UNIVERSITY OF EXETER

Economics Department Discussion Papers Series

ISSN 1473 – 3307

Forecasting Value at Risk in Emerging Arab Stock Markets

C. Guermat, K. Hadri and C. C. Kucukozmen

Paper number 03/03

URL: http://business-school.exeter.ac.uk/economics/papers/

Forecasting Value at Risk in Emerging Arab Stock Markets

C. Guermat, University of Exeter, UK.

K. Hadri, University of Liverpool, UK.

C. C. Kucukozmen, BDDK, Turkey.

December 2003

Abstract

The economic and political instability of most of the Arab countries may lead to the assumption that Arab stock markets are riskier and less predictable than stock markets in developed countries. Value at Risk (VaR) measures risk exposure at a given probability level and is very important for risk management. In this paper extreme value theory with volatility updating is used to forecast Value at Risk in three emerging Arab stock markets and the US stock market. Several forecast accuracy criteria are used to compare forecast performance in the four stock markets, including a suggested asymmetric forecast criterion. The various criteria used in this paper suggest that Arab stock markets are less risky than the US stock market.

JEL Classifications: C22, C40, G10, G21.

Keywords: Value-at-Risk, Extreme Events, Hill Estimator, Volatility Updating.

1. Introduction

The importance of risk measurement and prediction has increased dramatically during the past few years. Value at Risk (VaR) has become a popular risk measure and has been estimated by a number of methods, including variance-covariance, historical simulation and Monte Carlo simulation methods (The Basle Committee, 1996; Beder, 1995; Hendricks, 1996; Mahoney, 1996; and Alexander and Leigh, 1997). These methods, however, are based on the whole distribution and may therefore fail under extreme market conditions. Extreme value (EV) theory concentrates on the tail of the distribution rather than the entire distribution. It has, therefore, the potential to perform better than other approaches in terms of predicting unexpected extreme changes. Dacorogna et al. (1995), Longin (1996, 1999), and Danielsson and de Vries (1997a) applied the EV distributions to extreme asset returns. Danielsson and de Vries (1997b) showed that the accuracy of the extreme event VaR approach outperforms other approaches, such as the historical simulation and variance-covariance approaches, at the extreme tails.

However, none of these studies has accounted for time-varying volatility. Empirical evidence shows that financial asset returns are conditionally heteroscedastic (see, Bollerslev et al., 1992; Bera and Higgins, 1993; and Bollerslev et al., 1994). Thus, the standard EV approach may understate or overstate the calculated risk measures. In the present paper, a volatility updated EV model is used to produce one step ahead forecasts for VaR statistics. Six years of daily data for Egypt, Jordan, Morocco and the US stock market returns are used.

The VaR approach is primarily concerned with the maximum loss to be experienced under a specific probability level. A VaR estimate tells how much a certain portfolio can lose within a given period of time for a given probability. A VaR thus corresponds to the left tail critical value of the portfolio profit and loss distribution. As with volatility, risk increases with increasing (absolute value) VaR measures. However, since the true VaR is unobservable, assessing VaR forecast performance requires measures that are different from used in the usual forecast comparisons. In this paper we use several accuracy measures and suggest a new measure based on a weighted cost function.

Emerging markets have drawn considerable interest. Errunza (1977, 1983) and Errunza and Rosenberg (1982) are among the earlier studies on emerging markets. Many have pointed out the potential benefits of investing in emerging markets. Bailey and Stulz (1990) and Bailey et al. (1990), for example, have shown that the potential benefits through diversification from the Pacific Basin stock markets are substantial. An effective diversification through investing in emerging markets may also result in reducing risk significantly (see Divecha et al. (1992), Wilcox (1992), Speidell and Sappenfield (1992), Mullin (1993), Errunza (1994)).

In a study of twenty new equity markets in emerging economies, Harvey (1995) found that the inclusion of emerging assets in a mean-variance efficient portfolio significantly reduces portfolio risk and increase expected returns. He also concluded that the amount of predictability found in the emerging markets is greater than that found in developed markets. Erb et al. (1996) discussed the characteristics of expected returns and volatility in 135 countries including Egypt, Jordan and Morocco. Bekaert and Harvey (1997) investigate the emerging market time-varying volatility and explored the forces that determine the difference of volatility in various emerging markets. Bekaert et al. (1998) detailed the distributional characteristics of emerging markets and explore how these characteristics change over time. However, Masters (1998) investigated the emerging market indexes and found them inherently inefficient and concluded that building a portfolio around a particular index may be less desirable in emerging markets than in other asset classes. Aggarval et al. (1999) examined the events which cause major shifts in emerging markets' volatility. They found that, unlike developed markets, large changes in volatility seem to be related to country-specific events. In all these papers, the analysis of risk was based on volatility models. In this paper, however, a different approach is proposed, which considers Value at Risk in three emerging Arab stock markets and the US stock market.

Because of the different economic and political circumstances, emerging markets might be considered to be more risky. Aggarval et al. (1999), for example, link shifts in risk (volatility) to country specific events. Arab countries suffer from political instability. The Middle East has always been highly volatile in this respect. Conflicts between Arab countries and Israel has led to three wars. Other conflicts involving Iran and Iraq still pose serious threats to the region's stability. In addition, the three Arab countries considered in this paper suffer from internal or local political instabilities. Egypt and Jordan have been threatened by the rise of fundamentalist terrorism, while Morocco has been in conflict with its neighbour, Algeria, since 1975. To the best of our knowledge, Value at Risk in the Arab countries has not yet been investigated. Risk in Arab stock markets has not drawn much interest in the literature. Among the few studies on volatility is the paper by Mecagni and Sourial (1999) who estimated stock market volatility in Egypt. El-Erian and Kumar (1995) found that emerging Arab countries are still struggling to internationalise their stock markets. They also confirmed that Middle Eastern stock markets suffer from three main problems, namely a negative perception of country risk, political instability, and institutional and legal rigidities. We intend to see whether such market instabilities are reflected in the Value at Risk measures with the US stock market as a benchmark.

The paper is organised as follows. The EV theory and the non-parametric Hill estimator are briefly reviewed in section 2. Section 3 discusses measures for evaluating VaR forecast accuracy. The data and preliminary statistics of the four stock markets are given in section 4. Section 5 discusses the empirical results, and section 6 concludes the paper.

2. Extreme Value Theory and the Hill Estimator

EV theory deals with the tail of distributions and the asymptotic behaviour of extreme order statistics of a random sample, such as the maximum or minimum order statistics. For a review of EV theory see Leadbetter et al. (1983), Embrechts et al. (1997) and Adler et al. (1998). A brief review of some of the most important EV results are given below.

Let X_1, X_2,...,X_N be a sequence of iid non-degenerate random variables with common distribution function F, such that $X_1 > X_2 > \ldots X_M > \ldots > X_N$. The fundamental theorem in EV theory is the Fischer-Tippett theorem (see Resnick, 1992, for a proof of the theorem). It states that there are three possible types of limiting distribution for normalised maxima or minima.

1. Gumbel distribution (Type I): $H_1 = \exp(-e^{-x}),\ x \in \Re$

The Normal, Gamma, Exponential, Logistic and Lognormal distributions belong to Type I extreme value distributions and are all thin-tailed distributions.

2. Fréchet distribution (Type II): $H_2 = \exp(-x^{-\alpha}),\ x > 0,\ \alpha > 0$

This type includes heavy tailed distributions such as Student-t, Pareto, Loggamma, Burr and Cauchy. Since financial returns exhibit fat tails the Type II family of extreme value distributions is commonly employed in financial applications.

3. Weibull distribution (Type III): $H_3 = \exp(-(-x)^{-\alpha}),\ x < 0,\ \alpha > 0$

Type III distributions have a finite upper limit on the range of the variables. The uniform and beta distributions belong to this family.

Danielsson and de Vries (1997a) suggested that for a heavy-tailed distribution $F(x)$, under mild regulatory conditions, a parametric form for the tail shape can be obtained by taking a second-order Taylor expansion of $F(x)$ as $x \to \infty$ as

$$F(x) \approx 1 - ax^{-\alpha}[1 + bx^{-\beta}],\ \alpha, \beta > 0 \tag{1}$$

where α is the tail index parameter, a determines the scale, and, b and β are second-order equivalents to a and α. For decreasing order statistics $X_1 > X_2 > \ldots X_M > \ldots > X_N$, given the threshold level M and an estimated α, they discuss the following estimator for the tail probabilities:

$$\hat{F}(x) = p = \frac{M}{T}\left(\frac{X_M}{x}\right)^{\hat{\alpha}} \tag{2}$$

for $x>M$. Here, M is the ordered rank of the start of the tail and T denotes the number of total observations. Hence, the extreme quantile estimator can be simply obtained by taking the inverse of $\hat{F}(x)$ as

$$\hat{x}_p = X_M \left(\frac{M}{pT} \right)^{\frac{1}{\hat{\alpha}}} \tag{3}$$

This result equally applies to the minima (i.e. the lower tails). For $p<M/T$, equation (3) gives the desired probability-quantile estimate (VaR estimate) pairs.

This estimator is conditional on the tail index parameter α, which can be estimated using the nonparametric Hill (1975) estimator. Other estimators can be found in Longin (1996), Embrechts et al. (1997) and Diebold et al. (1998). The maximum-likelihood estimator of α using T observations is given as

$$\frac{1}{\hat{\alpha}_{T,M}} = \hat{\gamma}_{T,M} = \frac{1}{M-1} \sum_{i=1}^{M-1} \log \frac{X_i}{X_M} \tag{4}$$

where M is the random threshold. Both parameters (α and M) determine the curvature of the tail. The estimator $\hat{\gamma}$ is consistent (Mason, 1982) and asymptotically normal with mean 0 and variance γ^2 (Goldie and Smith, 1987). However, $\hat{\gamma}$ depends also on the starting point in the tail, M. Increasing M reduces the variance but increases the bias. Hall's (1990) subsample bootstrapping procedure is used here to estimate the optimal M. The procedure is summarised as follows:

1. Draw resamples of T_1 observations with replacement ($T_1<T$) and order the data.

2. Estimate the subsample optimal M_1^* by minimizing the subsample MSE

$$\min_{M_1} E[\{\gamma^*_{T_1,M_1} - \hat{\gamma}_T\}^2] \tag{5}$$

where $\hat{\gamma}$ is an initial full sample estimate with an arbitrary M_0.

3. Calculate the full sample M^* by setting $\beta=\alpha$ from

$$M^* = M_1^* \left[\frac{T}{T_1} \right]^{\frac{2\beta}{2\beta+\alpha}}. \tag{6}$$

4. Calculate the tail index parameter $1/\hat{\alpha}_{T,M}$ using the optimal threshold M^* for the full sample in equation (4), and use this result in equation (3) to calculate the quantile estimate at the desired probability levels.

The remaining problem is β. However, previous studies suggest two possibilities. The first is to set $\beta=\alpha$ (Hall, 1990) as many of the known distributions satisfy this condition. The second is to set $\beta=2$ (Danielsson and de Vries, 1997a) which satisfies the Student-t distribution with α being the degrees of freedom parameter. Dacorogna et al. (1995) found that results were not sensitive to the choice of β.

The standard EV approach assumes iid data. However, high-frequency financial asset returns are likely to be conditionally heteroscedastic. Thus, following (Hull and White, 1998), a simple procedure is used to incorporate volatility updating scheme into tail index estimation. A conditional volatility (GARCH) model is fitted to capture the volatility dynamics of historical profit-loss series. The data is then scaled using the estimated conditional volatility model. Finally, the tail index of the scaled data is estimated.

3. Evaluating VaR Forecast Accuracy.

By their nature, VaR forecasts differ in many respects from other type of forecasts. The most obvious difference is that the 'true' VaR cannot be observed since we do not know the true potential profit and loss distribution. This is similar to the case of volatility forecasts, but for the latter a proxy, such as the squared actual returns or implied volatility, can be used (see Christodoulakis and Satchell, 1998, for a discussion). In VaR forecast, the only proxy available is the actual observations. Unfortunately, these are extremely noisy since the vast majority lie away from the left-hand tail. One alternative is to assume a distribution, estimate the quantiles and then use them as a benchmark. However, that would amount to comparing two different VaR approaches. The notion of forecast error is also different in VaR. By definition, VaR forecast should 'underpredict', for example, 95% of the times (at the 5% level). While the main concern in general forecasting is 'how close the forecasts are to the actual data', in VaR one major concern is ‘how many times did we overpredict’. Thus, most of the usual measures of forecast accuracy, such as the MSE and the MAPE, are not possible in the case of VaR forecasts. There are, however, alternative measures with which to compare VaR forecasts. A number of criteria have been discussed by Kupiec (1995), Lopez (1998), and Hendricks (1996). However, before discussing some of these criteria, a new criterion is presented first.

There are three important measures associated with VaR forecasts.

i. The Number or Proportion of Failures (shortfalls).

The number of shortfalls (failures) is a simple binary loss function. For each test period a VaR forecast is produced and compared with the actual loss. If the actual loss is more than the VaR forecast (in absolute value), then that particular forecast is considered a failure. The number of expected shortfalls (failures) depends on the length of the test period and the probability level. For example, for a 1000 day period, 50, 10, 5 and 1 failures are expected for the 0.05, 0.01, 0.005, and 0.001 levels respectively. Ideally, the VaR forecasts should not fail too often that is, the number of actual failures should not be significantly different from the expected number of failures. If the actual number of failures exceeds the expected number of failures then the model is inadequate.

ii. The Size of Failure (Failure Cost).

A model might produce the expected number of failures, say 1 in 1000 days at the 0.1% level. However, a single shortfall (underprediction) might be disastrous. The size of the shortfall is thus crucial to the investor, who is concerned about an extremely negative return that could wipe out so much capital that the risk of insolvency becomes very high. Failure Cost (FC) is the difference between the actual loss and the VaR when a failure occurs (i.e. when VaR is smaller than the loss in absolute value). Typically, the size of FC should be minimal, but the implications of FC is subjective and/or regulatory. However, as far as risk is concerned, higher FC means higher risk, all other things being equal.

iii. The Size of Coverage (Coverage Cost).

Ideally, at the 1% level, the VaR should cover 99% of actual profits/losses. This means that the VaR curve should be below the profit/loss curve in 99% of the cases. But this can only be done at a cost, since the investor or institution has to cover for potential losses by retaining a certain proportion of the capital, thus losing the opportunity to invest. This is what we call a coverage cost (CC), which is defined as the difference between the actual loss/profit and the predicted VaR when a success occurs (i.e. when the VaR is smaller than the profit/loss). As risk increases, the capital that needs to be held for protection against extreme losses also increases.

Thus, forecast accuracy can also be compared using measures such as average or total CC and FC. However, because there is a trade off between CC and FC, a comparison is possible only if one market has lower measures (total and/or average) in both CC and FC. It should be more interesting to use both types of cost to measure accuracy.

The suggestion is that accuracy should be a function that combines the proportion of failures, failure cost and coverage cost. We propose the following accuracy measure which is based on an asymmetric cost function of FC and CC. First we need to adjust for the proportion of failure that would make the various VaR forecasts have identical coverage proportion. We use the idea of Hendricks (1996) by multiplying each VaR series by a constant that would make the number of failures exactly equal to the expected one. This results in new VaR forecasts, say VaR^*, in which all series have identical coverage size. FC^* and CC^* are then evaluated based on VaR^*. The accuracy criterion is a weighted mean square defined as follows:

$$R_w = \sum_{PL<VaR^*} \frac{w}{M} \frac{FC_i^*}{VaR_i^*} + \sum_{PL \geq VaR^*} \frac{1-w}{T-M} \frac{CC_i^*}{VaR_i^*}$$

where M is the number of failures, T is the total number of forecasts, and w is a weight which determines the relative importance of cost of failure. The VaR and costs are evaluated in absolute value so that R_w becomes equivalent to the mean absolute percentage error (MAPE) for w=0.5. Obviously, higher costs lead to higher value for the criterion and thus lower accuracy. The use of relative costs makes comparison across different portfolio sizes possible. However, for obvious reasons, FC is at least of equal importance to CC. The above function is symmetric for w=0.5 where investors give equal importance to failure cost and coverage cost. However, for most investors, w will be greater than 0.5. In the case where even a small shortfall size may lead to insolvency, for example, w should be set to 1 or very close to 1. The weighted costs are squared to penalise larger costs. Finally, it can easily be verified that R_w ? 0 .

We also consider two tests for bias based on the proportion of failures. The bias criterion for VaR forecast is based on the proportion of failures. For example, at the 5% level, the proportion of failures is expected to be very close to 0.05. The Likelihood Ratio (LR) statistic (Kupiec, 1995) and the Z (normal test) statistic (Hull and White, 1998) are used to test for the difference between actual and expected proportion of failures.

The LR test statistic is given by

$$2\log[(1-v)^{n-f}v^{f}] - 2\log[(1-p)^{n-f}p^{f}]$$

were f is the number of failures, n is the total number of forecasts, v is the actual proportion of failures, and p is the probability level. The LR has a chi-square distribution with 1 degrees of freedom.

The Z statistic is given by $(v-p)/\sqrt{v(1-v)/n}$, and has a standard normal distribution.

Hendricks (1996) suggests comparing forecasts using the 'Multiple Needed to Attain Desired Coverage' (MNADC). This is basically the number that we should multiply all VaRs in order to obtain the expected number of failures at a given probability level. If the MNADC <1 it means that the forecasts produce less failures than expected, while MNADC >1 means that the model produces more failures than expected and is thus less accurate.

4. Data and Preliminary Statistical Analysis

In this section, using 6 years of daily data for Egypt, Jordan, Morocco and the US stock market indices, we compare the forecasting performance of VaR in the four markets. Because of its high capability of parsimonious approximation of conditional heteroscedasticity, we employ the simple GARCH(1,1) process for volatility estimation.

We use daily stock market price indices nominated in national currency of Egypt (EFG), Morocco (SE CFG 25), Jordan (AMMAN SE) and the S&P-500 (COMPOSITE) for the US stock market. Data for each of the four series were obtained from Datastream, for the six year period 01/04/1993-01/04/1999 (Datastream code PI).

Continuously compounded returns were calculated as the first difference of the natural logarithm of each series, which yields a total of 1566 daily observations for each series. Table 1 gives some useful statistics for each of the four return series. In particular, the table reports the first four moments of each series, the percentiles, the ARCH test on the squared returns, and the Ljung Box test for serial correlation in returns. The standard *t*-test results for skewness and excess kurtosis suggest that the underlying distributions of returns are positively skewed and leptokurtic. In addition, the extreme returns (i.e. the minimum and the maximum returns) are much larger than the standard 1st, 5th, 95th and 99th percentiles. More importantly, the ARCH tests on the squared returns provide evidence on the presence of conditional heteroscedasticity in Egypt, Jordan and the USA. The Ljung-Box statistics suggest that returns are serially correlated.

The statistics suggest a higher volatility in Egypt and Jordan compared with Morocco, and low stock market average return in Jordan which is around four times lower than Egypt and Morocco. The three Arab stock markets exhibit significant leptokurtosis and positive skewness, while the US data displays negative skewness.

The ARCH and Ljung-Box test results suggest that VaR forecasts based on the standard EV approach is likely to fail to cope with changing return volatility and serial correlation. Thus, it can erroneously overestimate or underestimate the implied risk. On the other hand, updating for volatility has the potential to cope with all of the observed characteristics of the return distributions presented in Table 1.

[Table 1 about here]

5. Empirical Results

Assuming a one-day holding period and using a moving window of 500 days data, we calculate 1000 daily VaR forecasts from the volatility updated EV for the four series at the 95%, 99%, 99.5% and 99.9% confidence levels. We concentrate on the left tail of the distribution (i.e. long positions in the underlying assets). For each period, 100 subsamples each with 100 observations is drawn with replication from the last 500 days historically simulated profit/loss series. We follow the three-step procedure outlined in the fourth_section. For each series, we estimate the maximum-likelihood function of the GARCH(1,1) model 1000 times using the BHHH algorithm (Berndt et al., 1974) as a result of the 1000 test periods. This recursive estimation also allows for variation in the parameters of the conditional variance equation.

A rough idea can be drawn from the level of VaR forecasts themselves, since a VaR value gives the largest potential loss for a specific confidence level. The average one-day ahead VaR forecasts are given in Table 2. The two specifications provide very similar forecasts. As expected, the VaR forecast increases with increasing confidence level. On a country basis, Morocco has the lowest VaR, followed by Jordan. The result for Egypt and the USA is mixed. At the 0.05 and 0.01 levels Egypt has lower values, but at the extreme tail (0.005 and 0.001) the USA has lower VaR.

[Table 2 about here]

Table 3 and 4 display the VaR forecast accuracy statistics produced by the first specification (β=α). The results for the other specification (β=2) were virtually identical and are omitted.

In terms of proportion of failures, the null hypothesis that the actual proportion of failures equals the probability level is rejected only in three cases (Egypt at 5%, Morocco at 1%, and USA at 1%). However, if we concentrate on the lower tail (0.005 and 0.001), all actual proportions are accepted as significantly equal to the hypothetical probability level in all markets. The MNADC is close to one in general, but the most accurate forecasts in terms of the MNADC is Jordan, while the worst seems to be the USA.

The costs are based on a portfolio of $100 million. As expected, total failure cost decreases, while total coverage cost increases with decreasing probability levels. In terms of average and total FC and CC, Morocco produces the lowest figures, followed closely by Jordan. USA stock market produces the highest costs.

Table 4 shows the suggested index (R_w) of forecast accuracy at various weight values. At *w*=0.5 we assume that investors give equal importance to underpredictions (coverage cost) and overpredictions (failure cost). However, as *w* increases, more weight is given to failure cost. When *w*=1, only failure cost is taken into account. A desirable result would be for R_w to decrease rapidly with increasing *w* because it is important for investors that failure cost is minimal. This pattern is seen in all three stock markets. The forecast performance based on this index depends on the confidence level. For example, at the 95% level, Morocco produces the least accurate forecasts while the other markets are very similar. However, at the 99.9% confidence level it becomes clear that the Arab stock markets are more accurately predicted than the US stock market at all weights. The values of R_w are smaller for the Arab markets, which means that the combination of weighted failure cost and coverage cost are smaller and thus forecasts are more accurate. Moreover, the decay in R_w is very fast in the Arab markets and slow in the US market. At *w*=1, the average failure cost represents 0.03%, 1.77% and 2.28% of the VaR for Egypt, Jordan and Morocco respectively. However, for the same weight, the average failure cost represents 50.73% of the VaR in the US. The index for the 95% and 99.9% levels is shown in Figure 1 and 2.

[Tables 3,4 and Figures 1,2 about here]

6. Conclusion

This paper considered comparing VaR forecast accuracy using measures which are adapted to the objectives of VaR. The comparison was based on the out of sample prediction of VaR using a volatility updated EV model. These measures were applied to three emerging Arab stock markets and one developed stock market. The EV models resulted in comparable proportions of failures, but the total and average costs were generally lower in the Arab stock markets. At the same time, the average and total coverage costs were also lower in the Arab stock markets. Our measure of forecast accuracy, however, shows that VaR forecast accuracy depends on two main factors. First, forecast accuracy may be different at different levels of confidence. In this study, for example, US forecasts were more accurate than Morocco forecasts at the 95% level, while the opposite was found at the 99.9% level. The second factor is the weight that should be given to both failure cost and coverage cost.

Overall, the various forecast accuracy measures employed in this paper indicate that forecasts produced for the three Arab stock markets are more accurate than those produced for the US stock market, especially at the extreme tail. As value at risk is primarily a measure of risk, the superiority of forecasts of Arab stock markets and more particularly, the lower failure and coverage costs associated with these forecasts, seem to suggest that there is relatively lower risk in Arab stock markets. However, strictly speaking, cross-country risk cannot be assessed unless the VaR for exchange rates between Arab currencies and the US $ is incorporated into the model. The possibility of combining the VaR for stock market returns and the VaR for exchange rate is left for future research.

References

Adler, R.J., R.E. Feldman and M.S. Taqqu, 1998, A practical guide to heavy tails, statistical techniques and applications (Birkhäuser, Boston-Basel-Berlin).

Aggarwal, R., Inclan, C., Leal, R., 1999, "Volatility in Emerging Stock Markets", Journal of Financial and Quantitative Analysis 34, 33-55.

Alexander, C.O. and C.T. Leigh, 1997, On the covariance matrices used in value at risk models, The Journal of Derivatives, 4, 50-62.

Bailey, W., Stulz, R.M., 1990, "Benefits of International Diversification: The Case of Pacific Basin Stock Markets", The Journal of Portfolio Management 16, 57-61.

Bailey, W., Stulz, R.M., Yen, S., 1990, "Properties of Daily Stock Returns from the Pacific Basin Stock Markets: Evidence and Implications", in (eds.) Rhee, S.G., Chang, R.P., Pacific-Basin Capital Markets Research, Amsterdam: North Holland.

Basle Committee on Banking Supervision, 1996, Amendment to the capital accord to incorporate market risks, January.

Beder, T.S., 1995, VAR: Seductive but dangerous, Financial Analysts Journal, September/October, 51, 12-24.

Bekaert, G., Erb, C., Campbell, R.H., Viskanta, T.E., 1998, "Distributional Characteristics of Emerging Market Returnas and Asset Allocation", The Journal of Portfolio Management 24, 102-116.

Bekaert, G., Harvey, C.R., 1997, "Emerging Equity Market Volatility", Journal of Financial Economics 43, 29-77.

Bera, A.K. and M.L. Higgins, 1993, ARCH models: Properties, estimation and testing, Journal of Economic Surveys, 7, 305-366.

Berndt, E.R., B.H. Hall, R.E. Hall and J.A Hausmann, 1974, Estimation and inference in non-linear structural models, Annals of Economic and Social Measurement, 3, 653-665.

Bollerslev, T., R.F. Engle and D.B. Nelson, 1994, ARCH models, in: R.F. Engle and D. McFadden, eds., Handbook of econometrics, Vol. 1 (North-Holland, Amsterdam) 2959-3038.

Bollerslev, T., R.Y. Chou and K.F. Kroner, 1992, ARCH modelling in finance: A review of the theory and empirical evidence, Journal of Econometrics, 52, 5-59.

Dacorogna, M.M., U.A. Müller, O.V. Pictet and C.G. deVries, 1995, The distribution of extremal foreign exchange rate returns in extremely large data sets, Tinbergen Institute Working Paper, TI 95-70.

Danielsson, J. and C.G. de Vries, 1997a, Tail index and quantile estimation with very high frequency data, Journal of Empirical Finance, 4, 241-257.

Danielsson, J. and C.G. de Vries, 1997b, Extreme returns, tail estimation, and value-at-risk, paper presented at a conference on Issues in Empirical Finance, organised by LSE Financial Markets Group, 21-22 November.

Diebold, F.X., T. Schuermann and J.D. Stroughair, 1998, Pitfalls and opportunities in the use of extreme value theory in risk management, The Wharton School, Financial Institutions Center, Working Paper, 98-10.

Divecha, A.B., Drach, J., Stefek, D., 1992, "Emerging Markets: A Quantitative Perspective", The Journal of Portfolio Management 19, 41-50.

El-Erian, M.A., Kumar, M.S., 1995, "Emerging Equity Markets in Middle Eastern Countries", IMF Staff Papers 42, 313-343.

Embrechts, P., C. Klüppelberg and T. Mikosch, 1997, Modeling extremal events for insurance and finance (Springer, Berlin).

Erb, C.B., Harvey, C.R., Viskanta, T.E., 1996, "Expected Returns and Volatility in 135 Countries", The Journal of Portfolio Management ?, 46-58.

Errunza, V.R., 1977, "Gains from Portfolio Diversification into Less Developed Countries' Securitites", Jounal of International Business Studies ??, 83-99.

Errunza, V.R., 1983, "Emerging Markets: a New Opportunity for Improving Global Portfolio Performance", Financial Analysts Journal 39, 51-58.

Errunza, V.R., 1994, "Emerging Markets: Some New Concepts", The Journal of Portfolio Management 20, 82-87.

Errunza, V.R., Rosenberg, B., 1982, "Investment Risk in Developed and Less Developed Countries", Journal of Financial and Quantitative Analysis, ??? 741-762.

Goldie, C.M. and R.L. Smith, 1987, Slow variation with remainder: Theory and applications, The Quarterly Journal of Mathematics Oxford Second Series, 38, 45-71.

Hall, P., 1990, Using the bootstrap to estimate mean squared error and select smoothing parameter in nonparametric problems, Journal of Multivariate Analysis, 32, 177-203.

Harvey, C.R., 1995, "Predictable Risk and Returns in Emerging Markets", The Review of Financial Studies 8, 773-816.

Hendricks, D., 1996, Evaluation of value-at-risk models using historical data, Federal Reserve Bank of New York Economic Policy Review, April, 39-69.

Hill, B.M., 1975, A simple general approach to inference about the tail of a distribution, *The Annals of Statistics*, 3, 1163-1174.

Hull, J. and A. White, 1998, Incorporating volatility updating into the historical simulation method for value-at-risk, *Journal of Risk*, 1, 5-19.

Kupiec, P.H., 1995, "Techniques for Verifying the Accuracy of Risk Measurement Models", *The Journal of Derivatives.*

Leadbetter, M.R., G. Lindgren and H. Rootzèn, 1983, Extremes and related properties of random sequences and processes (Springer-Verlag, New York).

Longin, F.M., 1996, The asymptotic distribution of extreme stock market returns, Journal of Business, 69, 383-408.

Longin, F.M., 1999, From value at risk to stress testing: The extreme value approach, Journal of Banking and Finance, forthcoming.

Mahoney, J.M., 1997, Forecast biases in value-at-risk estimations: Evidence from foreign exchange and global equity portfolios, LSE Financial Markets Group, Special Paper Series, no. 93.

Mason, D.M., 1982, Laws of large numbers for sums of extreme values, Annals of Probability, 10, 756-764.

Masters, S.J., 1998, "The Problem with Emerging Market Indexes", The Journal of Portfolio Management 24, 93-100.

Mecagni, M., Sourial, M.S., 1999, "The Egyptian Stock Market: Efficiency Tests and Volatility Effects", IMF Working Paper, WP/99/48, April.

Mullin, J., 1993, "Emerging Equity Markets in the Global Economy", Federal Reserve Bank of New York Quarterly Review 18, 54-83.

Resnick, S.I. 1992, Adventures in stochastic processes (Birkhäuser, Boston).

Speidell, L.S., Sappenfield, R., 1992, "Global Diversification in a Shrinking World", The Journal of Portfolio Management 19, 57-67.

Wilcox, J.W., 1992, "Taming Frontier Markets", The Journal of Portfolio Management 19, 51-56.

Table 1. Summary statistics of daily returns

	Egypt	Jordan	Morocco	USA
Mean	8.56 $X10^{-3}$	1.81 $X10^{-3}$	8.64 $X10^{-3}$	6.74 $X10^{-3}$
S.Deviation	9.54 $X10^{-2}$	8.09 $X10^{-2}$	4.33 $X10^{-2}$	8.73 $X10^{-2}$
Skewness	1.1514*	0.7129*	2.5042*	-0.5792*
Kurtosis	15.6181*	28.8265*	24.9515*	8.3544*
Minimum	-0.0634	-0.0973	-0.0246	-0.0711
01-%ile	-0.0221	-0.0188	-0.0088	-0.0227
05-%ile	-0.0116	-0.0100	-0.0041	-0.0132
95-%ile	0.0158	0.0125	0.0075	0.0141
99-%ile	0.0306	0.0275	0.0171	0.0228
Maximum	0.0953	0.0869	0.0533	0.0499
ARCH(2)	17.8749*	189.0200*	0.0021	18.7849*
ARCH(4)	8.9477*	124.7835*	0.0038	9.3780*
ARCH(8)	4.4549*	69.0522*	0.0050	7.1896*
Ljung-Box (4)	115.16*	24.14*	185.79*	3.37
Ljung-Box (8)	159.97*	26.73*	226.81*	11.77

(*) denotes significance at 1% level. N=1566

Table 2. Average VaR forecasts (million $).

P level	0.05	0.01	0.005	0.001
Egypt				
($\beta=\alpha$)	-1.27962	-2.31569	-3.01838	-5.73676
($\beta=2$)	-1.28212	-2.31339	-3.01467	-5.74542
Jordan				
($\beta=\alpha$)	-0.98976	-1.77364	-2.28908	-4.17844
($\beta=2$)	-0.99225	-1.77174	-2.28357	-4.15733
Morocco				
($\beta=\alpha$)	-0.51923	-0.82194	-1.01385	-1.7066
($\beta=2$)	-0.53482	-0.81696	-0.99067	-1.59682
USA				
($\beta=\alpha$)	-1.40233	-2.36946	-2.98165	-5.13161
($\beta=2$)	-1.43403	-2.35815	-2.93504	-4.93269

Table 3. VaR Forecast Summary Statistics.

P	M	F	LR	Z	Av. FC	Av. CC	Tot.. FC	Tot. CC	MNADC
Egypt									
0.050	71	0.071	8.260*	2.585*	0.447	1.357	31.804	1260.799	1.140
0.010	13	0.013	0.830	0.837	0.754	2.286	9.805	2256.851	1.083
0.005	5	0.005	0.000	0.000	1.122	2.965	5.613	2950.180	1.000
0.001	0	0.000	_	_	_	5.673	0.000	5673.833	0.959
Jordan									
0.050	47	0.047	0.193	-0.448	0.388	1.065	18.244	1015.298	0.960
0.010	10	0.010	0.000	0.000	0.559	1.796	5.593	1778.255	1.000
0.005	7	0.007	0.715	0.759	0.449	2.302	3.144	2286.230	1.168
0.001	1	0.001	0.000	0.000	0.047	4.161	0.047	4156.707	1.000
Morocco									
0.050	56	0.056	0.731	0.825	0.228	0.638	12.773	601.841	1.044
0.010	19	0.019	6.473*	2.085*	0.176	0.905	3.343	887.477	1.128
0.005	6	0.006	0.189	0.409	0.274	1.080	1.646	1073.811	1.029
0.001	3	0.003	2.596	1.156	0.063	1.762	0.189	1756.226	1.062
USA									
0.050	61	0.061	2.388	1.453	0.715	1.606	43.609	1508.117	1.096
0.010	20	0.020	7.827*	2.259*	0.725	2.474	14.494	2424.353	1.218
0.005	9	0.009	2.596	1.339	0.839	3.044	7.549	3016.647	1.104
0.001	2	0.002	0.774	0.708	1.589	5.132	3.177	5121.268	1.111

(*) Denotes significance at the 5% level.

Table 4. Index of Forecast Accuracy.

w	95%	99%	99.5%	99.9%
Egypt				
0.5	0.8056	0.7517	0.7767	0.4974
0.6	0.7562	0.7019	0.7329	0.3980
0.7	0.7069	0.6522	0.6891	0.2986
0.8	0.6575	0.6024	0.6452	0.1992
0.9	0.6082	0.5527	0.6014	0.0997
1	0.5588	0.5030	0.5576	0.0003
Jordan				
0.5	0.7965	0.7219	0.5786	0.5096
0.6	0.7389	0.6630	0.4930	0.4112
0.7	0.6812	0.6041	0.4073	0.3128
0.8	0.6236	0.5452	0.3216	0.2145
0.9	0.5660	0.4862	0.2360	0.1161
1	0.5083	0.4273	0.1503	0.0177
Morocco				
0.5	0.9381	0.6709	0.7097	0.5375
0.6	0.8792	0.5854	0.6345	0.4346
0.7	0.8203	0.4998	0.5594	0.3316
0.8	0.7614	0.4143	0.4842	0.2287
0.9	0.7025	0.3288	0.4091	0.1257
1	0.6436	0.2433	0.3339	0.0228
USA				
0.5	0.8521	0.6643	0.7125	0.7632
0.6	0.7929	0.5879	0.6477	0.7120
0.7	0.7336	0.5115	0.5830	0.6609
0.8	0.6744	0.4351	0.5182	0.6097
0.9	0.6151	0.3586	0.4534	0.5585
1	0.5558	0.2822	0.3887	0.5073

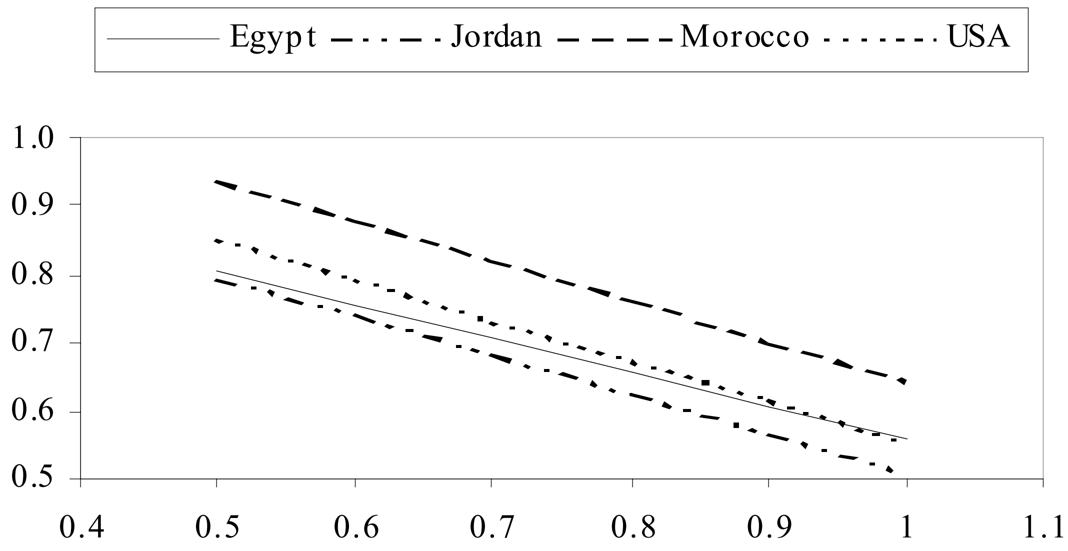

Figure 1. Forecast accuracy index (R_w) for the 95% level.

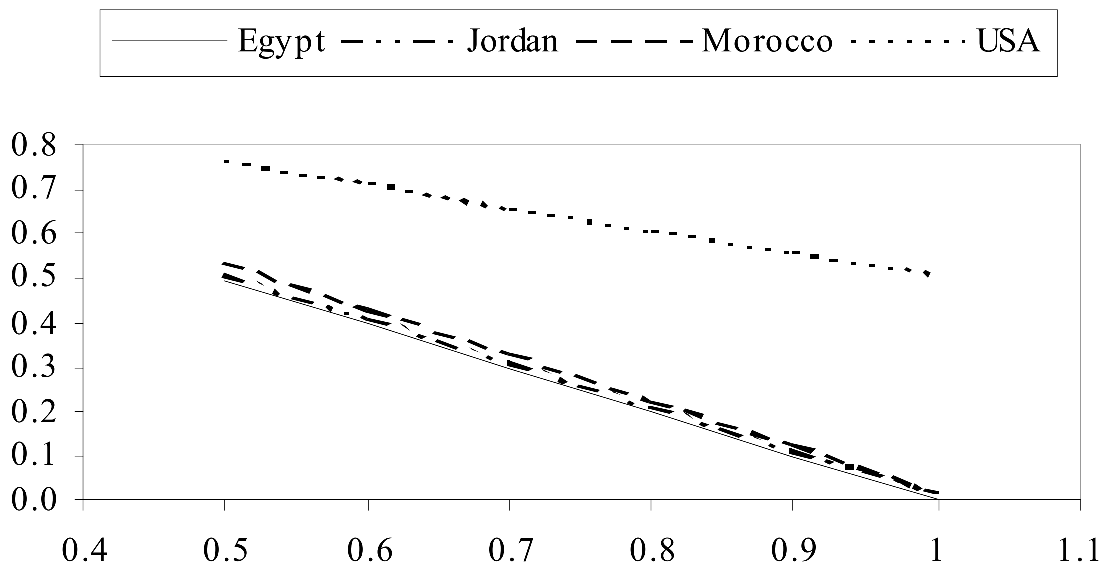

Figure 2. Forecast accuracy index (R_w) for the 99.9% level.