Efficient Value-at-Risk Estimation

Angelo Joseph

Nedbank Capital

AngeloJ@NedbankCapital.co.za

Jan Kruger

UNISA Graduate School of Business Leadership

jkruger@sbleds.ac.za

ABSTRACT

In economics and finance, the Value-at-Risk (VaR) is a measurement of the maximum loss not exceeded with a given probability over a specified time. The VaR is an important measurement, as it gives a financial institution with confidence the maximum loss it can incur over time. In this paper, we briefly appraise general VaR measures. Subsequently, we introduce the idea of using the market volatility to make the VaR estimate, more responsive and efficient to the changes in the financial market.

KEYWORDS

VaR, Estimation, Volatility, Markets

1. INTRODUCTION

In general, most VaR measurements are based on historical time series data. Historical VaR measures are good, if and only if, the forward period over which the VaR is applicable is less volatile. Given a lower forward volatility period, the VaR estimated using historical prices of high volatility, will always be sufficient [1]. This historical VaR measure however is prone to being over conservative and can allow for an overstated, problematic VaR estimate.

Some practitioners consider using Monte Carlo simulation to estimate the VaR more efficiently for a high forward volatility period. A good Monte Carlo VaR estimate however requires a very accurate estimation of the volatility [2]. Furthermore, the Monte Carlo VaR uses random numbers, which usage reduces the reproducibility of the VaR estimate. An efficient Monte Carlo VaR estimate therefore involves the non-trivial exercise of accurately estimating the volatility, and gives up the transparency and reproducibility of the VaR, which is problematic.

Other practitioners, uses a VaR measure that is not only based on the historical data or simulations, but based on parameters. The parameteric VaR is based on fitting a distribution function to the empirical price return distribution [3]. The VaR is then inferred using the fitted density function, and the derived conditional distribution parameters. Most parameteric VaR estimation techniques are based on the assumption that the price returns are normally distributed. In reality, the price return distributions are skewed, and analytics that are based on the normal distribution assumption are problematic for efficient VaR estimation.

2. VOLATILITY

The volatility of the financial market is a measure of the expected changes in the price returns realized in one year. The implied volatility is the volatility as implied by options that trade in the market. The implied volatility is interesting because it reacts when (and sometimes before) the market becomes distress. The implied volatility is therefore a good financial market fear gauge [4].

(See Fig. 1.). Moreover, the implied volatility used in conjunction with the historical volatility provides for an efficient measure to characterize the expected state changes of the market. In fact, as the market approaches the state of starting a trend the implied and historical volatility usually converges. These interesting properties were the motivation for using the volatility in developing a more efficient VaR estimate. We illustrate the VaR calculation using some measurement of volatility σ as follows;

$$VaR\ (99.95\%) = e^{3.5\sigma / \sqrt{252}} - 1$$

This formula states that the VaR at the 99.95% confidence level is the price return that corresponds to 3.5 daily standard deviations (as inferred from the volatility).

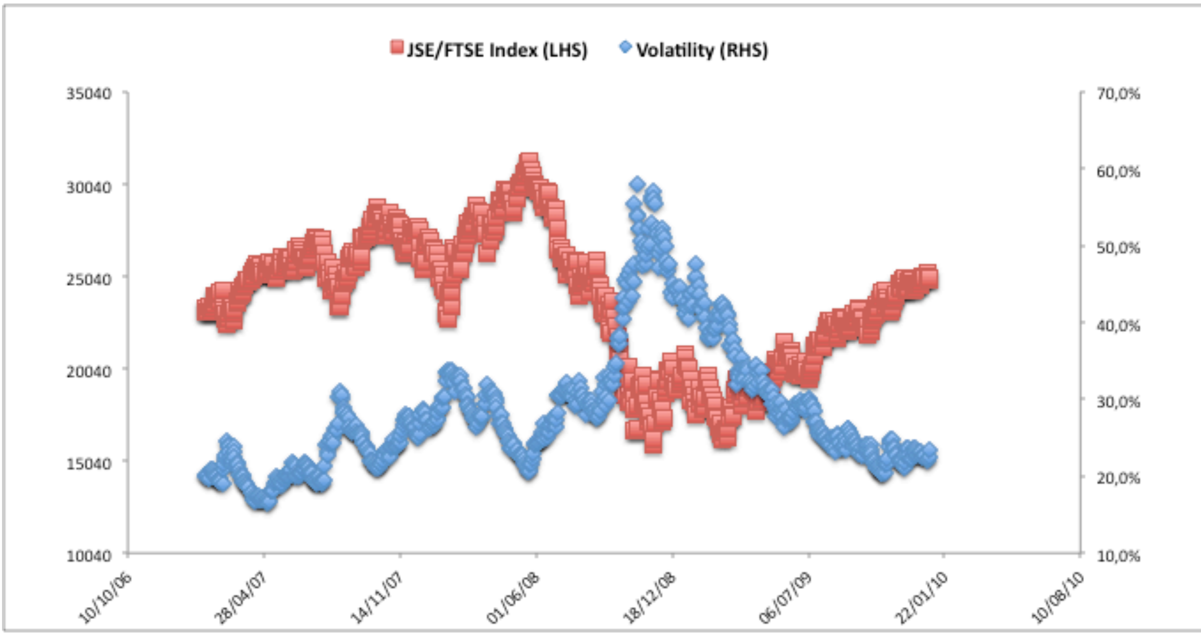

Figure 1: The JSE/FTSE Index and its volatility. When the index fall the volatility usually rises.

3. DATA

The data we used to show the efficiency of the VaR measurement using the volatility are the FTSE/JSE Top40 index. The FTSE/JSE Top40 index is known as the All-share Top 40 index in South-Africa. The implied volatility data we consider is the South-African Volatility Index, SAVI [5]. The SAVI is an at-the-money index option implied volatility, plus an allowance for the volatility skew as implied from traded FTSE/JSE Top40 index options. We consider 977 daily index trading, and SAVI levels ranging from 01/02/07 to 31/12/10.

4. RESULTS

The VaR horizon used is one-day; in otherwords all the VaR estimated is valid only for one-day. For regulatory purposes we restrict the analysis to a 1-day VaR at the 99.95% confidence level. This level of confidence allows for a 1-day VaR failure rate of approximately 2 per annum.

The historical 1-day VaR measurement is the 2^{nd} worst 3 day price return, scaled by the square root of time to give the 1-day VaR historical estimate. This historical 1-day VaR estimate by construction correspond to a confidence of 99% approximately.

The results show that incorporating the volatility into the VaR estimate, allows for a VaR estimate that is more responsive during the bearish FTSE/JSE trend in 2008. (See Fig. 2.). The Volatility VaR further also proved to have a smaller failure rate, than the historical VaR estimate.
(See Fig. 3.).

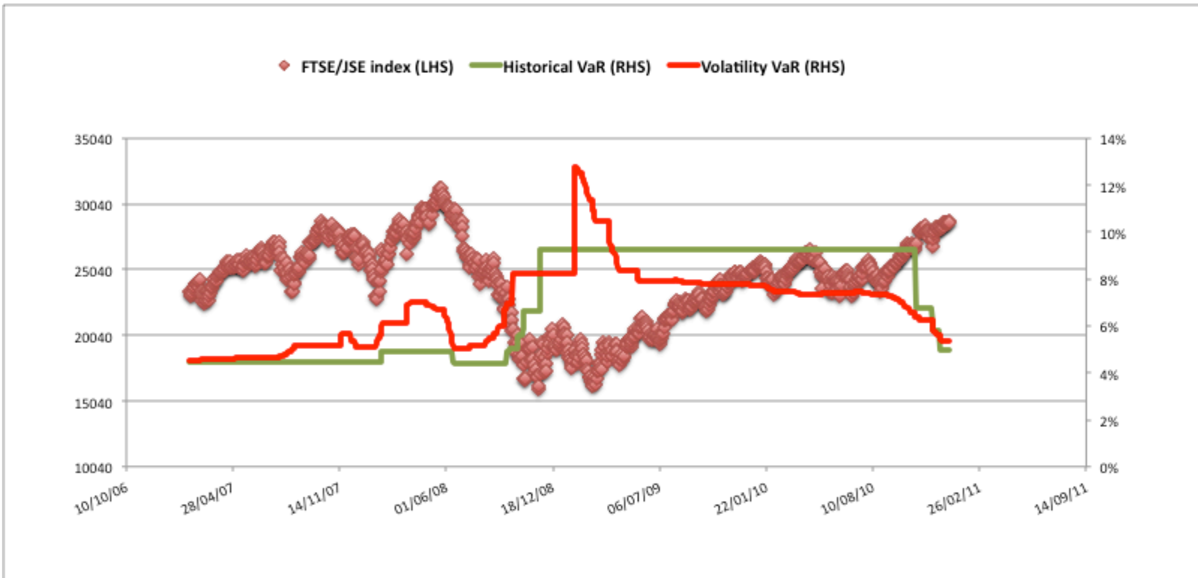

Figure 2: Historical and Volatility VaR of the FTSE/JSE index. The Volatility VaR is a more efficient VaR, as it reacts more timeously when the index turned bearish in 2008.

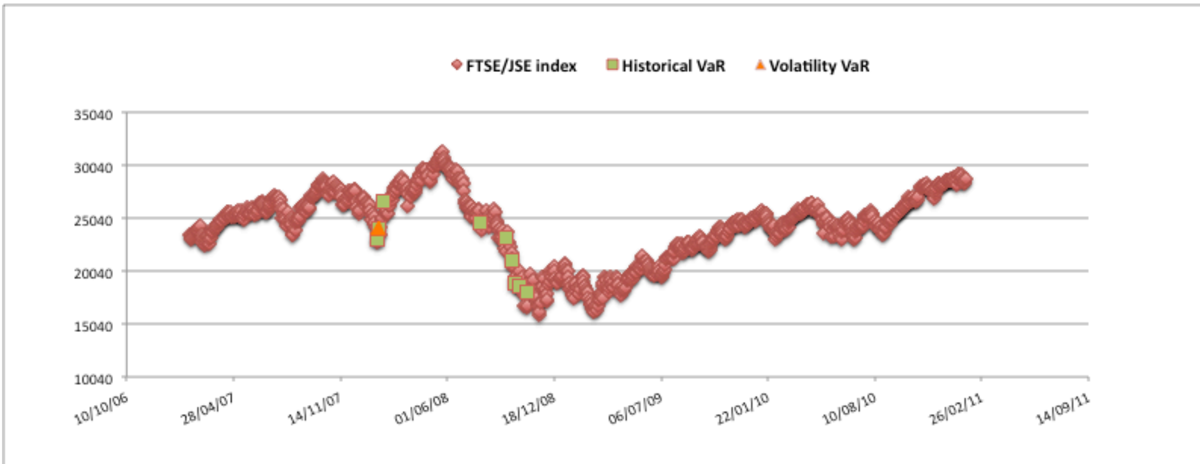

Figure 3: Failure of the Historical VaR and the Volatility VaR. The Volatility VaR is a more efficient VaR as it failed only once in understating the 1 day VaR.

5. SUMMARY

We briefly discussed some of the traditional methods of estimating VaR. We then introduced the idea of using the volatility to develop a VaR estimate that reacts more efficiently and timeously to the changes in the market price returns, and has a smaller VaR failure rate. The Volatlity VaR reacts swiftly to the market because it incorporates the market historical and implied volatility. In this way, the chances that the VaR is understated or overstated is decreased. Furthermore, the Volatility VaR do not depend on random numbers and are easily reproducible. These properties makes for a more efficient, and accurate VaR estimate.

6. ACKNOWLEDGEMENT

Many thanks to Dr Antonie Kotzé for fruitful discussions, and help with the literature search.

7. REFERENCES

[1] Barone-Adesi, G., and Giannopoulos, K., Non-parametric VaR techniques. Myths and Realities, Universita della Svizzera Italiana and City Business School, 2000.

[2] Alexander, C., Market Models, Guide to Financial Data Analysis, John Wiley and Sons, 2001.

[3] Hull, J., Options Futures and Other Derivatives, Pearson Education International, 2003.

[4] Gatheral, J., The Volatility Surface: a practitioner's guide, Wiley Finance, 2006.

[5] Kotzé, A., Joseph, A. and Oosthuizen, R., The new South-African Volatility Index new SAVI, Johannesburg Stock Exchange Equity Derivatives, 2009.