The Quarterly Review of Economics and Finance 50 (2010) 515–526

Contents lists available at ScienceDirect

The Quarterly Review of Economics and Finance

journal homepage: www.elsevier.com/locate/qref

# Value at risk models for volatile emerging markets equity portfolios

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ARTICLE INFO

*Article history:*
Received 30 September 2009
Received in revised form 14 May 2010
Accepted 29 June 2010
Available online 6 July 2010

*JEL classification:*
G1

*Keywords:*
Emerging stock markets
Risk management
Value at Risk

ABSTRACT

This paper investigates the issue of market risk quantification for emerging and developed market equity portfolios. A very wide spectrum of popular and widely used in practice Value at Risk (VaR) models are evaluated and compared with Extreme Value Theory (EVT) and adaptive filtered models, during normal, crises, and post-crises periods. The results are interesting and indicate that despite the documented differences between emerging and developed markets, the most successful VaR models are common for both asset classes. Furthermore, in the case of the (fatter tailed) emerging market equity portfolios, most VaR models turn out to yield conservative risk forecasts, in contrast to developed market equity portfolios, where most models underestimate the realized VaR. VaR estimation during periods of financial turmoil seems to be a difficult task, particularly in the case of emerging markets and especially for the higher loss quantiles. VaR models seem to be affected less by crises periods in the case of developed markets. The performance of the parametric (non-parametric) VaR models improves (deteriorates) during post-crises periods due to the inclusion of extreme events in the estimation sample.



## 1. Introduction

Value at Risk (VaR) summarizes in a single number the expected maximum loss of a portfolio over a target horizon at a certain confidence level. It has emerged as an important tool for managing and reporting financial risk, employed widely by financial institutions and regulators (see, for example, the Basle Committee on Banking Supervision, 2004). Despite the simplicity, popularity and importance of the concept, however, there is no universally accepted method to arrive at the VaR of a particular portfolio, while different models may lead to significantly different risk measures (see, amongst others, Kuester, Mittnik, & Paoella, 2006; McMillan & Kambouroudis, 2009). Thus, a main concern in the estimation of market risk with the VaR method is the choice of the appropriate model for the estimation, e.g. an ill-suited model may turn out to be costly or catastrophic for the risk taking vendor, as a consequence of inaccurate estimation of risk.

This paper aims to address the issue of VaR model selection for emerging and developed markets equity portfolios. Investigating VaR modeling for emerging equity markets is particularly interesting, mainly due to the following reasons: (a) market risk estimation for equity emerging markets' assets is particularly important for the global economic stability; (b) the issue of market risk quantification for emerging markets, to our knowledge has not been studied systematically; (c) diversities in risk quantification may be evident due to the different properties of emerging market returns (see Aggarwal, Inclan, & Leal, 1999 and references therein; Brooks, 2007, amongst others) and due to the process of emerging markets' liberalization and integration with the rest of the world during the past decade (Bekaert & Harvey, 2003).

Moreover, previous studies on VaR estimation for equity emerging markets leave many issues open. For example, some studies consider only Asian markets, a fact which renders generalizations for the universe of emerging markets problematic (see Da Silva, Beatriz, & de Melo Mendes, 2003; Lee, Bao, & Saltoglou, 2006). Also, the majority of previous empirical research has neglected the critical issue of conditional efficiency in the backtesting of VaR estimates. According to conditional efficiency, the violations of a VaR model should be conditionally unpredictable when conditioned upon the previous period's outcome; VaR models which yield clustered violations may induce solvency issues for the risk managers. Finally, most studies on emerging markets focus on Extreme Value Theory (EVT), a method that is not without shortcomings (see Diebold, Schuermann, & Stroughair, 2000). Da Silva et al. (2003) focus mainly on extreme value methods and find that the extreme value approaches are more conservative than traditional and historical methods in estimating VaR, when used to determine capital requirements. Lee et al. (2006) advocate to the superiority of filtered models against unfiltered and Riskmetrics models, while parametric Student's-*t* specifications outperform normality based approaches for the higher quantiles. Gencay, Selcuk, and Ulugulyagci (2003) extend their analysis to a larger num-

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doi:10.1016/j.qref.2010.06.006

ber of emerging equity markets and highlight the dominance of extreme value VaR over the traditional VaR approaches for high confidence levels. However, they employ a limited number of traditional VaR approaches and exclude GARCH models for producing highly volatile VaR estimates. The results of Gencay et al. (2003) are also echoed in Assaf (2009), while Maghyereh and Al-Zoubi (2006) find that the asymmetric power ARCH and the extreme value are the dominant methods for the estimation of VaR in the case of seven emerging Middle East and North African stock markets.

The aim of this paper is to address this gap in the literature by evaluating the accuracy and efficiency of various VaR approaches with data from 16 emerging and 4 developed stock markets, spanning over America, Asia and Europe. A plethora of traditional VaR approaches which are widely used by practitioners are examined in conjunction with extreme value and adaptive filtered methods. The sample period chosen for the analysis (1995–2003) is a period of excessive volatility in financial markets, when many significant economic events took place. This makes the period ideal for the empirical evaluation of a risk measure, such as VaR. For example, in 1997 Thailand floated the baht after a 13-year link to the dollar and within the day the currency declined by 17%, triggering a global financial crisis; in August 1998 Russia devalued the ruble and announced a moratorium on external debt servicing, triggering yet another global crisis of such an extent that the Federal Reserve had to rescue a hedge fund called Long-Term Capital Management in order to avoid further defaults. A year later Brazil was hit by contagion in the so-called Brazilian crises of 1999. Furthermore, on the 11 September 2001 the terrorist attack right in the center of the world's financial community resulted in turmoil in financial markets.

This study contributes to the relevant literature in many ways: (i) it allows for the first time direct comparisons to be made on the performance of various VaR models between emerging and developed markets by applying backtesting on VaR forecasts obtained from models applied on both emerging and developed markets during the same time period; (ii) it extends the analysis to countries beyond Asia, by using a larger and more representative sample of emerging stock markets, covering many different emerging markets for the regions of Latin America, Europe and Asia. Consequently, the findings are more suitable for drawing generalizations and making inferences for the universe of emerging equity markets; (iii) all of the employed filtered models are estimated adaptively in the sense that in each recursion the lag length which fits the data best is chosen. This is the first time, to our knowledge, that adaptive filtered models are used and compared with non-adaptive VaR models, providing a more realistic view of the VaR models' performance; (iv) it evaluates the performance of a wider spectrum of VaR models than previous studies and compares and contrasts these to the EVT and adaptive models; (v) the validity of the findings is enhanced by considering specific time periods, which are characterized by excessive volatility, such as the Asian financial crisis of 1997–1998, the Russian crisis of 1998 and the Brazilian crisis of 1999. Thus, the investigation of the behavior of the alternative VaR models during the crises periods offers many implications for the ongoing global financial crisis of the post-2007 period[1]; (vi) the performance of the various VaR methods is examined in terms of robustness, i.e. in terms of providing sufficiently accurate risk forecasts for various markets, estimation windows and VaR confidence levels; and (vii) the impact of the estimation window in the reliability of VaR estimates is studied by considering estimation windows of various lengths and of significantly different market conditions. That is, estimation samples containing crises periods are used for estimating VaR during the post-crises periods. The rest of the paper is organized as follows: Section 2 outlines the VaR models and testing methodologies which are employed in the paper, Section 3 discusses the data, Section 4 presents and discusses the results, Section 5 examines the robustness of the results during crisis and post-crisis periods and Section 6 concludes the paper.

## 2. Methodology and VaR models

Let $r_t$ be the change in the value of a portfolio over a certain horizon and $f_t(r)$ be the marginal probability function for $r_t$ (i.e. $r_t \sim f_t(r)$). Value at Risk (VaR) expresses the maximum amount of money that a portfolio may lose at the given confidence level $1-\alpha$ (e.g. $1-\alpha = 0.95$) over a given forecast horizon; see Jorion, 1997 for a general exposition of the concept of VaR. Mathematically:

$$\text{VaR} = F^{-1}(\alpha) = \int_{-\infty}^{\text{VaR}} f(r)\,\mathrm{d}r = P(r \le \text{VaR}) = \alpha \tag{1}$$

When the expected returns are assumed to follow a location-scale distribution (such as the Student's-$t$, the exponential and the symmetric stable (or Pareto-Lévy), the normal and the Cauchy distributions) then VaR is defined by:

$$\text{VaR}_{t+1}^{1-\alpha} = \hat{\mu}_{t+1} - F^{-1}(\alpha) \cdot \hat{\sigma}_{t+1} \tag{2}$$

where $F^{-1}$ denotes the standardized quantile of the assumed distribution (e.g. the normal distribution) and $\hat{\mu}_{t+1}$, $\hat{\sigma}_{t+1}$ are the estimated/forecasted location and scale parameters, respectively. According to Figlewski (1997), for short holding periods, it can be best to assume that the sample mean ($\hat{\mu}_{t+1}$) in Eq. (2) is zero. Kim, Malz, and Mina (1999) have also shown that mean forecasts for horizons shorter than 3 months are not likely to produce accurate predictions of future returns. In addition, since volatility is much larger than the expected return at short horizons, the forecasts of the future distribution of returns are dominated by the volatility estimate. Throughout this paper, the assumed distributions of the expected returns $F^{-1}$ are the normal, the Generalized Pareto and the Generalized Error distributions. The confidence levels examined are the most commonly used levels of 95% and 99%, and the holding period is set to 1 day. The methods followed for the estimation of parametric (i.e. the estimation of $\hat{\sigma}_{t+1}$) and non-parametric VaR are presented next.

### 2.1. Volatility models

The *Random Walk (RW)* parametric VaR model assumes that the previous period's volatility ($\hat{\sigma}_t$) is the best proxy of next period's volatility forecast ($\hat{\sigma}_{t+1}$). That is, $\hat{\sigma}_{t+1} = \hat{\sigma}_t$, where $\hat{\sigma}_t$ is the sample standard deviation. The stylized fact of volatility clustering evident in most financial time series is captured by the Generalized Autoregressive Conditional Heteroskedasticity (GARCH ($p$,$q$)) model, introduced by Bollerslev (1986). A GARCH ($p$,$q$) model can be written as:

$$\sigma_t^2 = \omega + \sum_{j=1}^{p} \beta_j \sigma_{t-j}^2 + \sum_{i=1}^{q} a_i u_{t-i}^2 \tag{3}$$

where $\omega > 0$. When $p < 1$, non-negativity conditions for $\hat{\sigma}_t^2$ require $\omega \ge 0$, $\beta_j$, $a_i \ge 0$. See Nelson and Cao (1992) for details on the restrictions of ARCH($p$) and GARCH (1,1) models. Throughout this

[1] The financial subprime crisis of 2008–2009 is not included in the analysis since it leaves no sufficient evaluation sample for the examination of the performance of the VaR models during the post crisis period.