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Historical Simulation (HS) Method on Value-at-Risk & its Approaches

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Abstract
Value at risk (VaR) is a management tool for measuring and controlling risk. Individual and institutional investors rely their investment decisions increasingly on the risk inherent in a security. In this theses, calculating of Va R are implemented using Historical Simulation and Monte Carlo approach on stock portfolio. Different Values of confidence levels are also used for each of the method. The study is conducted on six fundamentally different stocks. Data on daily prices on collected for a period of eight years (2007-2014) for all stocks assets and their corresponding log returns calculated. From our analysis, Monte Carlo Simulation had an optimal values of VaR as compared to Historical simulation in both the VaR 95% and VaR 99% confidence levels. Nonetheless, the VaR 95% has the highest simulation time.

Keywords: *Value at Risk, Risk Approach, Risk Simulation*

I. INTRODUCTION

Risk estimation has engrossed financial market participants since the beginning of financial history. Be that as it may, numerous past endeavors have turned out to be unreasonably perplexing. For instance, upon its presentation, Harry Markowitz's Nobel prize-winning theory of portfolio risk measurement was not embraced practically speaking as a result of its burdensome information prerequisites. In fact, it was Sharpe (2000) who, alongside others, made portfolio theory the standard of financial risk measurement in real world applications through the appropriation of the rearranging suspicion that all risk could be decomposed into two parts: systematic, market risk and the residual, company-specific or idiosyncratic risk. The resulting Capital Asset Pricing Model theorized that since just undiversifiable market risk is relevant for securities pricing, only the market risk measurement β is necessary, along these lines extensively decreasing the required information inputs, (Sharpe, 2000). This model yielded a promptly quantifiable evaluation of risk that could be practically applied in a real time market environment. The main issue was that β demonstrated to have just a tenuous connection with real security returns in this way throwing questions on β designation as the genuine danger measure. With β addressed, and with asset pricing all in all being at somewhat of a chaos as for whether the thought of "priced risk" is truly pertinent, market practitioners hunt down a replacement risk measure that was both precise and generally modest to evaluate. In spite of the thought of numerous different measures and models, VaR has been broadly received. Part of the reason prompting the widespread adoption of VaR was the choice of JP Morgan to make a straightforward VaR estimation model, called Risk Metrics. Risk Metrics was upheld by an openly accessible database containing the basic inputs required to appraise the model.

I. REVIEW OF RELATED LITERATURE

Markowitz (1952) conducted spearheading work in the field of statistical market risk analysis in the mid-fifty's by presenting the Modern Portfolio Theory (MPT). In MPT, market risk is measured as the standard deviation of returns, which are expected to follow normal distribution. Market risk in MPT context thus entails both upside and drawback potential. In recent years a concept called VaR has increased much consideration among scholastics and professionals. VaR gives an alternate way to deal with business sector risk: it is a measure of investment portfolio loss potential. VaR concentrates on the drawback risk the portfolio is presented to. Approach to risk management perceives that the risks happen just to the extent they cause financial losses.

Formally VaR is characterized as the greatest expected risk over a given horizon period at a given level of confidence, (Dowd, 1998) Mandelbrot (1963) observed that volatilities of market factors are time-dependent. This phenomenon known as volatility clustering has been affirmed by numerous studies from that point forward. Therefore, in modelling market factor distributions conditional methods (time-dependent) have appeared superior to unconditional methods (time- independent) in modelling market factor distributions for VaR calculations in many empirical studies (see, e.g., JP Morgan, 1996, Goorbergh et al., 1999a). Conditional methods represent time re- liance of business sector component conveyances while unconditional methods assume that market factor distributions stay consistent after some time and are free of past realizations.

An essential milestone in the improvement of VaR models was J.P. Morgan's choice in 1994 to make its VaR framework called Risk Metrics open and accessible on the Web. The Risk Metrics framework comprises of a methodology outlining the procedures to compute VaR figures, the required market data, and software for calculations (JP Morgan, 1996). The production of the Risk Metrics urged littler organizations to embrace the Risk Metrics way to deal with VaR. In the next years the Risk Metrics framework turned into a semi- standard within the financial industry and a benchmark for measuring market risk.

VaR models have been broadly discussed in writing. As the inadequacies of the ordinary VaR models are unquestionably comprehended, VaR-related investigation went for extra advanced methodologies with a particular deciding objective to improve the exactness and judicious power of VaR models. But new VaR approaches, for instance, Conditional Au- to regressive VaR (CAVaR) have been made, there are only few studies accessible looking at a more broad extent of VaR models including both, standard and propelled VaR models.

Commercial banks may pick their administrative capital conditions for business sector risk exposure using VaR models. As of late, there are three measurable strategies (the binomial strategy, the interval forecast techniques and the distribution forecast strategy) for assessing the accuracy of VaR models that are open to Controllers. Lopez (1997) proposed another evaluation methodology considering real scoring rules for probability forecasts and the simulations results exhibited that the proposed system was clearly capable of isolating among exact and option VaR techniques.
In their article, Sarma et al (2003) performed a two relevant contextual analysis in model decision for the S&P 500 list and India's NSE-50 record, at 95% and 99%. A two-stage model determination procedure was utilized. Class of models was tried for statistical ac- curacy and if different models survive rejection with the tests, a second stage filtering of the surviving models using subjective loss functions. The two-stage model determination methodology wound up being sensible in picking a VaR model. The study gives affirmation about the suitability and hindrances of current data on estimation and testing for VaR.

In the contextual relationship of finance, Value at Risk is an assessment, with a sensible level of sureness, of how much a monetary pro can lose from a portfolio over a given time period. The portfolio can be that of a solitary speculator, or it can be the course of action of a whole bank. As a disadvantage risk measure, Value at Risk spotlight on low likelihood occasions that exist in the lower tail of a scattering. In setting up a hypothetical form for VaR, Jorion (1997) clarifies the critical end of period portfolio value as the worst possible end-of-period portfolio value with a pre-determined confidence level "$1-\alpha$". These most discernibly terrible qualities should not be experienced more than 1% percent of the time over the given holding period.

Recently Value at Risk is being recognized by corporate risk managers as a huge apparatus in the general risk management approach. Preliminaries interest in VaR, in any case, originated from its conceivable executions as a regulatory too. As a result of a couple of budgetary incidents including the trading of auxiliaries things, for instance, the Barrings Bank breakdown, administrative offices, for example, the Securities and Trade Commission or the BIS, in organization with a few national banks, held onto VaR as a transparent mea- sure of downside market risk that could be useful in reporting risks related with portfolios of highly market sensitive assets such as derivatives. Since VaR focuses on disadvantage risk and is normally given in currency units, it is more consistent than other factual terms. It is frequently used for internal risk administration purposes and is further being broadcast for use in risk management purposes making by non-financial related firms.

II. WHY VALUE-AT-RISK

Since the distribution of JP Morgan's Risk Metrics in 1994 there has been an explosion of research in the areas of value of risk and risk management in general. While the fundamental ideas encompassing VaR are founded in the area of market risk measurement they have been extended, throughout the most recent decade, to different regions of risk management. Specifically, VaR models are presently ordinarily used to measure both credit and operational risks.
Value-at-Risk models are utilized to predict risk exposure of an investor or financial institution in the next period (day, quarter, and year). If a "bad period" happens as characterized by some statistical measure. For instance, a financial institution might wish to know its introduction to credit risk if one year from now is the worst year in 100 years (in this manner the purported 99th percentile most pessimistic scenario). With such a measure close by, the money related organization can then evaluate its capital sufficiency (in this way the measure of capital stores it has within reach to withstand such an expansive sudden misfortune). Regularly, the aggregate capital needs of a budgetary foundation have been evaluated by including required capital in various territories of risk exposure (example: market, credit, and

operational risks). Notwithstanding, with the rise of different ways to deal with measuring these diverse risks, for example, such as Value at Risk, the need for a more integrative methodology turns out to be clear.

III. HISTORICAL SIMULATION (HS) METHOD

Historical simulation can also be used in estimating the Value at Risk. Historical Simulation is more pliable than the Parametric method and avoids some of the pitfalls of the parametric method. This method has the benefit of simply handling options in the portfolio (Best, 1998). It also has the benefit of extensively accepted by trading communities and management mostly because of its clarity. The historical simulation method calculates potential losses using real historical data of the returns in the risk factors and hence captures the non-normal distribution of risk factor returns. Because the risk factor returns used for revaluing the portfolio are real past movements, the correlation in the estimation are also actual historical correlations. As Dan´ ielsson (2011) clearly stated, the main concept of this methodology is to predict future losses based on the historical performance. Historical simulation (HS) is a simple method for forecasting risk and relies on the assumption that history repeats itself, where one of the observed historical returns is anticipated to be the next period return. Each historical observation carries the same weight in HS forecasting. This can be a disadvantage, specifically when there is a structural break in volatility. Nevertheless, in the absence of structural breaks, HS tends to function better than alternative methods. It is less sensitive to the odd outlier and does not absorb estimation error in the same way as parametric methods. The importance of HS become especially clear when working with portfolios because it directly captures nonlinear dependence in a way that other methods cannot.

Values of the market components for a specific past period are fetched and changes in these values over the time horizon are observed for use in the calculation. For example, if a 1-day VaR is needed using the past 50 trading days, each of the market factors will have a vector of observed changes that will be made up of the 49 changes in value of the market factor. A vector of different values is generated for each of the market factors by adding the contemporary value of the market factor to each of the values in the vector of observed changes.

The portfolio value is constructed using the present and alternative values for the market factors. The variations in portfolio value between the recent value and the alternative values are then evaluated. The last step is to categorize the changes in portfolio value from the smallest value to highest value and ascertain VaR based on the required confidence interval. For a 1-day, 95% confidence level VaR using the past 100 trading days, the VaR would be the 95th most unfavourable change in portfolio value.
The risk is calculated with price changes:

1. Absolute change in price,
2. Logarithmic change in price,
3. Relative change in price, but should the change be relative to the initial price, then it is called return or rate of return.

1-day Period

The price in time t can be denoted as *Pt* (which represents one trading day). The relative rate of return (*Rt*), between *t* and $t - 1$ can be calculated as:

$$R_t = \frac{P_t - P_{t-1}}{P_{t-1}}$$

The logarithmic rate of return (*Rlt*) correspond to

$$(Rl_t) = \log \frac{P_t}{P_{t-1}} = \log(1 + R_t)$$

The absolute rate of return (*Rat*) for the same time period is

$$Ra_t = P_t - P_{t-1}$$

K- days Period

Return of the k-days period of time is defined as

$$R_t = \frac{P_t - P_{t-1}}{P_{t-k}}$$

The main assumptions of HS are:

- Selected sample period could describe the properties of assets very well,
- There is a probability of reiterating the past in the future, that is, the recreation the patterns appeared in the volatilities and correlations of the returns in historical sample, in the future. However, the past could be a good basis of the future forecast.

The process used to estimate the VaR of a given portfolio using historical simulation is as below:

1. A portfolio of M assets denoted by a vector of weights is defined;

$$\bar{\omega} = \begin{pmatrix} \omega_0, 1 \\ \omega_0, 2 \\ \omega_0, 3 \\ \vdots \\ \omega_0, M \end{pmatrix} \tag{3.6}$$

2. For each asset price or risk factor involved in the problem, obtain a series of returns for a given time period (for example, 200 days). When log-returns are used, they are calculated as below:

$$r_{k,t} = \log \frac{pk,t}{pk,t-1} \tag{3.7}$$

where $r_{k,t}$ and pk,t are respectively the return and price of the asset *k* at time *t*.

3. Consider each of the days in the time series of returns as a scenario for possible Changes in the next day. As there are M assets, each day t of historical data will form a scenario defined by:

$$\bar{r}_t = \begin{pmatrix} r_1, t \\ r_2, t \\ r_3, t \\ \vdots \\ \omega M, t \end{pmatrix} \tag{3.8}$$

It is important to notice that from this point on the scenarios $\bar{r}_t$ are no longer seen as time series, but just as a set of different possible realizations of the random vectors $\bar{r}_t$, obtained from historical data.

4. Apply each of the scenarios to the composition of the portfolio today, that is, do not apply the price changes in cascade to the portfolio. Indicating that the outcome of the application of scenario t to the portfolio is:

$$\bar{\omega} = \begin{pmatrix} \omega_0, 1 \\ \omega_0, 2 \\ \omega_0, 3 \\ \vdots \\ \omega_0, M \end{pmatrix} = \begin{pmatrix} \omega_0, 1.e^{r1,t} \\ \omega_0, 2e^{r2,t} \\ \omega_0, 3e^{r3,t} \\ \vdots \\ \omega_0, Me^{rM,t} \end{pmatrix} \tag{3.9}$$

Note that despite the fact that the notation *wt,k* is used to represent weights in Pth portfolio, they will not be normalized in this procedure, in such a way that $\sum_{k=1}^{N} w_{t,k}$ for $k \neq 0$ may be different than one.

5. The log-returns of the portfolio for each of the scenarios are estimated as:

$$R_t = \log(\sum_{k=1}^{N} w_{t,k}) \tag{3.10}$$

remembering that $\sum_{k=1}^{N} w_{t,k} = 1$

6. Categorize the portfolio returns (*Rt*) for the various scenarios into percentiles.
7. The VaR will be the return that correlate with the preferred confidence level. For instance, if there are 200 days and a confidence level of 99% preferred, the VaR will be the second worst return of the portfolio.

IV. MONTE CARLO SIMULATION METHOD

Monte Carlo simulation is more pliable. Unlike historical simulation, Monte Carlo simulation permits the risk manager to use real historical distributions for risk factor returns as opposed to having to assume normal returns. Monte Carlo simulation is an extensive method of stochastic modeling processes-processes entailing human selection for which we have insufficient information. It imitates such a procedure by way of random numbers obtained from probability distributions which are presumed to correctly describe the un- known constituents of the process being modeled. Monte Carlo simulation is largely used in physics and engineering as well as in finance.

Stanislaw Ulam created the Monte Carlo approach in 1946 (Eckhardt, 1987) and includes some method of statistical sampling used to estimate solutions to quantitative problems. In the procedure, the arbitrary procedure under analysis is imitated time after time, where in each simulation will be generated a scenario of conceivable parameters of the portfolio at the target horizon. By creating a substantial number of plans, ultimately the distribution acquired through simulation will converge towards the true distribution. A good illustration of this method can be obtained, for example, in Holton (2003, chapter 5).

Crouhy et al. (2001) stated that this approach is beneficial in that: it allows the performance of sensitivity analyses and stress testing; the method can be used to model any complex portfolio; and that any distribution of the risk factors may be used. He however stated that outliers are not incorporated into the distribution; it is very computer intensive. In addition to the strength of Monte Carlo simulation is that no assumptions about normality of returns have to be made. The method is also capable of covering nonlinear instruments, such as options, Damodaran (2007).

To add more to the benefits of this approach of VaR, Jorion (2001) reminds that Monte Carlo simulation initiates the whole distribution and consequently it can be used, for example, to estimate losses in excess of VaR. A possible weakness is also model risk, which arises due to wrong assumptions about the pricing models and underlying stochastic processes, a possible weak. If these are not properly stated, VaR calculations will be misrepresented, Jorion (2001).

Furthermore, Dowd (1998) points out that complex techniques related to this approach necessitate specific skills. Senior management may therefore have difficult time acquainting themselves of how VaR values are calculated when Monte Carlo is used.

V. CONCLUSIONS

The purpose for the popularity of VaR is predominantly its conceptual simplicity as it totals every one of the risks in a portfolio into a single number suitable for use in the boardroom, answering to controllers, or divulgence in a yearly report (Linsmeier & Pearson, 1996). VaR can quantify chance over a wide range of positions (almost any asset) and risk variables (not just market risk) and it gives a fiscal and probabilistic articulation of loss amounts. In spite of critical issues, the VaR idea can be used in several ways:

- Administration can set general risk targets and from that decide the relating risk position. Expanding VaR implies expanding risk for the firm.

- VaR can be utilized to decide capital requirements. New risk based capital sufficiency system Basel II, closely resembling Basel I, endorses VaR as an essential method for measuring credit risk and consequently capital adequacy. Further, as indicated by Basel Board, banks ought to keep adequate money to have the capacity to cover business sector misfortunes more than 10 days with 99 percent likelihood for all their exchanged portfolios. This sum is to be determined by VaR, (Basle Committee on Banking Supervision, 1996).

- VaR is useful for reporting and disclosing purposes.

- VaR-based decision rules can guide investment, hedging, trading and portfolio management decisions.
- VaR information can be utilized to give compensation tenets to brokers and directors and

- Systems based on VaR can measure other risks such as credit, liquidity and operational risks. (Dowd, 2005)

From among the critics, Taleb (1997) suggests suspension of VaR as a

- Potentially dangerous malpractice as it involves principal-agent issues and is often invalid in real world settings.
- Over-reliance on VaR can lead to bigger losses.

- VaR does not portray losses beyond the particular certainty level. Danielsson & Zigrand, (2003) contend that VaR utilized for regulatory purposes might bend great risk administration practices.
- Non-coherence because of non-subadditivity of VaR is seen as the most genuine down- side of VaR as a risk measure. It must be made sub-added substance while forcing typicality confinement on return circulation, what negates the truth of financial time series.

VaR is utilized by Bank of International Settlements (BIS) for deciding capital prerequisite to cover business sector risk by typical operations. This, notwithstanding, requires the hidden risk to be appropriately assessed, else it might lead institutions to overestimate (underestimate) their market risk and therefore to keep up unnecessary high (low) capital requirements. The outcome is an inefficient allocation of financial resources. These realities were proposed by Manganelli & Engle (2004).

Among recent critics Whalen (2006) takes note that over the previous decades VaR had all the earmarks of being compelling as there was little risk to quantify and that depending on false presumption in administrative system makes VaR a standout amongst the most unsafe and generally held confusions in financial world," (Whalen, 2006, p. 2).

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