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Value-at-Risk models and Basel capital charges Evidence from Emerging and Frontier stock markets

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ABSTRACT

In the wake of the subprime crisis of 2007 which uncovered shortfalls in capital levels of most financial institutions, the Basel Committee planned to strengthen current regulations contained in Basel II. While maintaining the Internal Model Approach based on Value-at-Risk, a stressed VaR calculated over highly strung periods is to be added to present directives to constitute Minimum Capital Requirements. Consequently, the adoption of the appropriate VaR specification remains a subject of paramount importance as it determines the financial condition of the firm. In this article I explore the performance of several models to compute MCR in the context of Emerging and Frontier stock markets within the present and proposed capital structures. Considering the evidence gathered, two major contributions arise: (a) heavy-tailed distributions – particularly Extreme Value (EV) ones-, reveal as the most accurate technique to model market risks, hence preventing huge capital deficits under current measures; (b) the application of such methods could allow slight modifications to present mandate and simultaneously avoid sVaR or at least reduce its scope, thus mitigating the impact regarding the enhancement of capital base. Therefore, I suggest that the inclusion of EV in planned supervisory accords should reduce development costs and foster healthier financial structures.

1. Introduction

The world financial system has undergone one of its most severe crisis in 2007–2008. Several factors acted simultaneously to ignite turmoil with devastating consequences felt all over the globe as a consequence of the interconnectedness of the national economies. One of the relevant effects brought about by the catastrophe has been represented by the inability of the banks to meet market losses: capital was insufficiently constituted to provide coverage for unexpected adverse events. The shortage was of such an extent that many institutions had to be bailed out by governments at the expense of the taxpayers' resources; although this action averted a complete deadlock in capital markets, it simultaneously introduced elements like moral hazard and subsidies.

The current framework contained in Basel II Capital Accord has established Value-at-Risk (VaR) as the official measure of market risk and enforced it to constitute the central point to the determination of capital charges. Moreover, as the Basel Committee on Banking Supervision (BCBS) has not hitherto recommended a particular VaR methodology, the adoption of the most appropriate VaR approach becomes a matter of the utmost importance to be decided purely on empirical grounds. However, the magnitude of the plight prompted the BCBS to put forward a proposal to increase the Minimum Capital Requirements (MCR) for market risks in accordance with the opinion of national regulators.[1] The intended scheme plans the introduction of a stressed VaR (sVaR) which ought to be added to the base VaR (cVaR) in order to form the new MCR in an attempt to curb the procyclicality of the measure in force.

The aforementioned context highlights the significance of developing a precise VaR model to cover market losses and simultaneously build a capital buffer high enough as to allow institutions to distribute dividends in light of a further BCBS directive which restricts the dividend payout unless the capital level exceeds MCR by a quantity called Capital Conservation Buffer equivalent to 2.5% of the amount of the risk weighted assets. Besides the traditional reluctance on the part of the academics to study Emerging and Frontier markets, BCBS's Consultative Documents have mostly been submitted to developed nations and it is unlikely that these

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[1] "Capital required against trading activities should be increased significantly (e.g., several times)" (Financial Services Authority, 2009, p, 7).

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proposals should be evaluated and its impact assessed in the spheres of Emerging and Frontier markets. This study aims at filling that empirical void, as I analyse the accuracy of several VaR specifications and gauge its effect on capital charges from the perspective of non-developed stock markets under the current and proposed regulations.

The article unfolds as follows. Section 2 briefly synthesises the basic concepts and models to be tried; Section 3 states the current and proposed theoretical frameworks; Section 4 delineates topics regarding the Data and Methodology; Section 5 describes the empirical results from the exercise in connection with BCBS directives while Section 6 offers the concluding statements. Finally, Section 7 stages a sensitivity analysis gauging the impact of BCBS's planned mandate whereas Section 8 presents some overall closing remarks regarding the new sVaR approach.

2. Theoretical background. Concepts and definitions

2.1. Definition of Value-at-Risk

VaR is a statistical risk metric that expresses the maximum loss in the value of exposures due to adverse market movements that a company is reasonably confident will not be exceeded if its positions are maintained static during a certain period of time t.[2] Losses are associated with confidence levels (α): those losses greater than VaR are only suffered with a specific small probability $(1-\alpha)$ (McNeil et al., 2005; Linsmeier and Pearson, 1996). Therefore, for some confidence level $\alpha \in (0;1)$, VaR at the confidence level α is the smallest number l such that the probability that the loss L exceeds l is smaller or equal than $(1-\alpha)$[3]:

$$\mathrm{VaR}(\alpha) = \inf\{l \in R : P(L > l) \leq (1-\alpha)\} = \inf\{l \in R : F_L(l) \geq \alpha\} \quad (1)$$

where F_L denotes the loss distribution function.[4] Given that $Pr(Loss_{t+1} > \mathrm{VaR}_{t+1}) = \alpha$, or equivalently in relative terms or returns[5] $Pr(r_{t+1} < \mathrm{VaR}_{t+1}) = \alpha$, VaR could be characterised as

$$\mathrm{VaR}(\alpha)_{t+1} = \sigma_{t+1} F^{-1}(\alpha) \quad (2)$$

with the following symbols meaning: σ_{t+1} is the volatility of the loss distribution function F (measured by the standard deviation) and $F^{-1}(\alpha)$ is the inverse of the loss distribution function, i.e., α-quantile of F.

2.2. Value-at-Risk models

A synopsis of the methods to be used in this research is stated below.

2.2.1. Historical Simulation (HS)

Arguably the simplest and most popular route to VaR, it only requires the estimation of the appropriate quantile employing the quantiles of a window of past sample returns:

$$\mathrm{VaR}(\alpha)_{t+1} = Q_\alpha(r_t; r_{t-1}; \ldots; r_{t-n+1}) \quad (3)$$

Despite the dimensionality problem is reduced to univariate category and conceptual simplicity and easiness of implementation are achieved, it is a logically inconsistent approach.[6] Its flaws ground fundamentally on the absence of assumptions about the dependence structure of returns (Manganelli and Engle, 2004), alongside the equal weighting structure and the extrapolation of the sample distribution to any forecasted term (Dowd, 2005), the length of the 'past',[7] because it must satisfy variance and bias constraints simultaneously and the likely presence of ghost or shadow effects.[8]

2.2.2. Filtered Historical Simulation (FHS)

Barone-Adesi et al. (1998) devised one significant improvement to HS by combining conditional volatility modelling[9] with the empirical distribution of returns, hence retaining the patterns of HS and simultaneously admitting ways to alter the unrealistic suppositions of HS (Dowd, 2005). FHS demands fitting some model (e.g. a GARCH-family technique) to the sample data to account for the empirical patterns in order to obtain the volatility predictions which are in turn employed to generate a set of iid standardised returns.[10] The α-quantile of the series of standardised returns is then multiplied by the volatility forecast to obtain the FHS VaR:

$$\mathrm{VaR}(\alpha)_{t+1} = \sigma_{t+1} F^{-1}(\alpha), \quad (4)$$

where σ_{t+1} is the volatility forecast derived from any (GARCH-family) volatility model and $F^{-1}(\alpha)$ is the inverse of the cumulative density function of the empirical distribution of residuals, i.e., α-quantile of F.

Although FHS takes into account the changing market conditions by blending conditional volatility modelling with the empirical distribution (Dowd, 2005), Pritsker (2001) affirms that FHS VaR is still unable to capture extreme events.

2.2.3. Linear specifications

Linear techniques only require the estimation of the standard deviation of the portfolio by means of the sample estimate of variance appropriately increased by the quantile of a pre-specified distribution, typically Normal or Student-t. Formally,

$$\mathrm{VaR}(\alpha)_{t+1} = \sigma_{t+1} \Phi^{-1}(\alpha) \quad (5)$$

$$\mathrm{VaR}(\alpha)_{t+1} = \sigma_{t+1} \sqrt{(d-2)d^{-1}}\, t_d^{-1}(\alpha) \quad (6)$$

where σ_{t+1} is the standard deviation of the sample of returns; $\Phi^{-1}(\alpha)$ is the inverse of the cumulative density function of the standard Normal distribution (α-quantile of Φ); $t^{-1}{}_d(\alpha)$ is the inverse of t_d, the distribution function of a standardised t (α-quantile of t); and d is the degrees of freedom of the t distribution.

Their simplicity appears overshadowed by their disadvantages, which derive both from the limitations of the standard deviation as a measure of risk – mainly the equal weighting structure and the inaccuracy beyond the mean[11] – and the inadequacy of the appended distribution.

2.2.4. Models of conditional volatility

Stylised facts present in financial time series like autocorrelation of squared returns and volatility clustering (Christoffersen, 2003; Dowd, 2005; McNeil et al., 2005) pave the way for developing time-varying variance models. Postulating the dependence

[2] Hence, VaR requires the estimation of a quantile of the distribution of profits and losses, i.e., the distribution of returns.
[3] McNeil et al. (2005).
[4] The subscript L will hereafter be dropped from F_L for simplicity reasons.
[5] Appendix A.
[6] Manganelli and Engle (2004).
[7] Manganelli and Engle (2004) recommend between six months and 2 years, Kuester et al. (2006) propose four years and Christoffersen (2003) suggests between one and four years, for example.
[8] Penza and Bansal (2001).
[9] Section 2.2.3. The selection of the GARCH model is not restricted to GARCH. The present research will also apply EGARCH specifications with Normal and t likelihood functions.
[10] Standardised returns are obtained dividing the realised returns by the respective GARCH volatility forecast: $\varepsilon_t = r_t(\hat{\sigma}_t)^{-1}$.
[11] Balzer (2005).