A Bootstrapped Historical Simulation Value at Risk Approach to S & P CNX Nifty [¨]

Debashis Dutta [♠]

&

Basabi Bhattacharya [§]

[¨] This is a preliminary version.

[♠] Research Scholar, Department of Economics, Jadavpur University, Kolkata, Telephone : (033)-65885601(R), 9920096400 (M) .Corresponding Author.
E-mail: debashis_dutta001@yahoo.com, dutt.debashis@gmail.com

[♣] Professor, Department of Economics, Jadavpur University, Kolkata–700032, India, Telephone : (033)-2422-4877 (R), (033)-2 414-6328 (O), (033)-2414-6328 (Fax –O), 9830337210(M),
E-mail: basabi54@yahoo.com , basabi54@gmail.com

A Bootstrapped Historical Simulation Value at Risk Approach to S & P CNX Nifty

Abstract

This paper proposes to evaluate the predictive performance of Value at Risk (VaR) methods, empirically applied to S&P CNX NIFTY, Index of National Stock Exchange of India. The traditional Value at Risk method assumes linearity as a distributional assumption, which entails high amount of model risk. The Value at Risk model based on historical simulation is a good candidate for the financial returns series, as it does not take any distributional assumption. The Bootstrapped Historical simulation VaR is found to be a better choice as it keeps the true distributional properties along with tackling the scarcity of adequate data point by bootstrapping, which is a necessity for historical simulation.

JEL classification: C51, G28

Keywords: Value at Risk, VaR, Bootstrapped Historical Simulation, Historical Simulation, S & P CNX Nifty.

A Bootstrapped Historical Simulation Value at Risk Approach to S & P CNX Nifty

I. Motivation:

The selection of appropriate Value at Risk methodology is a challenge for both researchers as well as practitioners. This has grown in its importance in wake of necessity for market risk capital charge computation for Internal Model approach of Basel II accord as well as the gradual global migration to Value at Risk based limit management system for prudent risk management purpose. The challenges take formidable shapes due to non-linearity of the data set and also non-availability of larger data set. The Historical Simulation Value at Risk can take care of the non linearity of the data set, as it does not take any distribution assumption like Variance Covariance method where underlying assumptions is that the data set follows a linear distributions. But conventional Historical Simulation method requires 3 to 5 years of data or more. The Bootstrapped Historical Simulation takes care of the non-availability of large data set, by bootstrapping, while retains the main characteristics of the true distribution. As most of the portfolio managers benchmark their portfolio with a reference index like S & P CNX Nifty, our study takes S & P CNX Nifty as data set. We applied various types of Value at Risk techniques along with conventional Historical Simulation Value at Risk method and also Bootstrapped Historical Value at Risk method. Our study focuses largely on their relative performance.

II. Literature Survey:

As Value at Risk has long been a central focus of risk measurement and management, there has been a huge array of literature. We have referred a few major studies with its appropriateness with our present study. Amongst earlier studies, Crnkovic and Drachman[1] (1995) developed a metric and compared relative performance comparison between standard variance-covariance method and historical simulation approach. Studies by Schinassi[2](1999) dwell on dependency of VaR models on historical relationships between price movements in different markets and their trend to break down during times of stress and turbulence in event of structural breaks in relationships across markets.

In the Indian context, some remarkable researches have been carried out on VaR. Srinivasan, Shah, Ganti and Shah[3] (2000) pointed that the computational cost involved as one of the drawbacks of the method and proposed the computational geometry techniques. Sarma, Thomas and Shah[4] (2000) evaluated performance of a few alternative VaR models, using India's Nifty stock market index as a case study and adopted a bi-direction approach i.e., statistical model selection and model selection based on a loss function. Dharba[5] (1999) presented a new method for computing the VaR for a set of fixed- income securities based on extreme value theory that models the tail

---

[1] Crnkovic, C. and Drachman, J., 1997, "Quality Control in VaR: Understanding and Applying Value-at-Risk", Risk Publications, ISBN 189933226X.
[2] Schinassi, G. (1999), "Systemic Aspects of Recent Turbulence in Mature Markets", Finance and Development, March, 30-33, IMF, Washington.
[3] Srinivasan, Ashok ; Shah, Viral; Ganti, Phanindra V. R. ; Shah, Ajay ; (2000). Application of Range Searching to Fast Financial Risk Estimation: January, pages 16.
[4] Sarma, M, Susan Thomas and Ajay Shah (2003), "Selection of Value-at-Risk Models", Journal of Forecasting, 22(4), pp. 337-358.
[5] Dharba, Gangadhar(2002); Value-at-Risk for Fixed Income portfolios - A comparison of alternative Models ; Technical Paper , National Stock Exchange, India, www.nse-india.com

probabilities directly without making any assumption about the distribution of entire return process. Nath & Reddy[6] (2003) worked on foreign exchange market in India and studied various VaR methods using the Rupee-Dollar exchange rate data to understand which method is best suited for Indian system. Varma[7] (1999) empirically tested of different risk management models in the Value at Risk (VaR) framework in the Indian stock market with special emphasis on EWMA model and GARCH-GED specification. Samanta & Nath[8] (2003) studied three categories of VaR methods, viz., Variance- Covariance (Normal) methods including Risk-Metric, Historical Simulation (HS) and Tail-Index Based approach. Raina & Mukhopadhyay[9] (2004) found out optimal allocation of a unit capital between the portfolio elements so as to maximize VaR. The algorithm has been validated using a three-asset portfolio example. Samanta G.P. and Thakur, S.K.[10] (2006) assess the accuracy of VaR estimates obtained through the application of tail-index. The database consists of daily observations on two stock price indices. BSE Sensex and BSE 100 from 1999 to 2005. Results show that tail index based methods provide relatively more conservative VaR estimates and have greater chances of passing through the regulatory backtesting. Among

---

[6] Nath, Golaka ; Reddy, Y. V. (2003). Value at Risk: Issues and Implementation in Forex Market in India : November, pages 26 ; www.nse-india.com.

[7] Varma, J. R.(1999) ; Value at Risk Models in Indian Stock Market; Indian Institute of Management, 1999. Working Paper no- 99-07-05, Indian Institute of Management,

[8] Samanta, G. P. and Golaka C. Nath (2003), "Selecting Value-at-Risk Models for Government of India Fixed Income Securities", International Conference on Business & Finance, December 15-16, 2003 at the ICFAI University, Hyderabad, India, Co-Sponsored by the Philadelphia University, USA.

[9] Raina, Ajoy and Mukhopadhyay, C (2004), "Optimizing a Portfolio of Equities, Equity Futures and Equity European Options by Minimising Value at Risk – A simulated Annealing Framework", ICFAI Journal of Finance, May 2004, Vol 10, No. 5.

[10] Samata, G.P. and Thakur, S.K., "On Estimating Value at Risk Using Tail Index: Application to Indian Stock Market", ICFAI Journal of Applied Finance, Vol 12, No. 6, June 2006.

a plethora of studies only broad contours of related literature are presented here.

III. Methodology and Data sources:

Methodology

In our study we have chosen the requisite confidence level, forecast horizon and historical observation period, which are enumerated below.

Confidence Level

The confidence level is p = (1- a), which defines the probability of the expected maximum loss. The market risk surface can be analyzed by varying the level of confidence. The most common confidence levels are between 95 % and 99 %, although they can vary between 90 % and 99.9% (Hendricks[11], 1996). The Basel Committee requires the use of 99 % confidence level in official reporting (Basel Committee, 2006)[12], as it must be high enough for capital requirement calculations, but a lower level of confidence (e.g. 95 %) can be used for internal reporting. In our study, we have selected 95% level of confidence in order to find out VaR for internal reporting purpose.

---

[11] Hendricks, D., 1996, "Evaluation of Value-at-Risk Models Using Historical Data", Economic Policy Review, Federal Reserve Bank of New York, April 1996, pp. 39-69.

[12] Basel Committee on Banking Supervision, 2006, "International Convergence of Capital Measurement and Capital Standards, Comprehensive Version - A Revised Framework", Basel Committee Publications, June 2006, Bank for International Settlements.

Forecast Horizon

The length of the period, for which the expected maximum loss is forecasted, is known as forecast horizon or holding period. Large deviations in the portfolio value are more probable over a long period than a short one, and VaR is usually greater for a holding period of one month than for a day, for instance. The portfolio composition is assumed to remain static for VaR over the holding period. The adequate length of the holding period depends on whether the risk is measured from a private or a regulatory perspective (Christoffersen et al.[13], 1998). Trading activity and the liquidity of the assets (i.e. the time and ability to convert a position to cash) has also an impact on the adequate length of the holding period (Khindanova and Rachev[14], 2000). In practice, the holding period can vary from one trading day to some years, but the Basel Committee requires the use of 10-day holding period for official reporting. They still permit the use of a shorter holding period and scaling of VaR to correspond 10-day holding period1 (Basel Committee[15], 2006). Khindanova and Rachev[16] (2000) suggest that a 10-day holding period is inadequate for frequently traded assets and restrictive for illiquid assets. As such we have taken 5-

[13] Christoffersen, P., Diebold, F. and Schuermann, T., 1998, "Horizon Problems and Extreme Events in Financial Risk Management", Economic Policy Review, Federal Reserve Bank of New York, October 1998, pp. 109-118.

[14] Khindanova, I. and Rachev, S. T., 2000, "Value at Risk: Recent Advances", Handbook on Analytic-Computational Methods in Applied Mathematics, CRC Press LLC, pp. 801-858.

[15] Basel Committee on Banking Supervision, 2006, "International Convergence of Capital Measurement and Capital Standards, Comprehensive Version - A Revised Framework", Basel Committee Publications, June 2006, Bank for International Settlements.

[16] Khindanova, I. and Rachev, S. T., 2000, "Value at Risk: Recent Advances", Handbook on Analytic-Computational Methods in Applied Mathematics, CRC Press LLC, pp. 801-858.

days horizon for computing VaR i.e. the reference data remains static for 5-day period.

Historical Observation Period

The length of the data sample in VaR calculation is known as the historical observation period. This observation period connects VaR to the history of the market risk factors, as the volatility of the risk factors is determined based on the length of the historical observation period. In practice the observation. The regulatory standard sets a minimum length of one year for the historical observation period (Basel Committee[17], 2005), while the period may vary from a month to several years in practice. A one-period VaR can be scaled to a long horizon VaR by multiplying by the square root of the length of the horizon. For instance, a one-day VaR may be scaled to ten-day VaR by multiplying it by 10. However, this is permitted only if short horizon returns are i.i.d., which is not always the case (Christoffersen et al.[18], 1998). The regulatory requirement of 250 trading days produces rather accurate VaR forecasts when used with the most common volatility models and Historical

---

[17] Basel Committee on Banking Supervision, 2006, "International Convergence of Capital Measurement and Capital Standards, Comprehensive Version - A Revised Framework", Basel Committee Publications, June 2006, Bank for International Settlements.

[18] Christoffersen, P., Diebold, F. and Schuermann, T., 1998, "Horizon Problems and Extreme Events in Financial Risk Management", Economic Policy Review, Federal Reserve Bank of New York, October 1998, pp. 109-118.

Simulation VaR (Hendricks[19], 1996). Longer historical observation periods provide the most accurate forecasts (Khindanova and Rachev[20], 2000). Hendricks[21] (1996) reports the superiority of 1,250-day historical observation period on the basis of an analysis of several VaR models with 95 % and 99 % levels of confidence. He finds the stability of unconditional distribution of changes in portfolio value to support the use of long periods. Hendricks[22]'s (1996) results highlight the Basel Committee requirement for a minimum historical observation period of 250 days, as he finds shorter periods to produce inaccurate VaR measures. We have taken considerable long period from 1st April 2000 to 31st March 2007 having 1755 data points.

Data sources

The data set used is S& P CNX Nifty as available from National Stock Exchange website for the period from 1st April 2000 to 31st March 2007 as for Historical Simulation Value at risk, time horizon should be 3 to 5 years at least.

---

[19] Hendricks, D., 1996, "Evaluation of Value-at-Risk Models Using Historical Data", Economic Policy Review, Federal Reserve Bank of New York, April 1996, pp. 39-69.

[20] Khindanova, I. and Rachev, S. T., 2000, "Value at Risk: Recent Advances", Handbook on Analytic-Computational Methods in Applied Mathematics, pp. 801-858.

[21] Hendricks, D., 1996, "Evaluation of Value-at-Risk Models Using Historical Data", Economic Policy Review, Federal Reserve Bank of New York, April 1996, pp. 39-69.

[22] Ibid.

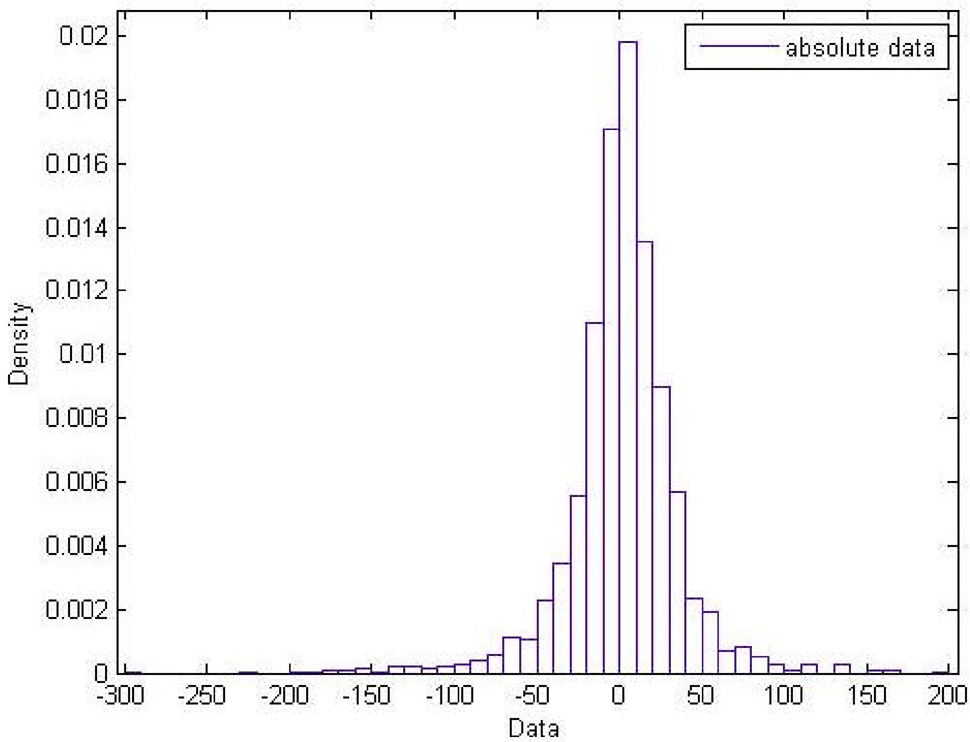
IV. Empirical Results

We have generated the profit and loss from the index returns, which replicate that of a portfolio. The profit and loss generated by an asset (or portfolio) over the period t, $P/L_{t,}$ can be defined as the value of the asst (or portfolio) at the end of t minus the asset value at the end of t-1:

$$P/L_t = P_t - P_{t-1}$$

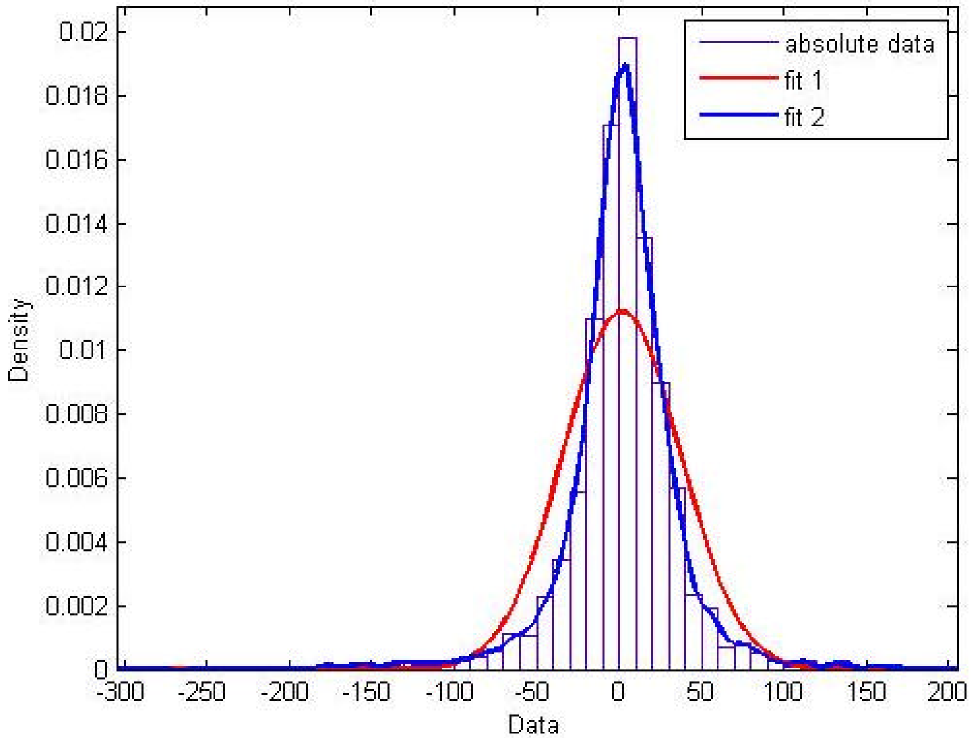
Wherein the positive value indicates profit, the negative value indicates loss.

Figure 1: Histogram of absolute Profit and Loss



Then we have attempted a distributional fitting to capture the nature of the distribution, as the distributional assumption is one of the key points for Value at Risk computation.

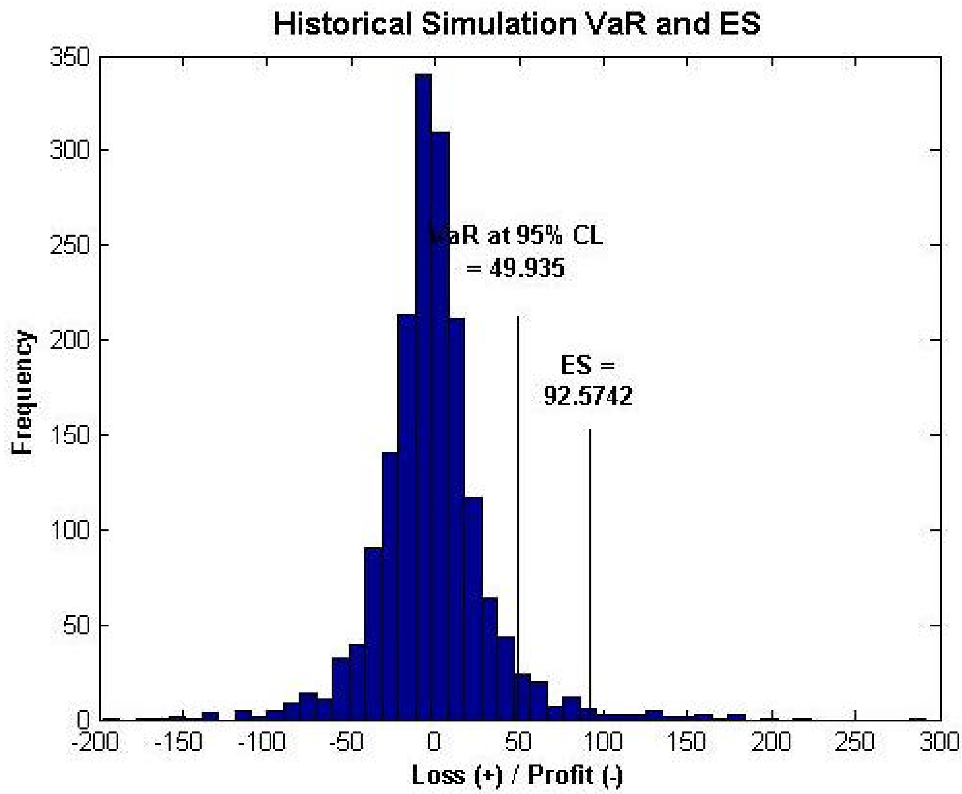
Figure 2: Fitting of Profit and Loss distribution



In the above diagram, fit 1 is normal and fit 2 is non-normal. The fitting is attempted to find the nature of the distribution as methods of value at risk computation that we shall approach is dependent on distributional assumptions. The fitting says that that the distribution in our study is a good candidate for non-normal one. Therefore, it is not a good candidate for general parametric value at risk measure, where underlying assumption is returns are normally distributed.

Then we have applied Historical Simulation method, which does not take any distributional assumption and as such a good candidate for Value at Risk. In the historical simulation, the distribution of the future shifts in the risk factors of a portfolio is a treated as the same way as the prior period distribution of shits to simulate the value at risk. The most advantage is that it is non-parametric and as such does not assume any distributional assumption as to normality. We computed Value at Risk (called as VaR) at risk and subsequent expected shortfall (called ES) as per historical simulation. Expected Shortfall is a coherent risk measure which considers risk beyond VaR level.

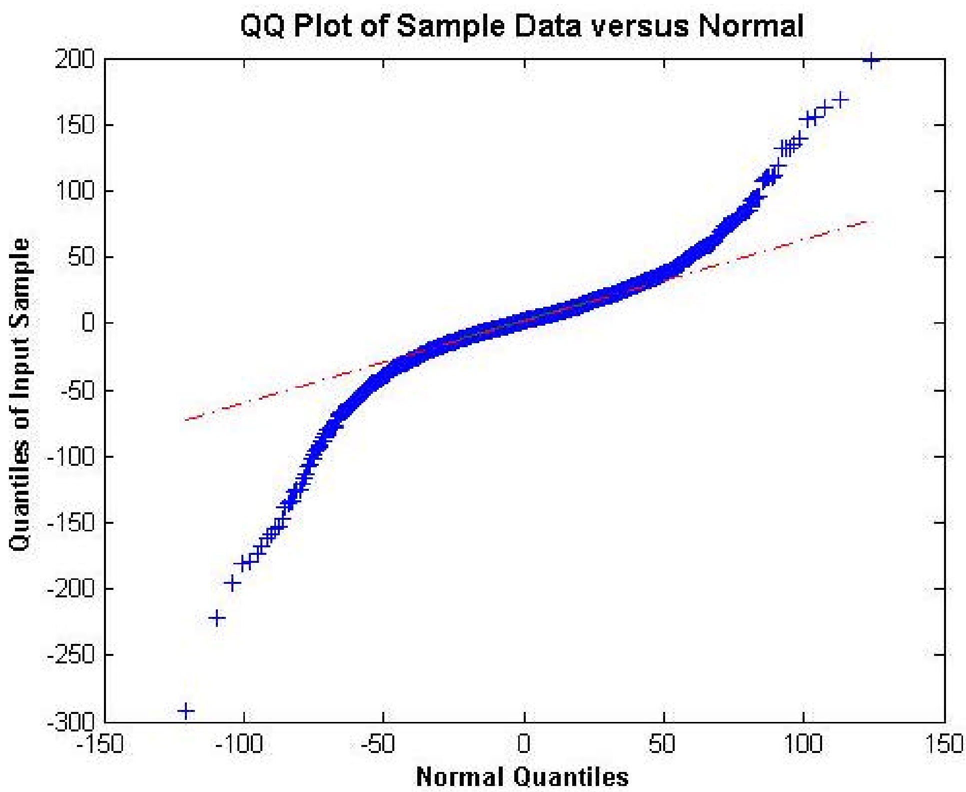
Figure 3: Historical Simulation Approach to VaR and Expected Shortfall



The empirical result for historical simulation VaR is 49.935 and Expected Shortfall is 92.5742.The major advantage of this method is that it neither assumes returns are normally distributed nor it assumes returns are identically distributed over time .As a result; historical simulation model can well accommodate the fat tail for VaR computation unlike other simple approaches. This model does not bear much model risk for incorrect estimation of parameters as there is no necessity to estimate any parameter like volatilities, correlations or others.

Further, an attempt has been made to identify the behaviour of the tail as it is an important tool for risk measurement. We have constructed exploratory tool like QQ plot to get a view of the heaviness of the tail.

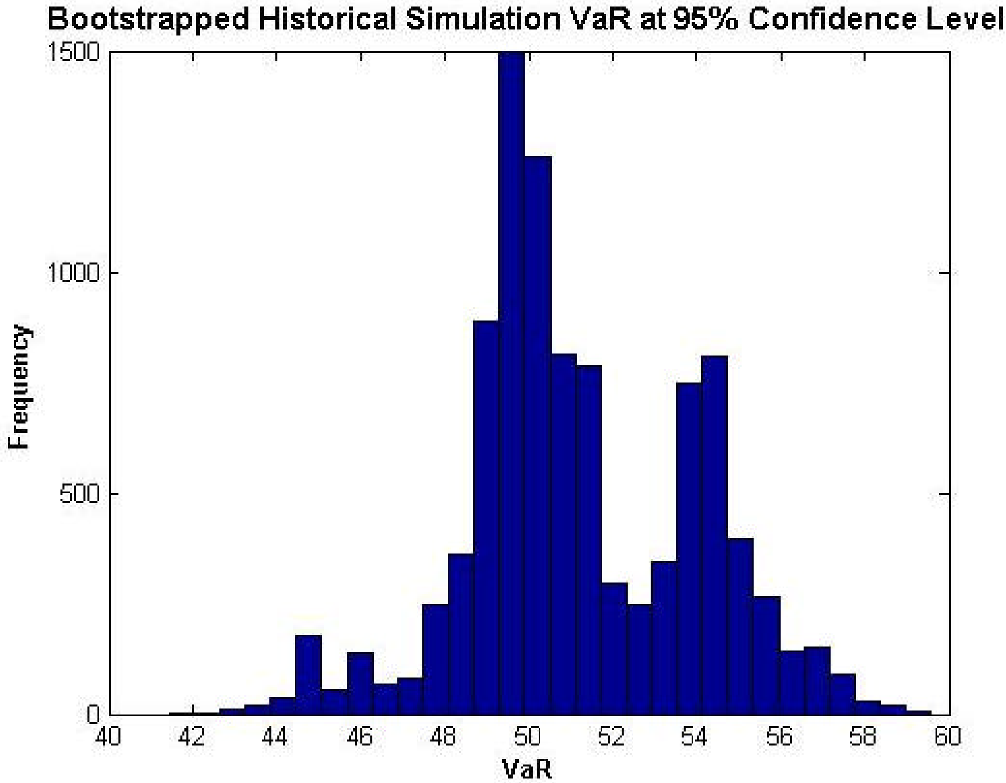
Figure 4: Application of Graphical Exploratory Tool: QQ Plot



As the QQ plot has steeper slopes at the tails and the tails have the slope different from the central mass, are suggestive of the empirical distribution have heavier , or thinner, tails than the reference distribution .This QQ plot is a good tool for identifying outliers (e.g. observations contaminated by large errors).

The improvement over the conventional Historical Simulation Approach is Bootstrap Approach. In bootstrap method the samples are drawn from same historical data with replacement. The benefit of the method is that it implicitly takes the volatilities and correlations present in the historical data. The major advantage of this bootstrap method is that we can draw any amount of large data which is essential for model validation that may be not be case in historical simulation with less historical data. Then we computed bootstrapped VaR as below:

Figure 5: Bootstrapped Historical Simulation VaR



The result of the bootstrapped historical VaR is 51.2312 with 10000 resample from the historical data set.

V. Concluding Observations

Result of our study for historical bootstrapped VaR is 51.2312, which is a little higher than historical VaR i.e. 49.935. The main purpose of using bootstrapped historical VaR is that it takes care of the necessity of large data for model validation even the sample size is not adequate. As we have shown above that historical simulation is used for non-linearity present in the data set as historical simulation method takes care of volatilities and correlations present in the referenced historical data. As such, in present context of non-linear data set which may not have all stressed scenarios, the use of bootstrapped historical VaR method is a better choice. It also be noted that the main motivation for this comparative study is that a well-defined optimization process of VaR accuracy would be a valuable asset to risk managers, though analytical derivation of such optimization process can be difficult, as the portfolio composition is not often static and the market risk factors change randomly. Accordingly, the statistical properties of VaR can vary. However, our present study leaves scope for further research as bootstrapped historical simulation, although does take care of the true distribution along with the stressed period present in the data set; it is unable to explain in full the true movement in full, where Extreme Value Theory based VaR is able to address the same.

References:

Allen, M. (1994), "Building a Role Model", Risk, 7, 73-80

Artzner, P., Delbaen, F., Eber, J. M. and Heath, D., 1999, “Coherent Measures of Risk”, Mathematical Finance, 9, pp. 203-228.

Basel Committee on Banking Supervision, 2006, “International Convergence of Capital Measurement and Capital Standards, Comprehensive Version - A Revised Framework”, Basel Committee Publications, June 2006, Bank for International Settlements.

Beder, T. (1995), "VaR: Seductive but Dangerous", Financial Analysts Journal, 51, 12-24.

Berkowitz, J., 2001, “Testing Density Forecasts, with Applications to Risk Management”, Journal of Business and Economic Statistics, American Statistical Association, October 2001, Vol. 19, pp. 465-74.

Berkowitz, J., Christoffersen, P. and Pelletier, D., 2005, “Evaluating Value-at-Risk Models with Desk-Level Data”, Fourth Joint Central Bank Research Conference on 9 Nov 2005, European Central Bank, Research Paper, Preliminary Version, Cited on 17.8.2006.

Berkowitz, J. and O’Brien, J., 2002, “How Accurate are the Value-at-Risk Models at Commercial Banks?”, Journal of Finance, Vol. 57, Issue 3, pp. 1093-1111.

Bollerslev, Tim, (1986). Generalized Autoregressive Conditional Heteroskedasticity, Journal of Econometrics, 31, 307-327

Campbell, J. Y., Lo, A. W. and MacKinlay A. C., 1997, “The Econometrics of Financial Markets”, Princeton University Press, ISBN 0691043019.

Campbell, S. D., 2005, “A Review of Backtesting and Backtesting Procedures”, Board of Governors of the Federal Reserve System, Finance and Economics Discussion Series 2005-21.

Cassidy, C. and Gizycki, M., 1997, “Measuring Traded Market Risk: Value-at-Risk and Backtesting Techniques”, Reserve Bank of Australia, Research Discussion Paper 9708.

Christoffersen, P., 1998, “Evaluating Interval Forecasts”, International Economic Review, Department of Economics, University of Pennsylvania and Osaka University Institute of Social and Economic Research Association, November 1998, Vol. 39, No. 4, pp. 841-862.

Christoffersen, P., Diebold, F. and Schuermann, T., 1998, “Horizon Problems and Extreme Events in Financial Risk Management”, Economic Policy Review, Federal Reserve Bank of New York, October 1998, pp. 109-118.

Christoffersen, P. and Pelletier, D., 2004, “Backtesting Value-at-Risk: A Duration-Based Approach”, Journal of Financial Econometrics, Oxford University Press, Vol. 2, No. 1, pp.84-108.

Crnkovic, C. and Drachman, J., 1997, “Quality Control in VaR: Understanding and Applying Value-at-Risk”, Risk Publications, ISBN 189933226X.

Danielsson, J. (2000), "The Emperor has No Clothes: Limits to Risk Modelling", London School of Economics, http://www.risk.is

Danielsson, J. and J. Morimoto (2000), "Forecasting Extreme Financial Risk: A Critical Analysis of Practical Methods for the Japanese Market", IMES Discussion Paper Series-2000-E-8, 3 http://www.risk.is.

Daracogna, M.M, Muller, U.A., Pictet, O.V and C.G. de Vries, (1995). The Distribution of Extremal Foreign Exchange Rate Returns in Extremely Large Data Sets. Tinbergen Institute, International and Development Economics, TI 95-70.

Dharba, Gangadhar(2002); Value-at-Risk for Fixed Income portfolios - A comparison of alternative Models ; Technical Paper , National Stock Exchange, India, www.nse-india.com.

Dempster, M. A. H. (editor), 2002, “Risk Management: Value at Risk and Beyond”, Cambridge University Press, ISBN 0521781809.

Diebold, F. X., Gunther, T. A. and Tay, A. S., 1998, “Evaluating Density Forecasts”, International Economic Review, Vol. 39, pp. 863-883.

Dowd, K., 2005a.,Measuring Market Risk, John Wiley & Sons Ltd,

Dowd, K., 2005b, “Spectral Risk Measures”, Financial Engineering News, March/April, 2005, No. 42, pp. 7.

Dowd, K., 2005c, “Coherent Risk Measures”, Financial Engineering News, January/February 2005, No. 41, pp. 7.

Dowd, K., 2004, “VaR and Subadditivity”, Financial Engineering News, November/December 2004, No. 40, pp. 7.

Embrechts, P., Kaufmann, R. and Patie, P., 2005, “Strategic Long-Term Financial Risks:Single Risk Factors”, Computational Optimization and Applications, Kluwer Academic Publishers, Vol. 32, Issue 1-2, ISSN 09266003, pp. 61-90.

Embrechts, P., Klüppelberg, C. and Mikosch, T., 1997, “Modelling Extremal Events for Insurance and Finance”, Springer Publishing, First Edition, ISBN 3540609318.

Embrechts, P. McNeil, A. and Straumann, D., 1999, “Correlation and Dependence in Risk Management: Properties and Pitfalls”, RiskLab Switzerland, Research Paper, Cited on 22.10.2006,Short version published in “Extremes and Integrated Risk Management”, edited by Embrechts, P., 2000, Risk Books, ISBN 189933274X, pp. 71-76.

Engle, R. F., 1982, “Autoregressive Conditional Heteroscedasticity with Estimates of the Variance of United Kingdom Inflation”, Econometrica, Blackwell Publishing, Vol. 50, No. 4, pp. 987-1008.

Engle, R. F. and Manganelli S., 2004, “CAViaR: Conditional Autoregressive Value-at-Risk by Regression Quantiles”, Journal of Business and Economic Statistics, Vol. 22, pp. 367-381.

Fisher, R. A. and L. H. C. Tippett (1928): “Limiting forms of the frequency distribution of the largest or smallest member of a sample”, Proceeding of Cambridge Philoshophical Society, 24, 180-190.

Gunter Loeffler 2004 An anatomy of rating through the cycle, Journal of Banking & Finance(28) , p695-p702.

Hendricks, D. (1996), "Evaluation of Value- at-Risk Models Using Historical Data", Federal Reserve Bank of New York Policy Review, April, 39-69

Fama, E. T., 1965, “The Behavior of Stock-Market Prices”, Journal of Business, Vol. 38, pp. 34-105.

Finkenstädt, B. and Rootzén, H. (Editors), 2003, “Extreme Values in Finance, Telecommunication and the Environment”, Chapman and Hall/CRC, ISBN 1584884118,pp. 101-168.

Glosten, L. R., R. Jaganathan and D. Runkle (1993), "On the Relationship Between the Expected Value and the Volatility of the Nominal Excess Return on Stocks", Journal of Finance, 48, 1779-1801.

Gnedenko , B. (1943): “Sur la distribution limite du terme maximum d’une s´erie al´eatoire”, Annals of Mathematics, 44, 423-453.

Group of 30, 1993, “Derivatives: Practices and Principles”, Washington DC, ISBN 1567080901.

Holton, Glyn A. (2003) : Value-at-Risk - Theory and Practice : Academic Press, 2003

Gumbel, E. (1958): Statistics of Extremes, New York: Colombia University Press.

Haas, M., 2001, “New Methods in Backtesting”, Center of Advanced European Studies and Research, Research paper, Cited on 22.10.2006,

Hallerbach, W. G., 1999, “Decomposing Portfolio Value-at-Risk: A General Analysis”, Tinbergen Institute Discussion Papers 99-034/2, Tinbergen Institute.

Hendricks, D., 1996, “Evaluation of Value-at-Risk Models Using Historical Data”, Economic Policy Review, Federal Reserve Bank of New York, April 1996, pp. 39-69.

Ho, L.C., P. Burridge, J. Cadle, and M. Theobald (2000), "Value at Risk: Applying the Extreme Value Approach to Asian Markets in Recent Financial Turmoil", *Pacific-Basin Finance Journal,* 8, 249-275.

Holton, G. A., 2003, “Value-at-Risk: Theory and Practice”, Academic Press, ISBN 0123540100.

Hill, B.M. (1975),"A Simple General Approach to Inference about the tail of a Distribution", Annals of Statistics, 19, 1547-1569.

Ho, L.C., P. Burridge, J. Cadle, and M. Theobald (2000), "Value at Risk: Applying the Extreme Value Approach to Asian Markets in Recent Financial Turmoil", Pacific-Basin Finance Journal, 8, 249-275.

Hoogland, J. and Neumann, D., 1999, “Taming Risks: Financial Models and Numerics”, Financial Mathematics ERCIM News No. 38, July 1999, The European Research Consortium for Informatics and Mathematics.

Hurlin, C. and Tokpavi, S., 2006, “Backtesting VaR Accuracy: A New Simple Test”, Pre and Post-Print documents halshs-00068384_v1, HAL, CCSd/CNRS, Cited on 4.11.2006.

Jackson, P., Maude, D. and Perraudin, W., 1997, “Bank Capital and Value at Risk”, Bank of England Working Papers 79, Bank of England, ISSN 1368-5562; and Journal of Derivatives ,1997, No. 4, pp. 73-90.

Jamshidian F. and Y. Zhu (1996), "Scenario Simulation Model for Risk Management", Capital Market Strategies, 12, 26-30.

Jamshidian F. and Y. Zhu (1997), "Scenario Simulation: Theory and Methodology", Finance and Stochastics, 1, 43-67.

Jorion, P., 2001, “Value at Risk: The New Benchmark for Managing Financial Risk”, McGraw-Hill, ISBN 0071355022.

Joy, C., Boyle, P. and Seng Tan, K., 1996, “Quasi-Monte Carlo Methods in Numerical Finance”, Management Science, June 1996,Vol. 42, No. 6, pp. 926-938.

J.P.Morgan/Reuters, 1996 December. RiskMetrics { Technical Document. New York, 4th ed.). www.riskmetrics.com

Kerkhof, J. and Melenberg, B., 2002, "Backtesting for Risk-Based Regulatory Capital", Discussion Paper 110, Tilburg University, Center for Economic Research.

Khindanova, I and Rachev, S. T., 2000, "Value at Risk: Recent Advances", Handbook on Analytic-Computational Methods in Applied Mathematics, CRC Press LLC, pp. 801-858.

Kellizi, Evis and Manfred Gilli , (2000). Extreme Value Theories for Tail-Related Risk Measures, Working Paper ;University of Geneva.

Koedijk, K.G., Schafgans, M.M.A. and C.G. de Vries, (1990). The Tail Index of Exchange Rate Returns. Journal of International Economics 29, 93-108

Kupiec, J. A., 1995, "Techniques for Verifying the Accuracy of Risk Management Models", Journal of Derivatives, Vol. 3, No. 2, ISSN 1074-1240, pp. 73-84.

Longin, F.M., (1996). The Assymptotic Distribution of Extreme Stock Market Returns, .Journal of Business 69,383-408.

Longin, F. M., 2000, "From Value at Risk to Stress Testing: The Extreme Value Approach", Journal of Banking and Finance, Vol. 24, pp. 1097-1130.

Lopez, J. A., 1999, "Methods for Evaluating Value-at-Risk Estimates", Economic Review, Federal Reserve Bank of San Francisco, pp. 3-17.

Nath, Golaka ; Reddy, Y. V. (2003). Value at Risk: Issues and Implementation in Forex Market in India : November, pages 26 ; www.nse-india.com

Neftci, S. (2000), "Value at Risk Calculations, Extreme Events, and Tail Estimation", Journal of Derivatives, spring, 23-38.

Nelson, D.B. (1991), "Conditional Heteroscedasticity in Asset Returns: A New Approach", Econometrica, 59, 2, 347-370.

Pickands, J. (1975): Statistical inference using extreme order statistics, Annals of Statistics, 3, 119–131.

Raina, Ajoy and Mukhopadhyay, C (2004), "Optimizing a Portfolio of Equities, Equity Futures and Equity European Options by Minimising Value at Risk – A simulated Annealing Framework", ICFAI Journal of Finance, May 2004, Vol 10, No. 5.

Sarma, M, Susan Thomas and Ajay Shah (2003), "Selection of Value-at-Risk Models", Journal of Forecasting, 22(4), pp. 337-358.

Samanta, G. P. and Golaka C. Nath (2003), "Selecting Value-at-Risk Models for Government of India Fixed Income Securities", International Conference on Business & Finance, December 15-16, 2003 at the ICFAI University, Hyderabad, India, Co-Sponsored by the Philadelphia University, USA.

Samata, G.P. and Thakur, S.K., "On Estimating Value at Risk Using Tail I ndex : Application to Indian Stock Market", ICFAI Journal of Applied Finance, Vol 12, No. 6, June 2006.

` Schinassi, G. (1999), "Systemic Aspects of Recent Turbulence in Mature Markets", Finance and Development, March, 30-33, IMF, Washington.

Sobehart J., Keenan S., Stein R (2001) Benchmarking Quantitative Default Risk Model A Validation Methodology. http://riskcalc.moodysrms.com/us/research/crm/53621.pdf

Srinivasan, Ashok ; Shah, Viral; Ganti, Phanindra V. R. ; Shah, Ajay ; (2000). Application of Range Searching to Fast Financial Risk Estimation : January, pages 16.

Tor Jacobsen, Jesper Linde, Kasper Roszbach. Credit risk versus capital requirements under Basel II: are SME loans and retail credit really different?. Sveriges Riksbank Working Paper Series No. 162, (April 2004).

Varma, J. R.(1999) ; Value at Risk Models in Indian Stock Market; Indian Institute of Management, 1999. Working Paper no- 99-07-05, Indian Institute of Management, 1999, July, pages 16.

.