Measuring the Effectiveness of VaR in Indian Stock Market

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Abstract *- Given the growing need for managing financial risks, risk prediction which is critical for the success of any business has now gained more importance, especially in the financial markets. The financial managers, the actuaries, the stock brokers and the regulatory authority such as SEBI have one common goal is to reduce risk of their investments. To understand and mitigate these risks several approaches were suggested one among them is Value at Risk method which answers the question of "What is the most I will lose if I invest in particular security or an asset?"*

This study has been taken up to estimate the risk involved in the Indian Stock Market by taking the daily data from 1st April 2007 to 31st March 2017. This study employs various Value at Risk methods such as Variance-Covariance Method, Monte Carlo Simulation using Brownian Motion, Filtered Historical Simulation, Generalised extreme value method, t Copula, Exponential Weighted Moving Average, GARCH and Hybrid models.

To assess the risk in NIFTY 50, we have selected the sectoral indices of Nifty Bank, Nifty IT, Nifty Private Bank, Nifty FMCG and Nifty Financial Services. We have calculated the risk for all these sectorial indices at 95% and 99% confidence level by using aforementioned methods. After evaluating these models, it has been observed that the hybrid method with GJR GARCH–EVT-t Copula model, performed better when compared to other methods considered in this study. The Empirical results clearly validates that the maximum loss and gain of GJR GARCH-EVT-t Copula based approach which outperforms traditional VaR.

Keywords — *VaR, GARCH, EVT, Copula*

I. INTRODUCTION

Financial markets play a crucial role in the economic development of any country through their contribution in the form of investments. However, the increasing financial fragility in financial markets have necessitated the use of derivative products in financial world. Several risk measurement tools have been suggested for mitigating growing financial risks. A uniform risk measurement methodology called value-at risk (VaR) has received a great deal of attention since 1994, when JP Morgan adopted this as their risk metric. It can be defined as the maximum potential loss of a specific portfolio for a given time horizon with certain level of confidence (Joion2007). Increasing availability of the financial data and rapid advances in computer technology has led various VaR models to be applicable for the risk management profession.

Over the past few decades, vast literature on VaR methodology has evolved. Existing VaR models can be classified into three main classes viz., parametric models which make assumptions about the return distribution before computing VaR, then nonparametric methods relies on the empirical return distribution, and semi-parametric techniques that combine the features of both parametric and non-parametric approaches.

Several studies have been conducted to estimate the risk by various VaR methodologies. Amongst few early studies are Allen (1994) evaluated performance of traditional VaR methods, historical simulation (HS) and variance-covariance. Zangari (1996) has investigated the VaR models under non-normality assumption. Jamshidian and Zhu (1996, 1997) studied the efficiency of Monte Carlo methods in comparison with variance-covariance approach. However, all these methods are based on the assumption of constant volatility i.e. homoscedasticity.

Recent approaches to quantification of market risk using econometric evaluation, Risk Metrics methodology, quantile estimation and estimation based on extreme value theory are presented in many papers. Econometric evaluation is derived from conditional heteroscedasticity of volatility using GARCH models, while Risk Metrics methodology uses integrated GARCH (IGARCH) model. To model the volatility in financial series Auto Regressive Conditional Heteroscedasticity (ARCH) model was introduced by Engel (1982) and later generalized by Bollereslv(1986) and is known as Generalized Auto Regressive Conditional Heteroscedasticity (GARCH) model. By using these models many researchers estimated the risk under the VaR framework for example, Da Silva, Beatriz, and de Melo Mendes (2003), Gencay and Selcuk (2004), Bao, Lee, and Saltoglu (2006), Žiković (2007) and Bučevska (2013), among others, used GARCH models in market risk evaluation.

In order to improve the estimation of extreme events Diebold, Schuerman, and Stroughair (1998) suggest the use of Extreme Value Theory (EVT). Gencay and Selcuk (2004) demonstrated that EVT-based VaR estimates are more accurate at higher Quantiles. Samanta.G. P and Thakur.S.K (2006) found that tail index based methods provide relatively more conservative VaR estimates and have a greater chance of performing better.

One of the key elements in portfolio VaR estimation is the dependence structure between financial assets in the portfolio. Copulas are a very general tool for describing dependence structures and have been successfully applied in many cases. Palaro & Hotta (2006) displayed a few concepts and properties of Copula functions and an application of the Copula theory in the estimation of VaR of a portfolio made by NASDAQ and S&P500 stock indices. Staudt, FCAS & MAAA (2010) discussed few modelling considerations when working with Copulas from the point of view of adequately representing the behaviour in the extreme tails of both the marginal and joint distributions.

Recently researchers have estimated the risk by employing the combination of VaR methodologies to accommodate all the charactecterstics of the data. For example, Huang, Chein & Wang (2011) applied the portfolio approach of VaR on G7 exchange rates by combining a GJR GARCH-EVT-Copula based method. Yi, Y., Feng, X., & Huang (2014) proposed a method to estimate extreme conditional quantiles by combining quantile GARCH model of Xiao & Koeniker (2009) and Extreme Value theory approach. GJR GARCH-EVT-Copula and filtered historical simulation were pitted against each other by Gondje-Dacka & Yang (2014) to fill the foreign exchange portfolio.

Unlike the financial markets of developed countries, the emerging financial markets are characterized with insufficient liquidity, the small scale of trading and asymmetrical and low number of trading days with certain securities (Andjelić, Djaković and Radišić, 2010). The emerging stock markets as relatively young markets and are not sufficiently developed to identify all information which affects the stock prices and therefore, does not respond quickly to the publicly disclosed information (Benaković and Posedel, 2010).Few studies have conducted to estimate the VaR in different emerging markets for example, Tae- Hw y Lee and BurakSaltoglu (2001) Selcuk, Gencay, R., and Fatuk. (2004),Andelic,G,. Dakovic,V., and Radisic,S, (2010), Nozari,M.,etal.(2010),JulijaCerovic et.al(2015) Su, J. (2015),Raghavan, R.R ., Rao and Guptha (2017) among others.

There is a general opinion in the empirical literature that there is no universal model giving the best estimation and forecast of VaR. Numerous papers observing the application of different approaches in developed financial markets confirm this, e.g. – Manganelli and Engle (2001), Christoffersen, et al. (2001), Angelidis, et al. (2004), Wong, et al. (2002), Alexander and Leigh (1997), Harmantzis, et al. (2006), Embrechts, et al. (1998), McNeil, et al. (2005), Guermat and Harris (2002).

On the other hand, there are very few studies such as Samanta.G. P and Thakur.S.K (2006)Tripathi, V., & Aggarwal, S. (2007) to compare the various VaR models in developing financial markets especially to the Indian stock market. Until recently Indian stock markets have received relatively little attention but now there is considerable interest due to the country's economic growth as well as stock market development and potential opportunities for investments. In this context, we have taken up this study with an objective to find a suitable method to measure VaR in Indian financial markets by comparing various existing methods.

The rest of the paper is organized as follows. In section II we describe the data and methodology used in this study. The empirical results are presented in section III and section IV concludes with summary and conclusions.

II. DATA AND METHODOLOGY

Data

Source

Data has been taken from five of the NIFTY 50 Sectoral Indices of the NSE namely:

- Nifty Bank.
- Nifty IT.
- Nifty Private Bank.
- Nifty FMCG.
- Nifty Financial Services.

Duration

01st April 2007 to 31st March 2017 - 10 year data of daily closing prices.

Formula

Returns are calculated as follows:

$$r_t = ln_e(P_t/P_{t-1})$$

Where r_t = returns from the portfolio, P_t and P_{t-1} are the closing prices of the portfolio at t^{th} and $(t-1)^{th}$ period.

Measurement of Value at Risk

The study considered the following models to validate VaR estimates:

a) Monte Carlo Simulation using Brownian Motion:
b) GJR GARCH-EVT-Copula Model
c) Filtered Historical Simulation
d) Copula Simulation
e) Generalised Extreme Value approach
f) Other Tests: The following tests are performed on VaR:
   - *Joint test of Kupiec test and Peter Christoffersen*:

The test statistic used is mentioned below

$$LR(joint) = LR(coverage) + LR(independence) \sim \chi_2^2$$

- *VaR Violation Ratio:* Condition used

$$\eta_t = \begin{cases} 1, if\ y_t \leq -VaR_t \\ 0, if\ y_t > -VaR_t \end{cases}$$

- *Berkowitz test:* Density function used for VaR Duration test is mentioned below:

$f(x)=\lambda\ e^{-\lambda x}$

III. EMPIRICAL RESULTS

- The summary statistics of the data shows that:
  - Average returns from top 5 Nifty Sectoral indices are positive.
  - The value of Kurtosis and Skewness shows that it is not symmetrically distributed and is leptokurtic.
  - The excessive Kurtosis confirms that almost all Nifty 50 sectoral indices returns have fat tails and are non-normally distributed.
  - Time series data of all the Nifty Sectoral Indices are stationary.

- The results of GARCH (1,1) with normal and EGARCH (1,1) model with student-t & generalized error distribution indicates that, when the results are normally distributed, they are ineffective and inaccurate for estimating the daily prices of Nifty 50 Sectoral Indices.

- In the case of Exponential Weighted Moving Average with alpha 0.5 and 0.1 give the lowest value of RMSE than the 5-term moving average.
- Minimum AIC indicated a closer fit to the correlation structure of historical data in the case of Gaussian Copula.

Estimation of VaR for the following methods is shown in Appendix Tables 1.1 to 1.5.

IV. CONCLUSIONS

In this analysis, the effectiveness of the VaR is evaluated based on various methodologies:

- From Table 1.5 above, we can state that:
  - CEVT-Copula based approach given the estimated optimal degree of freedom as 8.4108 performs best followed by t Copula.
  - Generalized Extreme Value approach and Filtered Historical Simulation overestimate the portfolio VaR.
- Monte Carlo simulation method, Gaussian Copula, Exponential Weighted Moving Average Approach, GARCH (1,1)-norm, GARCH (1,1)-std, GARCH (1,1)-ged, E-GARCH (1,1)-ged, E-GARCH (1,1)-std were found not suitable to evaluate the effectiveness of VaR in case of chosen Nifty Sectoral Indices.
- Variance-Covariance approach, Historical Simulation and the Monte-Carlo simulation using Brownian motion were suitable at both 99% and 95 % confidence levels for Nifty 50 Sectoral Indices.
- Conclusion from VaR violation ratio indicates that GJR GARCH model with the Copula-EVT based approach, t Copula, Generalised Extreme Value Approach and Filtered Historical Simulation are reliable for forecasting the risk relative to others mentioned above.
- It has been observed that the hybrid method with GJR GARCH–EVT-t Copula model, performed better when compared to other methods considered in this study. The Empirical results clearly validates that the maximum loss and gain of GJR GARCH-EVT-t Copula based approach performs best followed by t copula which outperforms traditional VaR.

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APPENDIX

Tables 1.1 to 1.5

Estimation of VaR for the following methods is shown below:

Table 1.1- Estimated VaR for Nifty 50 Sectoral Indices (2007-2017)

VaR Technique (using 2478 days of observations, Unless Stated Otherwise	99% VaR	95% VaR
Evt-t Copula – GjrGarch	-11.73%	-6.73%
Filtered Historical simulation	-9.94%	-5.55%
t-copula	-4.32%	-4.21%
Generalised Extreme Value Distribution	-12.41%	-7.29%
Monte Carlo Simulation	-4.45%	-2.23%
Gaussian Coupula	-3.57%	-3.55%
Exponential Weighted Moving Average	-2.26%	-1.41%
Garch(1,1)-norm	-2.31%	-1.44%
Garch(1,1)-Std	-2.25%	-1.40%
Garch(1,1)-ged	-2.27%	-1.41%
Variance-Covariance approach	-3.41%	-2.41%
E-Garch(1,1)-ged	-3.08%	-1.92%
E-Garch(1,1)-std	-3.06%	-1.91%
Historical Simulation	-4.20%	-2.26%
Monte Carlo simulation using Brownian Motion	(-2.7% to -2.9%)	(-1.75% to -1.9%)

Table 1.2-VaR test results for various VaR Technique at 99%,95% Confidence levels for Nifty Sectoral Indices

	VaR test results for various VaR Technique at 99%,95% Confidence Levels													
	alpha	EE	AE	uc.Ho	uc.LRstat	uc.critical	uc.LRp	uc.Decision	cc.HO	cc.Lrstat	cc.critical	cc.LRp	cc.Decision	VR
Exponential-Weighted Moving Average	0.01	19	10	**Correct Exceedances**	5.967039	6.634897	0.0145757	Fail to Reject H0	Correct Exceedances & Independent	NaN	9.21034	NaN	NA	**0.52631579**
	0.05	98	42	**Correct Exceedances**	43.5649	3.841459	4.101E-11	"Reject H0"	Correct Exceedances & Independent	NaN	5.991465	NaN	NA	**0.42857143**
Garch(1,1)-norm,std,ged	0.01	19	84	**Correct Exceedances**	116.6419	6.634897	0	"Reject H0"	Correct Exceedances & Independent	119.5141	9.21034	0	Reject H0	**4.42105263**
	0.05	98	181	**Correct Exceedances**	58.22884	3.841459	2.331E-14	"Reject H0"	Correct Exceedances & Independent	62.85464	5.991465	2.24E-14	Reject H0	**1.84693878**
Variance-Covariance Approach	0.01	19	30	**Correct Exceedances**	4.604995	6.634897	3.19E-02	Fail to Reject H0	Correct Exceedances & Independent	5.109716	9.21034	0.07770326	Fail to Reject H0	**1.57894737**
	0.05	98	119	**Correct Exceedances**	4.049165	6.634897	4.42E-02	Fail to Reject H0	Correct Exceedances & Independent	7.196783	9.21034	0.02736771	Fail to Reject H0	**1.21428571**
E-Garch(1,1)-ged	0.01	19	50	**Correct Exceedances**	32.76395	6.634897	1.04E-08	"Reject H0"	Correct Exceedances & Independent	NaN	9.21034	NaN	NA	**2.63157895**
	0.05	98	50	**Correct Exceedances**	30.85301	3.841459	2.78E-08	"Reject H0"	Correct Exceedances & Independent	NaN	5.991465	NaN	NA	**0.51020408**
E-Garch(1,1)-std	0.01	19	54	**Correct Exceedances**	40.62728	6.634897	1.84E-10	"Reject H0"	Correct Exceedances & Independent	NaN	9.21034	NaN	NA	**2.84210526**
	0.05	98	54	**Correct Exceedances**	25.51089	3.841459	4.40E-07	"Reject H0"	Correct Exceedances & Independent	NaN	5.991465	NaN	NA	**0.55102041**
Historical Simulation	0.01	19	13	**Correct Exceedances**	2.670676	6.634897	0.1022126	"Fail to Reject H0"	Correct Exceedances & Independent	NaN	9.21034	NaN	NA	**0.68421053**
	0.05	98	72	**Correct Exceedances**	8.47145	3.841459	0.0036076	"Reject H0"	Correct Exceedances & Independent	11.98952	5.991465	0.002491777	"Reject H0"	**0.73469388**
Monte-Carlo Simulation using Brownian Motion	0.01	19	20	**Correct Exceedances**	0.002462612	6.634897	9.60E-01	Fail to Reject H0	Correct Exceedances & Independent	0.4112587	9.21034	0.8141348	Fail to Reject H0	**1.05263158**
	0.05	98	100	**Correct Exceedances**	0.01283352	6.634897	9.10E-01	Fail to Reject H0	Correct Exceedances & Independent	2.841788	9.21034	0.241498	Fail to Reject H0	**1.02040816**

Table 1.3- VaR test results for various VaR Technique at 99%,95% Confidence levels for Nifty Sectoral Indices

VaR test results for various VaR Technique at 99%,95% Confidence Levels

	alpha	EE	AE	uc.Ho	uc.LRstat	uc.critical	uc.LRp	uc.Decision	cc.HO	cc.Lrstat	cc.critical	cc.LRp	cc.Decision	VR
Evt-Copula-GjrGarch	0.01	19	0	Correct Exceedances	NaN	6.634897	NaN	NA	Correct Exceedances & Independent	NaN	9.21034	NaN	NA	0
	0.05	98	0	Correct Exceedances	NaN	3.841459	NaN	NA	Correct Exceedances & Independent	NaN	5.991465	NaN	NA	0
Filtered Historical Simulation	0.01	19	1	Correct Exceedances	31.77019	6.634897	1.74E-08	"Reject H0"	Correct Exceedances & Independent	NaN	9.21034	NaN	NA	0.05263158
	0.05	98	8	Correct Exceedances	145.8933	3.841459	0	"Reject H0"	Correct Exceedances & Independent	NaN	5.991465	NaN	NA	0.08163265
tCopula	0.01	19	0	Correct Exceedances	NaN	6.634897	NaN	NA	Correct Exceedances & Independent	NaN	9.21034	NaN	NA	0
	0.05	98	1	Correct Exceedances	191.626	3.841459	0	"Reject H0"	Correct Exceedances & Independent	NaN	5.991465	NaN	NA	0.01020408
Generalised Extreme Value Distribution	0.01	19	0	Correct Exceedances	NaN	6.634897	NaN	NA	Correct Exceedances & Independent	NaN	9.21034	NaN	NA	0
	0.05	98	0	Correct Exceedances	NaN	3.841459	NaN	"Reject H0"	Correct Exceedances & Independent	NaN	5.991465	NaN	NA	0
Monte-Carlo Simulation	0.01	19	7	Correct Exceedances	11.10057	6.634897	0.000863	"Reject H0"	Correct Exceedances & Independent	NaN	9.21034	NaN	NA	0.36842105
	0.05	98	45	Correct Exceedances	38.46128	3.841459	5.59E-10	"Reject H0"	Correct Exceedances & Independent	43.82509	5.991465	3.04E-10	"Reject H0"	0.45918367
Gaussian Copula	0.01	19	4	Correct Exceedances	18.8998	6.634897	1.38E-05	"Reject H0"	Correct Exceedances & Independent	NaN	9.21034	NaN	NA	0.21052632
	0.05	98	4	Correct Exceedances	168.8515	3.841459	0	"Reject H0"	Correct Exceedances & Independent	NaN	5.991465	NaN	NA	0.04081633

Table 1.4- VaR Duration test for various VaR technique at 99%,95% Confidence level for Nifty Sectoral Indices

	VaR Duration Test for various VaR technique at 99%, 95% Confidence level						
Column 1	alpha	b	uLL	rLL	LRp	H0	Decision
EWMA	0.01	0.7655983	-56.99677	-57.53355	0.3001399	Duration Between Exceedances have no memory (Weibull b=1 = Exponential)	Fail to Reject H0
	0.05	0.7857101	-197.4988	-199.927	0.02754354	Duration Between Exceedances have no memory (Weibull b=1 = Exponential)	Reject H0
Filtered Historical Simulation	0.01	2	-1.00E+10	-1.00E+10	1	Duration Between Exceedances have no memory (Weibull b=1 = Exponential)	Fail to Reject H0
	0.05	0.8261413	-46.32153	-46.50752	0.5419269	Duration Between Exceedances have no memory (Weibull b=1 = Exponential)	Fail to Reject H0
Gaussian Copula	0.01	0.001	-39.81745	-22.47369	1	Duration Between Exceedances have no memory (Weibull b=1 = Exponential)	Fail to Reject H0
	0.05	0.8526419	-22.41613	-22.47369	0.7343969	Duration Between Exceedances have no memory (Weibull b=1 = Exponential)	Fail to Reject H0
GEV Distribution	0.01	2	-1.00E+10	-1.00E+10	1	Duration Between Exceedances have no memory (Weibull b=1 = Exponential)	Fail to Reject H0
	0.05	2	-1.00E+10	-1.00E+10	1	Duration Between Exceedances have no memory (Weibull b=1 = Exponential)	Fail to Reject H0
GjrGarch-Evt-Copula	0.01	2	-1.00E+10	-1.00E+10	1	Duration Between Exceedances have no memory (Weibull b=1 = Exponential)	Fail to Reject H0
	0.05	2	-1.00E+10	-1.00E+10	1	Duration Between Exceedances have no memory (Weibull b=1 = Exponential)	Fail to Reject H0
Historical Simulation	0.01	0.001	-135.9654	-73.25922	1	Duration Between Exceedances have no memory (Weibull b=1 = Exponential)	Fail to Reject H0
	0.05	0.7528866	-300.4644	-307.2285	0.000235016	Duration Between Exceedances have no memory (Weibull b=1 = Exponential)	Reject H0
Monte Carlo Simulation	0.01	0.001	-61.87365	-34.90202	1	Duration Between Exceedances have no memory (Weibull b=1 = Exponential)	Fail to Reject H0
	0.05	0.6904513	-218.9364	-226.4947	0.000101063	Duration Between Exceedances have no memory (Weibull b=1 = Exponential)	"Reject H0"
t-copula	0.01	2	-1.00E+10	-1.00E+10	1	Duration Between Exceedances have no memory (Weibull b=1 = Exponential)	Fail to Reject H0
	0.05	2	-1.00E+10	-1.00E+10	1	Duration Between Exceedances have no memory (Weibull b=1 = Exponential)	Fail to Reject H0

Benchmark Model Characteristics:

a) VaR Exceedances needs to be correct according to unconditional coverage test results
b) VaR Exceedances must be correct as well as independent of previous exceedances according to the conditional coverage test.
c) The critical values for the VaR exceedances test for the confidence levels 99% and 95% are given as:Unconditional coverage test- (6.634897, 3.841459); Conditional coverage test-(9.21034, 5.991465)
d) VaR violation ratio should be equal to value one. But, this may be difficult in reality. The range for a good violation ratio can be between 0.8 and 1.2.

Table 1.5- Value-at-Risk Calculations for the various models.

	Value at Risk for the different Models			
Models	**CEVT+t(8.4108) copula**	**Filtered Historical Simulation**	**t Copula**	**Generalised Extreme Value Method**
Max Loss	27.33%	30.86%	29.86%	35.81%
Max Gain	17.69%	15.18%	16.20%	21.69%
95% VaR	-6.73%	-5.55%	-4.21%	-7.29%
99% VaR	-11.73%	-9.94%	-4.32%	-12.41%