
Punjab National Bank	0.49	**Accept**	6.77	Reject	6.93	Reject	7.43	Reject
Reliance Capital Ltd.	34.25	Reject	7.15	Reject	8.88	Reject	43.13	Reject
Reliance Industries Ltd.	34.25	Reject	15.48	Reject	2.90	**Accept**	37.15	Reject
Reliance Infrastructure Ltd.	31.36	Reject	5.50	Reject	n/a	n/a	n/a	n/a
State Bank of India	37.36	Reject	15.79	Reject	3.37	**Accept**	40.73	Reject
Steel Authority of India Ltd	11.41	Reject	7.15	Reject	10.73	Reject	22.15	Reject
Sun Pharma	7.75	Reject	9.46	Reject	4.74	Reject	12.49	Reject
Tata Consultancy Services	23.85	Reject	15.48	Reject	11.47	Reject	35.32	Reject
Tata Motors Ltd.	19.65	Reject	7.15	Reject	4.70	Reject	24.36	Reject
Tata Power Co. Ltd.	28.68	Reject	7.15	Reject	2.15	**Accept**	30.84	Reject
Tata Steel Ltd.	26.18	Reject	11.25	Reject	6.45	Reject	32.64	Reject
Wipro Ltd.	37.36	Reject	15.90	Reject	n/a	n/a	n/a	n/a
L&T	48.36	Reject	9.04	Reject	n/a	n/a	n/a	n/a
Cipla	6.71	Reject	n/a	n/a	7.90	Reject	14.62	Reject
NTPC	29.16	Reject	46.81	Reject	n/a	n/a	n/a	n/a

5. Discussions

Table 3 compiled the output for four methods. For Kupiec's POF test, decision is based on three variables i.e. total number of observations (T), failure rate (p) and actual number of VaR violations. For present case, number of observation are 773 and confidence level is 5%. Total number of VaR violation estimates is 38.65 (5% of 773). Estimated VaR violations are then compared with actual VaR violations to find whether VaR is underestimating risk or overestimating risk. It can rarely be the case when actual numbers of VaR violations are equal to estimated number of VaR violations. To check whether difference is statistically significant, Likelihood Ratio is calculated (Refer equation 2) which is Chi-squared distributed with one degree of freedom. The drawback of this method is it doesn't capture any type of dependence in VaR violations. This method has low power in differentiating good VaR model from bad VaR model. For Kupiec's TUFF test, exceptions are assumed to be binomially distributed, where the probability of the exception is inverse probability of the VaR confidence level. For VaR calculated at 95% confidence level, exception can be expected every 96^{th} day. For this method 'v' is calculated i.e. time it takes for the first exception to occur. The test criterion is Likelihood ratio (Refer equation 4) which is Chi-squared distributed with one degree of freedom. This method also has low power of differentiating good VaR model from bad VaR model.

For Christoffersen's interval forecast test, decision criteria is indicator variable that gets a value of 1 if VaR violations occur and value of 0 if there is no VaR violations. 2x2 contingency matrix is prepared compiling four values i.e. first, when no VaR violation is followed by no VaR violation 'n (00)'; Second, when VaR violation is followed by no VaR violation 'n(10)'; Third when no VaR violation is followed by VaR violation 'n(01)'; Fourth, when VaR violation is followed by VaR violation 'n(11)'. The output of 2x2 matrixes is summarised in Table 3 of this paper. The test criteria are Likelihood ratio (Refer equation 5) which is Chi-squared distributed with one degree of freedom. Christoffersen's test has low power in capturing dependence because it captures only one type of dependence i.e. only in two successive observations. To study the coverage and independence both Christoffersen's joint test is applied. Joint test has a critical value with two degree of freedom because it combines Christoffersen's Interval forecast test and Kupiec's POF test (Refer equation 6).

While measuring risk on the basis of VaR value, it should be considered that on what assumptions this VaR value is derived, its Backtest results and Backtest method used also should be considered. This paper empirically shows the inconsistency across methods and emphasizes the need to improve the existing Backtest methods. Our empirical findings suggest that at present these Backtest methods are not very efficient and have low statistical power in differentiating good VaR model from bad VaR model. In conclusion we want to mention that this study is not exhaustive in nature rather this paper emphasized the need to improve the existing Backtesting methods.

Endnotes

i Definition of Back testing methods is taken from Haas (2001)

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