Risk Management in Emerging Markets: Practical Methodologies and Empirical Tests

Article *in* Multinational Finance Journal · December 2006

DOI: 10.17578/10-3/4-2

Risk Management in Emerging Markets: Practical Methodologies and Empirical Tests

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Risk management has undergone a remarkable transformation over the past fifteen years, with most new methods having been designed for the concerns of large institutions operating in well-developed financial markets. This paper addresses a problem faced by smaller institutions operating in emerging markets, namely the significant lack of data. As many risk management techniques are data intensive, this problem may seem insurmountable. This paper introduces a new method, enriched historical simulation, which supplements the data in an emerging market with data from other markets. The principle behind this methodology is that when many markets are considered, the essence of emerging market economies comes to the fore, with local idiosyncrasies being washed out. This principle is illustrated on the problem of estimating Value-at-Risk on the Cyprus and Athens Stock Exchanges. Numerical tests show that standard models underestimate risks, but that estimates are improved significantly with the use of external data (JEL: C10, C80, G10, G15).

Keywords: risk management, historical simulation, value-at-risk, emerging markets

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(*Multinational Finance Journal*, 2006, vol. 10, no. 3/4, pp. 179–221)

I. Introduction

Emerging markets present unique challenges for the design and implementation of risk management systems. There are many reasons why the time is ripe to study these challenges. The first is globalization and the fact that local economies are gradually integrating with more developed, highly competitive markets. The second is that the methodologies for risk management (and in particular market risk management) are at a stage where they are well developed and understood in advanced markets; the peculiarities of emerging markets can perhaps be understood as perturbations of these common models. The third is the adoption of the internal models approach for measuring market risk by the Basel Committee on Risk Management of the Bank for International Settlements. Emerging market banks face a substantial competitive disadvantage if they are forced to continue using the standardized approach. Finally, in emerging markets risk management is being developed concurrently with the financial system as a whole. This is in contrast to the situation in more developed economies where financial markets developed over time, and were quite advanced before risk management became a hot topic. It makes the study of risk management in such environments vital, as these economies try to "hit the ground running".

A. The State of Risk Management in Emerging Markets

Risk managers in emerging markets face a number of challenges that do not present themselves to their colleagues in more developed economies. The first and most apparent is the often chaotic state of the local economy. The second is the short history of these markets. This has a number of significant consequences. One is the relative novelty of financial markets (both to institutions and households; this can be a major cause of speculative bubbles). Another problem, equally important from a risk management point of view, is that there is a startling scarcity of available data. Often, the institutional mechanisms that lead to the plethora of data in advanced markets do not exist (e.g. derivatives exchanges, secondary markets, and even regular auctions of a standard set of government bonds). Furthermore, those data that are available are contaminated for many reasons. Since many emerging markets have gone through some period of crisis, the history of local financial variables is of questionable value in calibrating mathematical models for assessing future risks. Any current price data that are available must be viewed in light of the low volumes and liquidity of local markets. All of these factors lead to tremendous difficulties for risk management.

Emerging markets often bear significant liquidity risk. During periods of business as usual, volumes on the exchange are often extremely low, while during unusual periods volumes are extremely high. The monthly volumes and the level of the Cyprus Stock Exchange are presented in figure 1.[1] Institutional restrictions frequently prohibit short-selling, and it is unlikely to have a liquid derivatives market, or even a secondary market for instruments such as government bonds. Further evidence of the impressive illiquidity in some emerging markets is provided by the presence of large transactions costs. Figure 2 shows the average bid-ask spreads for both the Cypriot FTSE 20 and the German DAX 30 stock indices during the period 4/1/1999 to 29/12/2000. This figure illustrates that transactions costs in emerging markets can be dramatically greater than in developed markets, even during periods of business as usual. This situation is only exacerbated during times of crisis.

It is impossible to arrive at a completely satisfactory solution to the problems posed by the absence of data in emerging markets. There is no way to develop and calibrate a theoretically consistent model using the limited resources available while taking into account all of the (often significant) idiosyncrasies of the local market. In such an environment there is no choice but to attempt to develop methods that are intuitively plausible and effective in practice, both in historical tests and in the current market. This is the approach taken in this paper.

The main novelty in this paper is the use of data from other emerging markets, referred to as enriched historical simulation (EHS), to supplement risk management calculations in the local market. This approach is illustrated on the problem of calculating Value-at-Risk on the Cypriot and Greek stock exchanges. The justification for this method is that emerging markets share many common properties, as discussed above, and that when many of them are considered, local idiosyncrasies are dwarfed by the influence of these common factors. Therefore, data from other markets, while seemingly unrelated to the local market, may carry important information that is relevant to risk management. It should be noted that using foreign markets' experiences

1. In this paper, all stock exchange values are plotted in log-scale.

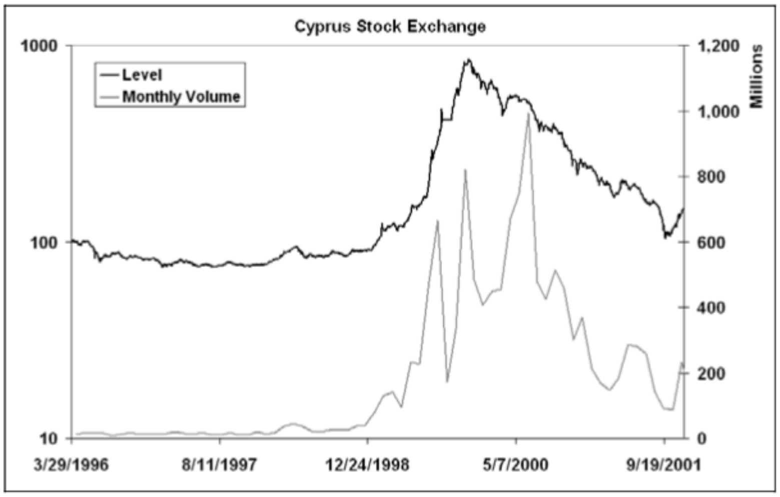

FIGURE 1.— Level and Monthly Volumes of the CSE Index

as possible scenarios for the local market in a stress testing framework has already been suggested by Dembo et al. (2000).

This paper discusses two methodological issues in emerging markets. The first is the best method for estimating the standard risk measure Value-at-Risk (VaR) (see, for example, Jorion ([2000]).[2] The second is how to address problems arising from the lack of data. The proposed method is to use data from other emerging markets to supplement the data in the local market for the purpose of scenario generation. The inclusion of data from many other emerging markets highlights the commonalities that exist between these markets, while local idiosyncrasies have less effect. Ultimately, the test of any scenario generation methodology is how well it performs in practice. This paper presents extensive tests of the proposed methodology on the stock exchanges of both Cyprus (a less developed market) and Athens (a more developed market).

In the present study, the focus is on the perspective of a local investor, with substantial (perhaps all) of its investment in the emerging

2. This should in no way be interpreted as an endorsement of VaR as an ideal (or even adequate) risk measure on the part of the authors. Rather, this measure is used in the current work due to its standing as a benchmark in financial risk management, and because of its practical importance in light of current regulations. Some of the (many) shortcomings of VaR along with some alternatives are discussed briefly later in the paper.

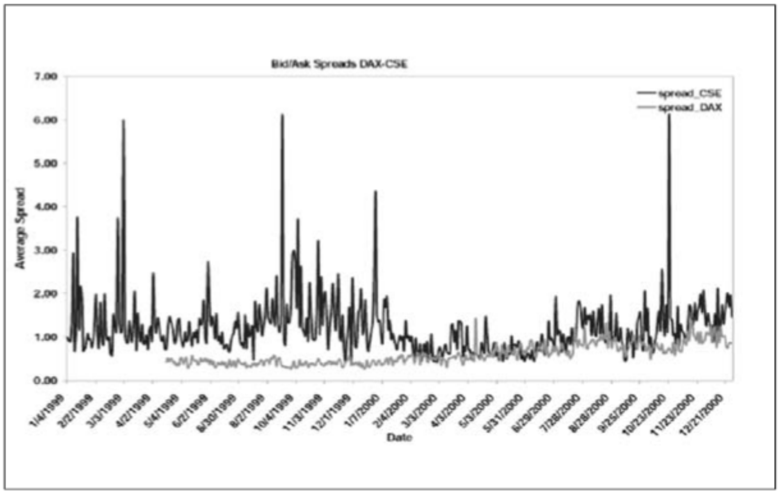

FIGURE 2. — Bid-ask Spreads for Cypriot and German Capital Markets

market. Consequently, considerations such as currency risk, which would play an important role in the risk management of, for example, a global emerging markets fund, are ignored in this study. In many developing markets (as was the case with Cyprus for the period of this study), there are strict controls on the amount of a portfolio that can be held outside the country. Investors are therefore forced to concentrate on the local market and its constituent risks. This motivates the focus of the current paper.

The remainder of the paper is structured as follows. The second section outlines the statistical models of returns that are used throughout the paper. The third section presents a statistical analysis of the history of the Cyprus and Athens Stock Exchanges. The fourth section discusses risk measurement in general, and in particular the industry standard measure Value-at-Risk. The fifth section discusses methodologies for scenario generation and VaR estimation, focusing on the new method of enriched historical simulation (i.e. on the use of data available from other markets for the purpose of risk measurement). The sixth section presents the results of back-testing our methodology on the Cyprus and Athens Stock Exchanges. The seventh section reviews the results and presents general conclusions.

II. Statistical Methodology

This section presents the basic statistical models of returns that will be employed throughout the rest of the paper. The return between time t – 1 and time t is defined to be:

$$r_t = \ln\left(\frac{S_t}{S_{t-1}}\right),$$

where S_t is the closing level of the index at time t. The methodologies that will be used can be divided into two categories: parametric and non-parametric. Effectively, these methodologies correspond to the two general models considered below.

A. Parametric Models

A general specification for the returns is given by:

$$r_t = \mu_t + \sigma_t \varepsilon_t$$

where, conditional on the information up to time t, μ_t and σ_t are the expected return and standard deviation of returns respectively, and ε_t are *i.i.d.* random shocks.

The Exponentially Weighted Moving Average (EWMA) and the Generalized Autoregressive Conditionally Heteroskedastic (GARCH(1,1)) models are the most common models of this class.

$$\text{EWMA: } \sigma_t^2 = \lambda\sigma_{t-1}^2 + (1-\lambda)(r_{t-1} - \mu_{t-1})^2$$

$$\text{GARCH(1,1): } \sigma_t^2 = \omega + \alpha\,(r_{t-1} - \mu_{t-1})^2 + \beta\sigma_{t-1}^2$$

EWMA is just a special case of GARCH and is also known as Integrated-GARCH or IGARCH.[3] Statistical tests and parameter

3. The EWMA model is a GARCH(1,1) with $\omega = 0$, $\beta = \lambda$ and $\alpha = 1 - \beta$. It has the advantage that there is only one parameter which can be easily estimated using Ordinary Least Squares (OLS) by minimizing the squared deviation of the model variance from the unexpected squared returns, i.e:

$$\hat{\lambda} = \arg\ \min \sum_{t=1}^{n} \left[\sigma_t^2 - (r_t - \mu_t)^2\right]^2$$

where r_t are the observed returns and μ_t is the expected mean. This implicitly assumes that estimates for the above models are based on the assumption that the shocks et are *i.i.d.* standard normal random variables.

For the purposes of this paper, it is assumed that the expected return at all times is zero, i.e. $\mu_t = 0$ for all t. This assumption is common in many market risk calculations and over small time horizons, such as those considered in this paper, is not significant.

B. Non-Parametric Models

In these models, the returns are assumed to be independently and identically distributed (*i.i.d.*).[4] At time t, returns are simulated based on a discrete probability distribution P_t on a set of possible outcomes Ω_t. The method for determining the possible returns Ω_t and the corresponding probabilities P_t is what distinguishes each method in this class. Examples of models in this class include straightforward historical simulation, the weighted historical simulation algorithm of Boudoukh et al. (1998) and the enriched historical simulation method introduced in this paper.

III. Statistical Analysis of Emerging Market Exchanges

By a "bubble" we mean a particular pattern that often appears in emerging markets, when financial variables deviate for a prolonged time from their equilibrium values. The following sequence of market regimes is typical: The Calm Before the Storm: An initial period of low volumes and low volatility, when very few investors have entered the market; The Upswing: A period of rapid growth where many investors, both individual and institutional, enter the market. This period is marked

current volatility is given by the absolute value of the spot unexpected return. Moreover, this estimation technique, being a non-parametric one, does not require the shocks ε_t to be normally distributed. As a result, the normality test of the standardized returns is not an appropriate diagnostic to test the validity of the model. A better way to estimate the parameters of both of the models is to use Maximum Likelihood Estimation (MLE), which is consistent with the GARCH model and can be easily tested. Assuming the ε_t are *i.i.d.* standard normal random variables, the distribution of the return r_t conditional on the information up to and including time $t-1$ is normal with mean μ_t and standard deviation σ_t. Therefore, using the conditional densities we can construct the likelihood function and estimate the parameters. The GARCH method is estimated using maximum likelihood and setting $\mu_t = 0$. For more details see the technical report by Nerouppos et al. (2002).

4. This can be achieved by taking $\mu = 0$ and $\sigma = 0$ so that $r_t = \varepsilon_t$.

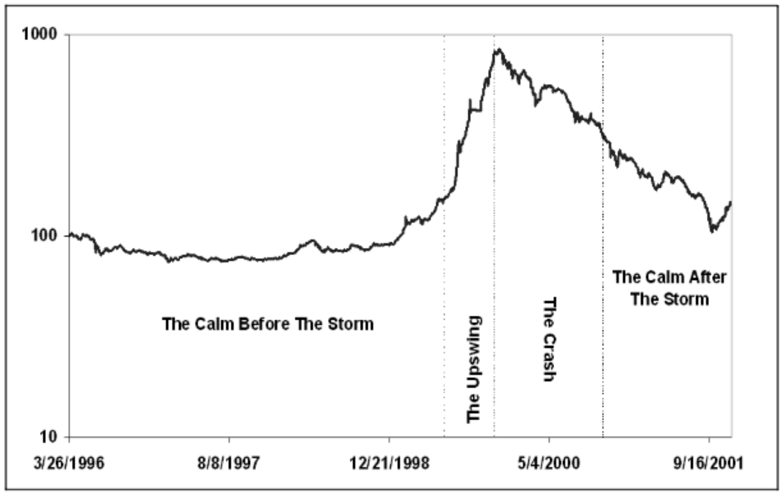

FIGURE 3. — The Periods of the Speculative Bubble of the CSE

by high volumes and a rapid growth in the level of the general market index; The Crash: The euphoria subsides, as investors realize that the securities traded on the market are overvalued. Panic selling ensues, and the market plummets back towards its initial level; The Calm After the Storm: Volumes and volatility reduce as investors are once bitten, twice shy. Unfortunately, this stage is often the calm before the next storm.

The second and third of these stages will sometimes be grouped under the heading "the storm". The typical stages are illustrated in figure 3. Speculative bubbles are a remarkable phenomenon of mass psychology. While it is not the purpose of this paper to address this directly, we point out the interesting work of MacKay (1995–first published in 1852) and Shiller (2000).

The Cyprus Stock Exchange (CSE) started operating on 29/3/1996 and its history can be best explained when divided into three periods. The first period was characterized by low investor interest, thus low volumes, particularly low volatility and persistence of the CSE General Index around the initial level of 100. The first period was followed by a typical speculative bubble, when interest in investment became substantial. It took less than one and a half years for the bubble to burst. The after-bubble period dropped the General Index back to the initial level. It was substantially less volatile than the second period, while at the same time significantly more volatile than the first. The complete

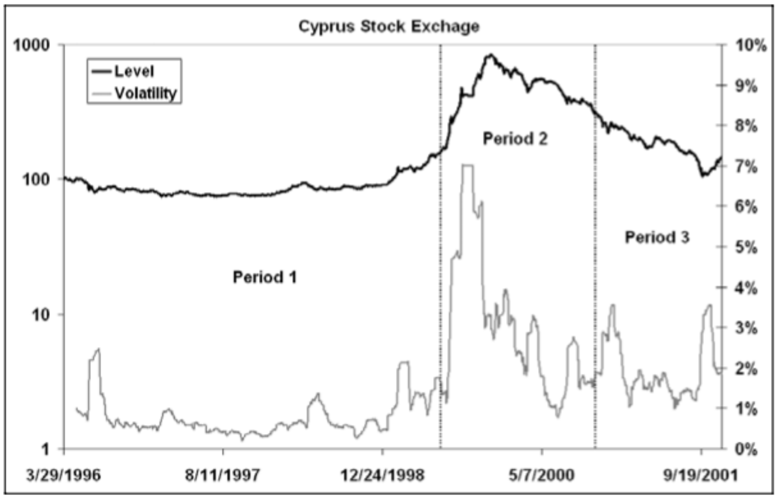

FIGURE 4. — Level and Volatility of the CSE Index

history of the CSE General Index is shown in figure 4, together with the period division and the monthly volatilities.[5] The three periods are defined as: Period One: 29/3/1996 – 30/6/1999 (The Calm Before the Storm), Period Two: 1/7/1999 – 31/10/2000 (The Storm), Period Three: 1/11/2000 – 23/11/2001 (The Calm After the Storm). Of course, this division is based on a posteriori knowledge about the presence of the bubble. This knowledge is used only to test the models under different stock market regimes. It is not used in any way in developing the models.

The descriptive statistics of the daily returns on the CSE index both for the entire history as well as the three periods separately are presented in table 1. The assumption of unconditional normality is soundly rejected by statistical tests.[6] Note particularly the positive skewness and high excess kurtosis; these will make it more difficult to efficiently measure risk. Furthermore, note that the behavior of the CSE

5. In the graphs displaying histories of indices, monthly volatilities are calculated using the historical estimate $\sigma = \sigma_{25,t} = \sqrt{\frac{1}{24}\sum_{i=0}^{24}\left(r_{t-i} - \overline{r}_{25,t}\right)^2}$ where $\overline{r}_{25,t} = \frac{1}{25}\sum_{i=0}^{24} r_{t-i}$.

6. Normality was also tested visually using QQ-plots and histograms with fitted normal distributions, but these figures are not shown here.