Published in: MAIMS: A Journal of Management: 9(2); 2014; 44-50.

ARE SENSEX FUTURES RISKIER THAN SENEX?

Authors

Poornima BG
Assistant Professor
Department of Commerce
Goa University
Goa- 403206
Email: poornima79mysore@gmail.com

Y Srujan Reddy
Asst.Manager,
Strategic Risk Management
Credit Suisse,
Powai,, Mumbai
Email: srujan90@gmail.com

Prof YV Reddy
Dean
Faculty of Commerce
Goa University
Goa- 403206
Email: yvreddy@unigoa.ac.in

Abstract

In this paper, an attempt has been made to measure the Indian Stock Market risk using BSE Sensex and Index Future. Stock Index futures are the most popular financial derivative instrument which is widely traded on exchanges. The changes of the prices in Stock Indexes are reflected in the Stock Index Futures. Stock index futures are the derivative instruments used to hedge the stock index risk. But we often fail to understand how risky is the hedging instrument itself than its underlying asset. Historical Value at Risk methodology has been used at 90%, 95% and 99% confidence level to assess the market risk for the period from January 2007 to December 2012. Historical VaR method is one of the simplest form of calculating Market Risk which considers that past is a good indicator of future. Findings show that Index Futures are riskier than the underlying asset i.e Sensex. But Historical VaR method has failed in the prediction of 1 day and 10 days VaR for the spot market at all confidence levels. Overall, the study reveals that futures market tends to reflect more volatility than the spot market.

.

1. A): Introduction

Risk may be defined as the probability of the future returns to vary from the expected returns. (Vivek & P.N, 2009) Risks arise from various sources and affect the values of the assets held. Risks can be minimised but cannot be eliminated. As such measuring the risks helps one to understand the level of risk exposure. One such popular measuring tool is Value at risk which has become a benchmark methodology among investors and banks for measuring market risk. Market risk is the risk of losses due to adverse movements in financial market variables.(Crouchy, Galai, & Mark, 2001) The Bank of International Settlements (BIS) defines market risk as the "the risk that the value of 'on' or 'off' balance sheet positions will be adversely affected by movements in equity and interest rate markets, currency exchange rates and commodity prices". (Köseoğlu & Ünal, 2012)Market risk for future indices is more complex compared to market risk of the underlying stock indices. While stock index is related to the possibility of rise and fall of equity prices, future market risk is related to changes in the underlying assets due to other speculative trades. (Köseoğlu & Ünal, 2012) Future market instruments are used both for hedging and speculative purposes. This feature of Future Markets makes it very risky more than the Equity market. In this regard, the paper's main intention is to is to measure and compare the market risk of these two different markets which are inter related and inter dependent. The paper is structured as follows. In section 2, necessary definitions, background information and various VaR computations are discussed. Section 3 deals with methodology and data structure, Section 4 makes empirical analysis which includes introduction to data sets, their descriptive statistics and empirical calculations procedure through hypothesis testing. Concluding remarks is done in section 5.

2. B): **Review of Literature**

Tripathi and Gupta (2012), evaluated the accuracy of various VaR models estimates in equity investments in India of two major Stock Indices – BSE Sensex and NSE Nifty for the period January 2006 to February 2007. They demonstrated that Portfolio normal method of VaR computation is a better risk measure for estimating portfolio risk as compared to risk on individual securities. They find that VaR estimate does not accurately measure the risk in equity investments in India. Varma J.R (1999), make empirical tests of different risk management models in the VaR framework in the Indian Stock Market. As per the findings, GARCH-GED performs exceedingly well at all common risk levels. EWMA model used in JP Morgan's Risk Metrics methodology does well at 10% and 5% risk levels but breaks down at 1% and lower risk levels. The paper provides evidence to improve the performance of the VaR models by taking into account the price movements in foreign stock markets. Fotios C, Linyan & Yifan (2006), test different models of measuring VaR and ES in the popular indices of S&P500, DAX, CAC, Nikkei, TSE and FTSE and currencies (US Dollar Vs Euro,Yen,Pound and Canadian Dollar) for over ten years. In estimating VaR, the results show that models which capture rare events can predict risk more accurately than non fat tailed models. Timotheos & Stavros(2005), investgate the accuracy of parametric, nonparametric and semiparametric methods in predicting the one-day ahead VaR measures in three types of Markets(Stock,Commodity and Excahnge rates), for long and short positions. Modelling of the main characteristics of asset returns produces the most accurate VaR forecasts.

Several research on risk measures has been carried out even in futures stock market of late. Huang & Lin (2004) investigated the forecasting performance of EWMA, Normal APARCH and Student APARCH models for VaR estimations of two stock index futures contracts in Taiwan namely TAIFEX and SGX-DT, in which all the three stock index futures prices showed long memory characteristics. Tang and Shieh (2006) showed that HYGARCH models with student-t distributions performed well for S&P500 and Nasdaq100 futures. Kasman (2009) calculated VaR estimations of Turkish stock index futures contracts by using the FIGARCH model with normal, student-t, and skewed student-t distributions for the period between 2005 and 2008 and the findings supported an evidence of long memory in volatility in Turkish stock index futures. A comparative study of market risk of Stock index and the index futures was done by Sinem and Unal (2012) in ISE30,DAX30,S&P500,Nikkei225 and FTSE100 indices through various VaR methods, in which they demonstrated that futures market risk is higher than the underlying stock market risk for Nikkei 225 and S&P 500. Oscar & others(2009), estimated one day VaR ahead in the spot and future equity markets for three stock indices Viz., S&P 500,DAX 30 and Nikkie 225 using ARMA GARCH CTS Models. They have introduced trading volume in the CTS model and found that lagged trading volume relative change helps in predicting one day ahead VaR for the stock index futures contracts. The number of violations is also less in the future market in case of CTS model with trading volume considered. Cotter & Dowd(2006), estimate VaR and Expected Shortfall for 5 prominent equity futures contract. They find that all risk measures increase dramatically and their estimators deteriorate in precision when their respective conditioning parameter increases. Results also suggest that estimates of spectral risk measures and their precision levels are of comparable orders of magnitude as those of more conventional risk measures.

2. C): **Conceptual Framework: Value at Risk**

Value at Risk or VaR is a concept developed in the field of risk management that is defined as the maximum amount of money that one could expect to lose with a given probability over a specific period of time. There are three main approaches for measuring VaR: First, the Variance-Covariance matrix approach, second, Historical Simulation approach and third, Monte Carlo Simulation approach. Variance – Covariance approach is a method that calculates the parameters underlying a profit and loss distribution i.e mean and standard deviation, in order to come up with the potential loss of an asset or portfolio., given a holding period and confidence level. After deriving the mean and standard deviation, statistical theory is applied to come up with a VaR estimate. Hence the name Variance-Covariance. Delta normal and Delta Gamma method are Variance – Covariance approaches.

(Das, 2006) Historical Simulation takes into account the past performance of the portfolio assuming that past is a good indicator of the near-future. Historical VaR is based on the revaluation of the current portfolio using historical rates and prices to arrive at the risk of the positions. [1] This method requires a long history of returns in order to get a meaningful VaR. [2]The method of calculating VaR under this method is very simple. (Varma, 2008) The following method is followed for calculating Historical VaR:

- Let P_0 be the value of the portfolio using current market rates and prices
- For each of *n* historical scenarios:

  Use the market rates of scenario *i* to calculate the scenario portfolio value *Pi*

  Compute the change in portfolio value as $\delta P = P_i - P_0$
- The set of δP is the profit/loss distribution. The percentile of this gives the VaR.

This method does not make any assumption of the return distributions of the assets in the portfolio. This removes any risk of masking any skew or kurtosis in the distribution. There is no need to estimate the volatilities and correlations between the various assets. This method has the inherent capacity to capture the effects of

[1] Das Satyajit, Risk Management,Wiley Finance,pp 94
[2] https://www.jpmorgan.com/tss/General/Risk_Management/1159369485859

gamma(convesity risk), vega (volatility risk) and theta (impact of time decay) [3]. Historical VaR requires merely limited manipulation of the data to re-base it [4]. But it suffers from serious limitations[5]. First, it relies completely on historical dataset and its idiosyncrasies. Second, it fails to accommodate changes in the market structure. Third, this method may not be computationally efficient when the portfolio contains complex securities or a very large number of instruments. Fourth, it fails to handle sensitivity analyses.

Montecarlo Simulation bears some similarities with the historical simulation on the basis of the approach followed. The difference is that scenarios are not based on historical data but are generated by computer software based on a theoretical distribution.

Back Testing: Whatsoever VaR is calculated using various methods it can be reliable only when it is considered as accurate and has the predictive ability of capturing future market risk. This can be done by Backtesting. (Nieppola, 2009) Backtesting is the process of comparing VaR estimates with the actual returns. It helps in detecting weaknesses in the models and points to areas of improvements. Backtesting may be conditional or unconditional. Various backtesting methods that are used are Basel Committee's traffic light approach(1996), Kupie's proportion of failures test(1995), Christoffersen's interval forecast test(1998), unconditional coverage etc. In this paper Unconditional coverage method is used for backtesting the Historical VaR. Under this model the number of VaR exceptions is counted. If the number of exceptions is less than the selected confidence level, the model overestimates the risk, else it under estimates the VaR. Denoting the number of exceptions as x and the total number of observations as T, we may define the failure rate as x/T. In an ideal situation, this rate would reflect the selected confidence level. For instance, if a confidence level of 99 % is used, we have a null hypothesis that the frequency of tail losses is equal to p= (1-c) =1-0.99=1%. Assuming that the model is accurate, the observed failure rate x/T should act as an unbiased measure of p, and thus converge to 1% as sample size is increased. (Jorion, 2001). Each trading outcome either produces a VaR violation exception or not. This sequence of 'successes and failures' is commonly known as

[3] Das Satyajit, Risk Management,Wiley Finance,pp 94
[4] Das Satyajit, Risk Management,Wiley Finance,pp 94
[5] https://www.jpmorgan.com/tss/General/Risk_Management/1159369485859

Bernoulli trial. The number of exceptions x follows a binomial probability distribution:

$$f(x) = \binom{T}{x} p^x (1-p)^{T-x}$$

As the number of observations increase, the binomial distribution can be approximated with a normal distribution:

$$Z = \frac{x - p^T}{\sqrt{p(1-p)^T}} \approx N(0,1)$$

where p ^{T} is the expected number of exceptions and p(p-1) ^{T}, the variance of exceptions. (Jorion, 2001) By utilizing this binomial distribution we can examine the accuracy of the VaR model.

3. Methodology:

The basic objective of the study is to find whether Index Futures are more riskier than their underlying assets. In this paper daily Stock index and stock index futures data for the period from 1st January 2007 to 31st Dec 2012 of BSE Sensex and Index Futures are used for empirical analysis. For calculating risk the Historical VaR is employed. To analyse the characteristics and variance of Sensex and Index Futures F test, t test and descriptive statistics have been used. Backtesting is done using unconditional coverage method. In order to carry out this study null and alternative hypothesis has been framed.

H_0 = Sensex is **more or equally** risky as the Index Futures

H_1 = Sensex is less risky than Index Futures

F Test is used to test the equality of variances between the two normal populations. [6] The F Test Statistic used is the ratio of two sample variances. Let X1,......,Xn and Y1,........Ym be independent and identically distributed samples from two populations which each have a normal distribution. The expected values for the two populations can be different, and the hypothesis to be tested is that the variances are equal.

$$\bar{X} = \frac{1}{n}\sum_{i=1}^{n} X_i \ and \ \bar{Y} = \frac{1}{m}\sum_{i=1}^{m} Y_i$$

be the sample means. Let

$S_X^2 = \frac{1}{n-1}\sum_{i=1}^{n}(X_i - \bar{X})^2$ and $S_Y^2 = \frac{1}{m-1}\sum_{i=1}^{1}(Y_i - \bar{Y})^2$

[6] (wikipedia)http://en.wikipedia.org/wiki/F-test_of_equality_of_variances

be the sample variances. Then the test statistic

$$F = \frac{S_X^2}{S_Y^2}$$

has an F-distribution with $n - 1$ and $m - 1$ degrees of freedom if the null hypothesis of equality of variances is true. Otherwise it has a non-central F-distribution. The null hypothesis is rejected if F is either too large or too small.

Unequal sample sizes, unequal variances[7]

This test, also known as Welch's *t*-test, is used only when the two population variances are not assumed to be equal (the two sample sizes may or may not be equal) and hence must be estimated separately. The t statistic to test whether the population means are different is calculated as:

$$t = \frac{\bar{X}_1 - \bar{X}_2}{S_{\bar{X}_1 - \bar{X}_2}}$$

Where

$$S_{\bar{X}_1 - \bar{X}_2} = \sqrt{\frac{S_1^2}{n_1} + \frac{S_2^2}{n_2}}$$

Here *s*2 is the unbiased estimator of the variance of the two samples, *ni* = number of participants in group *i*, *i*=1 or 2. For use in significance testing, the distribution of the test statistic is approximated as an ordinary Student's t distribution with the degrees of freedom calculated using

$$d.f = \frac{(S_1^2/n_1 + S_2^2/n_2)^2}{(S_1^2/n_1)^2/(n_1 - 1) + (S_2^2/n_2)^2/(n_2 - 1)}$$

This is known as the Welch–Satterthwaite equation. The true distribution of the test statistic actually depends (slightly) on the two unknown population variances.

4. Data analysis

The data set consists of daily returns which are computed as log returns of closing prices of futures and stock indices. However, this paper employs only Historical VaR for quantifying the risk of the above indices.

[7] (wikipedia) http://en.wikipedia.org/wiki/Student's_t-test

The following Table 1 shows the descriptive statistics of SENSEX and INDEX Futures.

Table 1: Summary Statistics of both Sensex and Index Futures (Logarithmic Returns)

Descriptive statistics	*Sensex*		*Index Futures*	
	1 day	10 day	1 day	10 day
Mean	0.000223084	0.002289	0.000241	0.002548
Standard Deviation	0.017753043	0.055983	0.019374	0.058891
Kurtosis	7.37568021	2.50787	7.091604	1.896224
Skewness	0.214030218	-0.57943	0.260325	-0.48145

As per the descriptive statistics, the Sensex average return is equal to Index future. A high standard deviation is observed for sensex futures than Sensex. The kurtosis of the sensex futures is high compared to the Sensex. This indicates higher probability of extreme events and implies that the distributions of these returns are fat tailed or leptokurtic, resulting to higher probability of extreme events. The skewness values of both the Sensex and Index Futures logarithmic return series deviate from the normal distribution assumption. Index Futures are considered to be highly volatile with high Standard Deviation.

Table 2: F-Test Two-Sample for Variances (1 Day VaR)

	Index Futures	*Sensex*
Mean	0.000241	0.000223
Variance	0.000375	0.000315
Observations	1335	1487
Df	1334	1486
F	1.190936	
P(F<=f) one-tail	0.00052	
F Critical one-tail	1.091601	

Table 3: F-Test Two-Sample for Variances (10 day VaR)

	Index Futures	*Sensex*
Mean	0.002548	0.002289
Variance	0.003468	0.003134
Observations	1326	1478
Df	1325	1477
F	1.106571	
P(F<=f) one-tail	0.029089	
F Critical one-tail	1.091909	

H_0= Variances are equal

F calculated (F=1.190936) > F critical(1.091675) in case of 1 day VaR and 10 day VaR(F[1.106571] > F Critical[1.091675]) ; since f calculated value is high and greater than the F Critical Value, the null hypothesis of equality of variance is rejected. Henceforth emphasising the fact that Variance of Index Futures is high than the Sensex for 1 day and 10 Day VaR and are thus not equal.

Table 4: t-Test: Two-Sample Assuming Unequal Variances 1 day VaR		
	Sensex	*Index Futures*
Mean	0.000223	0.000239
Variance	0.000315	2.188135
Observations	1487	1348
Hypothesized Mean Difference	0	
df	1347	
t Stat	-0.00039	
P(T<=t) one-tail	0.499846	
t Critical one-tail	1.645986	

Table 5: t-Test: Two-Sample Assuming Unequal Variances 10 day VaR		
	Sensex	*Index Futures*
Mean	0.002289	0.002524
Variance	0.003134	3.784688
Observations	1478	1339
Hypothesized Mean Difference	0	
df	1340	
t Stat	-0.00441	
P(T<=t) one-tail	0.49824	
t Critical one-tail	1.645992	

As it is evident from the Table 4 and 5, since the calculated t Statistic (0.00039 in case of 1 day VaR & 0.00441 in case of 10 day VaR) is less than the t critical value(1.645986 in case of 1 day VaR & 1.645992 in case of 10 day VaR) respectively, it can be arrived at the conclusion that means are not statistically different.

Table 6: Historical VaR of Sensex			
Confidence Interval	90%	95%	99%
1 day VaR	-4.094463%	-2.424100%	-1.514749%
10 Day VaR	-12.034269%	-7.212414%	-5.627319%

No.of Breaches			
1 Day VaR	196	90	25
10 Day VaR	176	117	36
No of returns compared			
1 Day VaR	1387		
10 Day VaR	1378		
Failure Rates			
1 Day VaR	14.13%	6.49%	1.80%
10 Day VaR	12.77%	8.49%	2.61%
Remarks for VaR			
1 Day VaR	Under Estimated	Under Estimated	Under Estimated
10 Day VaR	Under Estimated	Under Estimated	Under Estimated

Table 7: Historical VaR of Index Futures			
Confidence Interval	90%	95%	99%
1 day VaR	-1.536560%	-2.624663%	-4.144174%
10 Day VaR	-5.403836%	-8.871919%	-11.924749%
No.of Breaches			
1 Day VaR	176	79	30
10 Day VaR	179	0	0
No of returns compared			
1 Day VaR	1235		
10 Day VaR	1216		
Failure Rates			
1 Day VaR	14.25%	6.40%	2.43%
10 Day VaR	14.72%	0.00%	0.00%
Remarks for VaR			
1 Day VaR	Under Estimated	Under Estimated	Under Estimated
10 Day VaR	Under Estimated		

It can be observed from the above table 7 that as the confidence level increases even the VaR percentage also dramatically increases in case of Index Futures. While the VaR percentage decreases as the CI increases in case of Sensex. VaR is seen to be higher at 90% CI for sensex for both 1 day and 10 day VaR than the index futures. VaR is higher for index futures at 99% for both 1 day and 10 day VaR. At 95% the VaR for both index futures and sensex is almost similar at both 1 day and 10 day VaR. However the failure rates of both Index Futures and Sensex indicates that the number of exceptions exceed the limits at 90%, 95% and 99% for sensex for 1 day VaR and as such Historical VaR is under estimated for the same. Similarly, Historical VaR is under estimated at all CI for 1 day VaR for Index Futures. Historical VaR is underestimated only at 90% for 10 day VaR. Overall, it can be concluded that Historical VaR fails to estimate VaR accurately at all CIs. It should be noted that over estimating is harmless; Underestimating VaR is a serious concern. As such Historical VaR cannot be considered as good measure of estimating VaR for the data under consideration. Further, Index Futures is highly volatile then Sensex at 99% CI and Sensex is highly volatile at 90% for both 1 day and 10 day VaR.

5. Conclusion

Even though Historical VaR due to its simplicity in calculation is popular, its serious limitation of assuming the past repeats in future distorts the VaR estimation. As such the results show that Historical VaR in majority of the above cases has under estimated VaR which is a matter of concern. Backtesting of the model is better only at 95% and 99% confidence level for 10 day VaR. Historical VaR fails to capture extreme situations of high or low volatility of the markets which may lead to extreme tail losses. Based on the findings it can be concluded that the market risk of Index Futures is higher at 95% and 99% CI. As such Index Futures is more risky than its underlying asset Sensex as the expected loss measured by Histoical VaR is higher in case of the former. Further, it is evident from the empirical results that futures market exhibit volatility than the spot market. The investor whether taking a long position or short position in the futures market should be conscious of the risks affecting the futures market than its underlying asset.

6. References:

1. Cotter, & Dowd. (2006). Estimating Financial Risk Measures for Futures Positions: A Non-Parametric Approach. *Working Paper, UCD Geary Institute, Discussion paper series. Geary WP2006/13*.

2. Crouchy, M., Galai, D., & Mark, R. (2001). *Risk Management.* McGraw Hill.

3. Das, S. (2006). *Risk Management* (Third ed.). John Wiley & Sons (Asia) Pte Ltd.

4. Fotios C., H., Linyan, M., & Yifan, C. (2006). Empirical study of value-at-risk and expected shortfall. *The Journal of Risk Finance,* Vol. 7 Iss: 2 pp. 117 - 135.

5. Huang, Y. C., & Lin, B. (2004). Value-at-Risk Analysis for Taiwan Stock Index Futures:Fat Tails and Conditional Asymmetries in Return Innovations. *Review of Quantitative Finance and Accounting*, 22: 79–95. Retrieved from http://link.springer.com/article/10.1023%2FB%3AREQU.0000015851.78720.a9#page-1

6. Jorion, P. (2001). *Value at Risk*, McGraw Hill Publishers,

7. Kasman. (2009). Estimating Value at Risk for the Turkish Stock Index Futures in The Presence of Long Memory Volatility. *CentralBank Review*, Vol,1,pp 1-14.

8. Köseoğlu, S. D., & Ünal, G. E. (2012). Market Risk of Index Futures and Stock Indices: Turkey as a Developing Country vs. Developed Countries. *Journal of Business and Policy Research*, Vol. 7. No. 3. September 2012 Special Issue. Pp. 159 – 177.

9. Nieppola, O. (2009). *Backtesting Value-at-Risk Models.* HELSINKI SCHOOL OF ECONOMICS, Deaprtment of Economics. Retrieved from epub.lib.aalto.fi/en/ethesis/pdf/12049/hse_ethesis_12049.pdf

10. Oscar, C., Svetlozar, T. R., Kimc, s. Y., Sund, W. E., & Fabozzie, J. F. (n.d.). Forecasting VaR in Spot and Futures Equity Markets. Retrieved from https://statistik.econ.kit.edu/.../Forecasting_VaR_in_Spot_and_Futures_E

11. S.L.Gupta. (2011). *Financial Derivatives Theory, Concepts and Problems.* New Delhi: PHI Learning Private Limited.

12. Tang, T. L., & Shieh, S. J. (2006). Long memory in stock index futures markets: A value-at-risk approach. *Physica A*, 437-448.

13. Timotheos, A., & Stavros, D. (2005). Emerald Article: Modeling risk for long and short trading positions. *The Journal of Risk Finance*, Vol. 6 Iss: 3 pp. 226 - 238.

14. Tripathi, V., & Gupta, S. (n.d.). Estimating the Accuracy of Value-at-Risk (VaR) in Measuring Risk in Equity Investment in India. Retrieved from papers.ssrn.com/sol3/papers.cfm?abstract_id=1134670

15. Varma, J. R. (1999). Value at Risk Models in the Indian Stock Market. Retrieved from www.iimahd.ernet.in/~jrvarma/papers/WP990705.pdf

16. Varma, J. R. (2008). *Derivatives and Risk Management.* Tata McGRaw Hill Education Private Limited.

17. Vivek, & P.N, A. (2009). *FinancialRisk Management* (First ed.). Himalaya Publishing House.

18. wikipedia. (n.d.). Retrieved from http://en.wikipedia.org/wiki/F-test_of_equality_of_variances