Chapter XVII

On the New Transformation-Based Approach to Value-at-Risk: An Application to the Indian Stock Market

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ABSTRACT

This chapter deals with the measurement of Value-at-Risk parameter for a portfolio using historical returns. The main issue here is the estimation of suitable percentile of the underlying return distribution. If returns were normal variates, the task would have been very simple. But it is well documented in the literature that financial market returns seldom follow normal distribution. So, one has to identify suitable distribution, mostly other than normal, for the returns and find out the percentile of the identified distribution. The class of non-normal distribution, however, is extremely wide and heterogeneous, and one faces a decision-making problem of identifying the best distributional form from such a wide class of potential alternatives. In order to simplify the task of handling non-normality while estimating VaR, we adopt the transformation-based approach used in Samanta (2003). The performance of the transformation-based approach is compared with two widely used VaR models. Empirical results are quite encouraging and identify the transformation-based approach as a useful and sensible alternative.

INTRODUCTION

The Value-at-Risk (VaR), in recent years, has emerged as an important tool for managing financial risks. Though originally proposed for handling ‘market risk’, domain of VaR application was soon found much wider, and conceptually VaR is useful in managing even other financial risks, such as credit risk and operational risk. The VaR, as a risk management tool, serves several
purposes: (a) it provides a risk measure, so useful to compare risk involved in different portfolios; (b) it is a measure of potential loss from a portfolio; and (c) it is a key parameter prescribed by central banks across countries to their regulated banks to determine required capital for market risk exposure (Jorian, 2001; Wilson, 1998).

The VaR, when used for market risk, gives a single number that represents the extent of possible loss from an investment portfolio due to market swings in the future. The concept is defined in a probabilistic framework, and VaR provides a threshold on maximum loss from a portfolio in such a fashion that the instance of actual loss exceeding the threshold during a predefined future time period has certain fixed/predefined probability. In cases of other risk categories (such as credit risk and operational risk), VaR would quantify the maximum possible loss (in probabilistic sense), due to changes in corresponding risk factors. However, specification and implementation of VaR vary across risk categories. Throughout this chapter, we discuss VaR in the context of the market risk.

The VaR for a portfolio can be estimated by analyzing the probability distribution of the respective portfolio’s return—the VaR simply gives a threshold return which corresponds to a suitable percentile of the underlying distribution. If returns follow normal distribution, the required percentile can be derived from the corresponding percentile of standard normal distribution (which is readily available from the standard normal distribution table) and mean and standard deviation of the observed return distribution. But in reality, financial market returns seldom follow normal distribution, and the task of estimating VaR has been a challenging one.

The empirical evidence across countries shows that distribution of financial market returns generally poses fat-tails (excess-kurtosis) and may be significantly skewed. The fat-tail distribution may occur primarily due to the ‘volatility-clustering’ phenomenon observed in financial markets and indicate the occurrence of large or extreme returns more frequently than predicted by normal distribution. Whereas skewed distribution would tell us to analyze the observations in two tails (i.e., large/rare negative returns in the left tail and large/rare positive returns in the right tail) differently. In either case, normality assumption to the underlying return distribution might be a potential source of error in VaR estimation. If the specific form of the non-normality were known, one would still be able to estimate VaR easily from the percentiles of the specific distributional form. But in reality the form of the underlying distribution is not known and one has to discover it from the data. The class of non-normal distributions includes all possible (in our case continuous) distributions other than normal, thus extremely wide and heterogeneous. So, while estimating VaR, one is essentially facing a decision-making problem of selecting one distributional form from a vast set of possible alternatives. A mis-specified VaR model may cost an institute heavily and the associated hazards may be covered under what is known as ‘model risk’.

The conventional approaches to handle non-normality fall under three broad categories: (1) non-parametric approaches, such as historical simulation; (2) fitting suitable non-normal or mixture distribution; and (3) modeling the distribution of extreme return or modeling only the tails of return distribution. The non-parametric alternatives, like historical simulation, do not assume any specific form of the return distribution and are quite robust over distributional forms. Besides, these techniques are easy to understand and implement. But this approach suffers from the lack of analytical flexibility and several other disadvantages of what non-parametric approaches share. Alternatively, one can simply fit the parametric form of a suitable non-normal distribution to the observed returns. The class of distributional forms considered would be quite wide including, say, t-distribution, mixture of two or more normal distributions, hyperbolic distribution, Laplace