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Capturing downside risk in financial markets: the case of the Asian Crisis

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Abstract

Using data on Asian equity markets, we observe that during periods of financial turmoil, deviations from the mean-variance framework become more severe, resulting in periods with additional downside risk to investors. Current risk management techniques failing to take this additional downside risk into account will underestimate the true Value-at-Risk with greater severity during periods of financial turmoil. We provide a conditional approach to the Value-at-Risk methodology, known as conditional VaR-x, which to capture the time variation of non-normalities allows for additional tail fatness in the distribution of expected returns. These conditional VaR-x estimates are then compared to those based on the RiskMetrics™ methodology from J.P. Morgan, where we find that the model provides improved forecasts of the Value-at-Risk. We are therefore able to show that our conditional VaR-x estimates are better able to capture the nature of downside risk, particularly crucial in times of financial crises. © 1999 Elsevier Science Ltd. All rights reserved.

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1. Introduction

A number of Asian economies have recently been characterized by highly volatile financial markets, which when coupled with high returns, should have been seen as an attractive avenue down which one could diversify portfolios. The recent financial turmoil, however, has had a severe impact on investors' exposure to these markets,

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with investors having fled these markets en masse.¹ The risk thus appears to have been too great and the resultant capital flight has led to even greater pressures, creating further turbulence in markets all over Asia.

To ensure a stable financial system, being able to accurately identify, measure, and control financial risk are crucial.² This is why regulation was introduced worldwide. The goal has been to tighten up risk management, and thus avoid the potential damage from bank runs and systemic risk. These regulatory changes in turn have had two dimensions: the imposition of minimum capital requirements for financial institutions as designed by the Basle Committee³ and the adoption of the Value-at-Risk method of assessing capital adequacy as a risk management technique.

Banks are now required to hold enough capital so that they should be able to withstand large potential losses. With recurrent banking crises occurring all over Asia it would appear that the risk during such periods was of a much greater magnitude than existing risk management techniques were able to capture.

Large negative returns on emerging market returns have been shown to occur more frequently than predicted under the assumption of normality, even when the distribution is made conditional.⁴ The use of the estimated variance of an asset's return distribution as the sole measure of risk may therefore lead to a serious underestimation of the true risk involved in holding such assets. We investigate the implications of such non-normality for risk management in general and the estimation of Value-at-Risk in particular. We show that the use of an additional parameter to account for the additional downside risk can provide a more accurate tool for risk management. This is the conditional VaR-x⁵ method.

In periods of turmoil in which the risk is higher, we find the deviations from conditional normality to be even greater, and in periods of financial crisis they become very severe indeed. This additional downside risk is not captured in current VaR methods, which assume conditional-normality, such as in the J.P. Morgan RiskMetricsTM methodology.

The implications from the inclusion of additional downside risk however go beyond the use of Value-at-Risk as a risk management technique. If volatility alone is insufficient in estimating the amount of risk, then the additional use of downside risk may provide us with a more accurate measure for risk. Pricing risk lies at the heart of finance theory and an improved measure for risk may unravel many of the puzzles concerning the size of the premium attached to risk. For example the equity premium puzzle. Using volatility to measure risk, and a moderate level for investors' aversion to risk, the premium paid for taking on the additional risk from investing in equity is excessively large. Additional risk in the downside implies a greater level of risk for a given level of return, and hence the premium attached would be more

¹ See the EIU, 1998a,b

² Jorion (1997) gives a good overview of Value-at-Risk.

³ Basle Committee on Banking Supervision (1996).

⁴ See Bekaert et al. (1998) for an analysis of the time-varying nature of the distributional characteristics of Emerging Market returns.

⁵ See Huisman, Koedijk and Pownall (1998) for an application of unconditional VaR-x.

in line with observed attitudes to risk. Another puzzle is the tendency for investors to invest a greater proportion of their assets in the domestic market than finance theory would suggest: the so-called home bias phenomenon. Again given a moderate level for investors' risk aversion, and volatility as the measure for risk, a similar puzzle to the equity premium puzzle arises: the risk of investing internationally appears to be too great for the premium received (home bias). Including the additional downside risk into the measure for risk may therefore explain the extent of the risk perceived by investors, and for the premium prevailing, why investors tend to prefer to invest in their home markets.

The paper is organized as follows. We begin in Section 2 by introducing the current risk management technique of Value-at Risk, and discuss its suitability for the Asian markets. In Section 3 we analyze downside risk, particularly apparent in periods of financial crises. Estimating Value-at Risk conditionally and unconditionally is introduced in Section 4. Here we compare current approaches, emphasizing in particular their ability to forecast Value-at-Risk during periods of financial crises. The implications from the inclusion of downside risk for asset allocation is pursued in Section 5. Conclusions are drawn in the final section of the paper.

2. Risk management in Asian markets

The accurate measurement and control of financial risk in international markets is crucial to institutions exposed internationally. Asian markets have been characterised as particularly risky over recent years, with extremely volatile returns on equity markets. Looking at the IFC Asia 50 Index⁶ on a daily basis, for the whole period for which data is available, January 1993 until January 1998, we see that average volatility on a yearly basis has been 22.04%. By the end of 1997, the average yearly return since 1993 has been negative, -2.18% ; with the enormous growth of the early nineties having been more than completely wiped out during the financial crises in 1997 alone. Summary statistics for the entire period along with the individual years is given in Table 1. Taking the period as a whole the data also exhibit highly significant skewness and kurtosis.

When breaking the sample down into years, with an average of 259 trading days each, we see that the unprecedented 92.68% drop in the value of equities during the financial crises in 1997 was accompanied by a higher than average volatility at 31.29%. Indeed the only other year in the sample with a negative return, be it a much less significant fall of -14.58% in 1994, was also a year of higher than average volatility.

It is this measure, the standard deviation of the return distribution, which is most commonly used in financial theory for capturing risk: implying that the more frequent the occurrence of large returns, whether positive or negative, the higher the expected

⁶ IFC emerging market indices are employed by Bekaert and Harvey (1995) where they discuss the suitability of the data series for empirical work.

Table 1
Sub-Sample Summary Statistics for Asia 50 Index^a

| Asia 50 Index | Whole Sample | 1993 | 1994 | 1995 | 1996 | 1997 |
|---------------------------|--------------|--------|---------|--------|--------|---------|
| Annual Average Return | -2.176 | 80.181 | -14.582 | 3.6813 | 12.403 | -92.675 |
| Annual Standard Deviation | 22.040 | 17.425 | 24.784 | 18.438 | 11.945 | 31.290 |
| Maximaum Daily Return | 9.801 | 3.536 | 8.398 | 5.176 | 2.890 | 9.801 |
| Mimumum Daily Return | -7.498 | -2.832 | -5.972 | -4.333 | -2.788 | -7.498 |
| Skewness | 0.165 | 0.093 | 0.300 | 0.805 | 0.077 | 0.362 |
| Kurtosis | 10.161 | 3.005 | 7.783 | 6.642 | 5.161 | 8.270 |

^a This table contains the statistics on the Asia 50 Price Index for the whole period January 1993 until January 1998 using a total of 1302 daily returns, and, for the individual years, using an average 259 daily returns.

exposure to risk. The higher the volatility the greater the risk faced by institutions. Risk management techniques, such as Value-at-Risk, aim to capture the increased market risk concurrent with more volatile financial assets, and since Value-at-Risk is associated with a particular fractal of the distribution, the use of normality implies the use of the standard deviation as the measure for risk.

2.1. Value-at-Risk

The most commonly used technique in risk management to assess possible losses in financial markets is Value-at-Risk. By estimating the worst expected loss over a chosen time horizon, within a given confidence interval, it aims to summarise the market risk. If an amount W , is the initial portfolio investment, then taking R as the rate of return, the expected value of the portfolio at the end of a chosen time horizon is:

$$W = W_0(1 + R). \quad (1)$$

Since we are interested in the lowest portfolio value at a particular confidence level, devoted by c , we are interested in finding the rate of return R^* resulting in this lowest portfolio value W^* :

$$W^* = W_0(1 + R^*). \quad (2)$$

Letting the average return be denoted by μ , gives us the estimate for the VaR relative to the mean to be written as:

$$\text{VaR} = W_0(1 + \mu) - W_0(1 + R^*). \quad (3)$$

This in turn simplifies to:

$$\text{VaR} = -W_0(R^* - \mu). \quad (4)$$

The crux of being able to provide an accurate estimate for the Value-at-Risk is in being able to accurately estimate the expected return R^* associated with the portfolio value W^* . Value-at-Risk estimation therefore requires knowing the probability distribution of the expected returns, which of course is unknown. Hence the various methods for estimating VaR depend on the assumption made about the probability distribution of the expected returns.

One method is to consider the actual empirical distribution, based on past observations, as best representing the probability distribution of expected returns. The historical VaR is then found from substituting the point R^* from the histogram of the empirical distribution based on historical returns into the above formula. R^* is the point, below which, the fraction $1-c$ of the returns fall.

Alternatively one can assume that the returns can be approximated by a specific statistical distribution, with the exact form of the analytical distribution being determined from parameters, estimated from past observations. For example, it has been commonly assumed in finance theory that asset returns are normally distributed. Then the point on the standard normal distribution N^* , at which the area $1-c$ falls to the left, can be converted to a distribution with mean μ , and standard deviation σ , to find the cut off return R^* :

$$R^* = -N^*\sigma + \mu. \quad (5)$$

Substituting this value for R^* into Eq. (4) gives us the relative parametric-normal VaR equal to $W_0N^*\sigma$. Hence by assuming normally distributed returns only the standard deviate of the portfolio, multiplied by a factor depending on the confidence level, is required to find the relative VaR.

The estimates of the VaR using the two approaches for various confidence levels are presented for the whole period in the first two columns of Table 2. We see how the VaR estimates for both estimates increase, the higher the confidence level taken. However the parametric-normal approach underestimates the exposure to market risk at higher confidence levels, with the difference growing as we move further into the tail of the distribution. This is due to the existence of non-normality in the data, a negatively skewed distribution with fatter than normal tails will tend to generate higher VaR estimates than captured by the assumption of normality.

During periods of high volatility however, the VaR estimates are by definition larger, and hence any deviations from normality become more crucial. Indeed we see that the deviations from normality are more severe in 1997, during the financial crises, than in 1996, when the distribution exhibits highly significant skewness and kurtosis. Hence the deviation in the VaR estimate from using the parametric-normal distribution is also greater. The extent to which the parametric-normal underestimates the VaR at high confidence levels during the period of financial crises is depicted in Fig. 1. The sample period has been split into two, with parameters having been unconditionally estimated for the two periods specifically.

It is well documented that the return distributions of many financial assets show

Table 2
Comparison of Value-at-Risk Estimates^a

| Confidence Level (Left Tail) | Whole | | Asia 50 Index 1996 | | Asia 50 Index 1997 | |
|---------------------------------|--------------------------------|-----------------------------|--------------------------------|-----------------------------|--------------------------------|-----------------------------|
| | Empirical VaR (\$100 mill.) | Normal VaR (\$100 mill.) | Empirical VaR (\$100 mill.) | Normal VaR (\$100 mill.) | Empirical VaR (\$100 mill.) | Normal VaR (\$100 mill.) |
| 95 | 1.9896 | 2.2484 | 1.1962 | 1.2191 | 3.1538 | 3.1814 |
| 95.5 | 2.1398 | 2.3175 | 1.2103 | 1.2566 | 3.3067 | 3.2792 |
| 96 | 2.2372 | 2.3931 | 1.2403 | 1.2976 | 3.4081 | 3.3861 |
| 96.5 | 2.3736 | 2.4768 | 1.2565 | 1.3430 | 3.5589 | 3.5046 |
| 97 | 2.4869 | 2.5709 | 1.3181 | 1.3940 | 3.7240 | 3.6378 |
| 97.5 | 2.8156 | 2.6792 | 1.3245 | 1.4527 | 4.0313 | 3.7909 |
| 98 | 3.1603 | 2.8074 | 1.5347 | 1.5222 | 4.6725 | 3.9723 |
| 98.5 | 3.5866 | 2.9664 | 2.2766 | 1.6084 | 5.6070 | 4.1974 |
| 99 | 4.2016 | 3.1800 | 2.3117 | 1.7243 | 6.4717 | 4.4996 |

^a The Value-at-Risk Estimates have been estimated for the two asset classes using the Empirical Approach (using the historical data) and the Parametric-Normal approach. The Normal VaR estimates assume Normally distributed returns. The relative VaR estimates, expressed in millions of dollars, have been calculated for a position of \$100 million in the particular asset, and for a range of confidence levels.

serious deviations from normality⁷, so that the VaR tends to be underestimated as we move to higher confidence intervals. Bekaert et al. (1998) give some well known country characteristics to try and explain the degree with which emerging market data deviates from normality. We indeed find that the distribution is more fat tailed during the financial crises, exhibiting more frequent extreme returns than the normal distribution. Parametric methods for estimating the VaR using the assumption of normality therefore severely underestimate the VaR as we move to higher confidence levels. This is depicted in Fig. 2.

The extra probability mass should be partially captured in the tails by allowing for the distribution to be time-varying. Allowing for a conditional distribution to capture this changing volatility over time can easily be implemented into the VaR estimation. A generalised autoregressive conditionally heteroskedastic (GARCH) process can be used to estimate conditional volatility and thus substituted into Eq. (5). Estimating a GARCH process is the basis of the RiskMetrics™ methodology introduced by JP Morgan.

2.2. RiskMetrics™

Implementing conditional volatility into Eq. (5) by means of a GARCH model is the approach adopted in the RiskMetrics's™ methodology. It is well known that volatility tends to exhibit clustering behaviour, with periods of high and then low volatility. This type of behaviour was first captured by Engle (1982) through the use

⁷ See for example Mandelbrot (1963); Fama and Roll (1968); Taylor (1986) and Huisman et al. (1998).

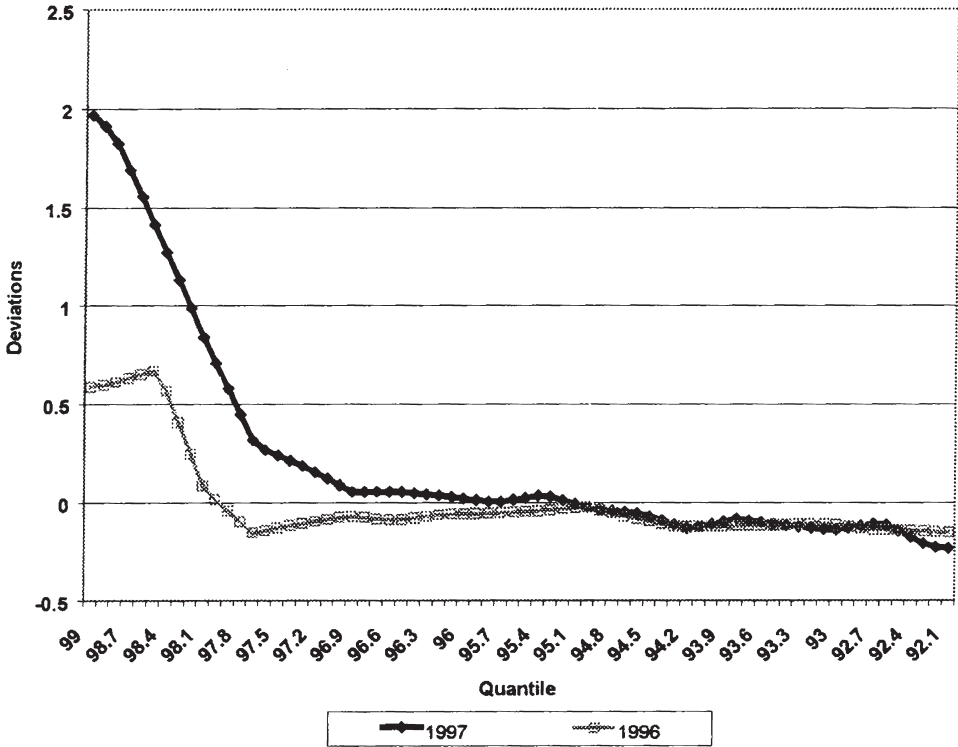


Fig. 1. Value-at-Risk Estimates. The graph depicts how much the Parametric-Normal VaR estimates differ from the Empirical VaR estimates for the two sub-samples of data from the Asia 50 Index over a range of confidence levels. The Parametric-Normal approach assumes Normally distributed returns and the Empirical Approach uses the observed frequency distribution. The difference is the error generated by using the assumption of Normally distributed returns and is estimated for a \$100 million position in the particular asset.

of an autoregressive conditional heteroskedastic (ARCH) process. ARCH modelling allows the conditional variance to change over time leaving the unconditional variance constant. The ARCH process was generalised by Bollerslev (1986) so that the conditional variance is not only a function of past errors but also of lagged conditional variances. GARCH modelling has since then become extremely popular in empirical applications for the second moment in financial time series. A GARCH(p,q) process can be written as:

$$h_t = \alpha_0 + \sum_{i=1}^q \alpha_i \varepsilon_{t-i}^2 + \sum_{i=1}^p \beta_i h_{t-i}; \tag{6}$$

where ε_t^2 is the sample variance, and h_t is the conditional variance both at time t . Following the RiskMetrics^{TM8} methodology, the optimal conditional variance is esti-

⁸ See the JP Morgan Bank RiskMetrics Technical (1996) for an introduction to RiskMetricsTM.

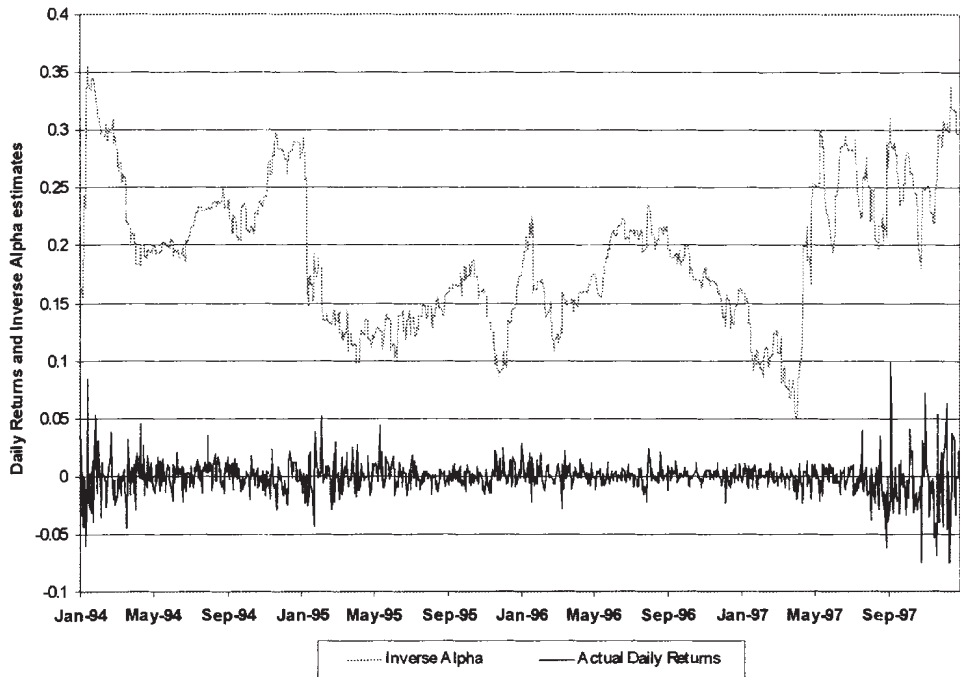


Fig. 2. Value-at Risk Estimates. The graph depicts how the inverse alpha estimates for the tail index vary over time. The tail index is estimated using a modified version of the Hill estimator and uses the previous years data (260 daily observations) for estimation. Also plotted are the actual daily returns on the Asia 50 Index.

mated by a GARCH(1,1) model with zero constant and the parameters α and β summing to unity. Imposing such a restriction gives us a process formally known as Integrated GARCH (IGARCH):

$$h_t = \lambda h_{t-1} + (1 - \lambda) \varepsilon_{t-1}^2 \quad (7)$$

Instead of estimating volatility unconditionally using an equally weighted moving average, the RiskMetrics™ approach therefore uses exponential weights, so that the more recent observations weigh more heavily. The rate of decline of the exponential weights depends on the decay factor λ , thus expressing the persistence with which a shock will decay. They suggest setting the decay factor to 0.94 for daily data and 0.97 when using monthly data. The fact that only the one parameter λ need be estimated facilitates estimation and provides for greater robustness against estimation error.⁹

Unfortunately tail fatness is not captured completely by the use of conditional

⁹ See Jorion (1997) for a good discussion of the applicability of the RiskMetrics™ Methodology.

volatility. This can be seen for example by comparing how forecasts of bi-weekly VaR for the Asian market index from the two approaches compare to their theoretical values over time. We provide rolling bi-weekly forecasts, using an empirical sample of 260 trading days to provide the 10-day VaR, as recommended by the Basle Committee.¹⁰ By undergoing such an out-of-sample test we find that the both the unconditional parametric-normal and the conditional approach using the RiskMetrics™ methodology would have vastly under predicted the VaR at the 99% confidence level. The forecasts are based on data from the year prior, and the exact number of exceedances are provided against their theoretical values in Table 3. Over the whole sample however the unconditional approach would have been slightly more reliable than the conditional approach with actual bi-weekly returns exceeding the bi-weekly forecast of the VaR 6.00% of the time rather than 7.26% of the time. We see that the benefit from allowing volatility to be conditional is only valid when taking the period of financial turmoil alone, with the 18.77% of exceedances from using unconditional VaR dropping to 11.49% of the time when using the RiskMetrics™ conditional approach.

Since the actual bi-weekly returns exceed the VaR forecasts for the 99% confidence level more often than the theoretical 1% of the time, it would appear that the assumption of normality results in conditional volatility failing to capture all of the risk. The degree to which normality fails becomes quite dramatic during periods of financial crises, when risk management should become even more conservative. We shall first investigate the nature of this additional downside risk using Extreme Value

Table 3
Number of Exceedances for Unconditional and Conditional Parametric-Normal VaR using Rolling Bi-Weekly Returns^a

| | Exceedences of Parametric-Normal VaR At 99% Confidence Level | | |
|---------------|--|---------------|-------------|
| | Number of Exceedences | | |
| | Theoretical | Unconditional | Conditional |
| Whole Sample | 10.33 | 62 | 75 |
| 1/1944-1/1997 | 7.73 | 13 | 45 |
| 1/1997-1/1998 | 2.60 | 49 | 30 |
| | Percentages | | |
| | Theoretical | Unconditional | Conditional |
| Whole Sample | 1.00% | 6.00 | 7.26 |
| 1/1994-1/1997 | 1.00% | 1.68 | 5.82 |
| 1/1997-1/1998 | 1.00% | 18.77 | 11.49 |

^a This table contains the statistics on the Asia 50 Price Index for the period January 1993 until January 1998 using 1293 rolling bi-Weekly total returns. The forecasts are based on yearly samples of daily data (260 returns), and a decay factor of 0.94 is used for the IGARCH(1,1) model for conditional volatility.

¹⁰ For an analysis of the Internal Model Based Approach to Market Risk Capital Requirement see the Basle reports by the Bank for International Settlements.

Theory (EVT), and then shall show how EVT can be used to provide unconditional and conditional VaR-x estimates, which shall be compared to both the unconditional parametric-normal approach and to RiskMetrics™. The use of EVT enables us to estimate VaR-x and hence capture the additional downside risk faced in times of financial crises.

3. Downside risk and financial crises

Volatility is highly important as a risk measure, especially during periods of financial turmoil. However we have seen that during the turmoil period on Asian markets in 1997, even the conditional normal under-predicts the actual VaR at high quantiles. Bollerslev (1986) also provides evidence that estimating volatility conditionally does not fully capture fat tailedness in asset prices, resulting in underestimation in the VaR at high quantiles. This would imply the existence of additional downside risk, risk that becomes more severe during periods of financial turmoil.

Deviations from normality would imply a movement away from the mean-variance framework, and the inclusion of higher moments of the distribution into risk management. Intuitively any additional downside risk should be captured by the extent to which the left tail of the return distribution deviates from conditional normality.¹¹ An estimate for the tail index of this left tail, through the use of Extreme Value Theory, will help us not only to capture tail fatness, but also indirectly capture any skewness that the distribution may have.

3.1. Tail index estimation

We use Extreme Value Theory to provide us with estimates of tail indices. EVT looks specifically at the distribution of the returns in the tails, and the tail fatness of the distribution is reflected by the tail index. This approach was first introduced by Hill (1975), and measures the speed with which the distribution's tail approaches zero. The fatter the tail the slower the speed and the lower the tail index given. An important feature about the tail index is that it equals the number of existing moments for the distribution. A tail index estimate equal to 2 therefore reveals that both the first and second moments exist, in that case the mean and the variance, however higher moments will be infinite. By definition the tail index for the normal distribution equals infinity since all moments exist. Since the number of degrees of freedom reflects the number of existing moments, the tail index can thus be used as a parameter for the number of degrees of freedom to parameterise the Student-t distribution. Hence the link to the Student-*t* distribution, a fatter tailed distribution, which also nests the normal distribution, which we use in VaR-X.

To obtain tail index estimates we use a modified version of the Hill estimator, developed by Huisman et al. (1997). Their estimator has been modified to account

¹¹ Of course if a short position is held then the concern becomes that of the right tail of the distribution.

for the bias in the Hill estimator, with the additional advantage of producing almost unbiased estimates in relatively small samples. Specifying k as the number of tail observations, and ordering their absolute values as an increasing function of size, we obtain the tail estimator proposed by Hill. This is denoted below by γ and is the inverse of α :

$$\gamma(k) = \frac{1}{k} \sum_{j=1}^k \ln(x_{n-j+1}) - \ln(x_{n-k}). \tag{8}$$

Following the methodology of Huisman et al. (1997) we can use a modified version of the Hill estimator (1997) to correct for the bias in small samples. The bias of the Hill estimator stems from the fact that the bias is a function of the sample size. A bias corrected tail index is therefore obtained by observing the bias of the Hill estimator as the number of tail observations increases up until κ , whereby κ is equal to half of the sample size:

$$\gamma(k) = \beta_0 + \beta_1 k + \varepsilon(k), \quad k = 1 \dots \kappa \tag{9}$$

The optimal estimate for the tail index, is the intercept β_0 . And the α estimate is just the inverse of this estimate. This is the estimate of the tail index that we use to parameterise the Student- t distribution.

Looking first at the alpha estimates for the whole sample and the individual years in Table 4, we see that the alpha estimates become smaller the larger the deviation from normality. This would imply that the tail index is able to capture some of the additional downside risk. In Fig. 2 the inverse alpha estimates using the previous years sample of daily data are plotted next to the actual daily returns. We see that the more the returns fluctuate the higher the inverse alpha estimate and the greater the deviation from normality. Indeed the correlation between volatility and alpha is -0.429 , which is significant at the 95% confidence level.

Since we observe fatter tails during periods of instability, we would expect the use of the alpha estimates in our VaR- x framework to provide more accurate estimates of

Table 4
Tail Index Estimates for Asia 50 Index and Sub-Samples^a

| Asia 50 Index | Whole Sample | 1993 | 1994 | 1995 | 1996 | 1997 |
|-----------------|--------------|-------|-------|-------|-------|-------|
| Gamma Left Tail | 0.291 | 0.164 | 0.280 | 0.174 | 0.162 | 0.298 |
| Standard Error | 0.036 | 0.047 | 0.084 | 0.048 | 0.045 | 0.090 |
| Alpha Left Tail | 3.436 | 6.103 | 3.567 | 5.754 | 6.186 | 3.357 |
| Observations | 329 | 67 | 61 | 71 | 71 | 60 |

^a This table contains the statistics on the Asia 50 Price Index for the whole period January 1993 until January 1998 using a total of 1302 daily returns, and for the individual years, using an average 259 daily returns. The alpha estimate is calculated using a modified version of the Hill estimator for the tail indexes and is presented for the left tail.

the VaR during periods of high volatility, especially during financial crises. We now develop the VaR-x methodology to account for conditionality, to see if we are able to capture any of the additional downside risk, that becomes so important during periods of financial turmoil.

4. VaR-x

To capture the existence of any non-normalities in the data into Value-at-Risk we use the VaR-x approach. This allows us to move away from the mean-variance framework and the assumption of normally distributed returns, allowing the return distribution to be fatter tailed if the data exhibit more frequent negative returns than predicted under the normal distribution. The additional parameter, the alpha estimate, for the left tail of the distribution, is then used to parameterise the Student-*t* distribution. To be able to compare the approach with the RiskMetrics™ methodology we thus use the same IGARGH(1,1) model for estimating conditional volatility. However instead of assuming normality we use the standard Student-*t* distribution, parameterised by the tail index. This enables us to estimate S^* , the point on the distribution at which the area $1-c$ falls to the left. This value then needs to be converted from its zero mean and variance of $\alpha/(\alpha-2)$ so that we use the scale factor θ equal to:

$$\theta = \frac{\sigma}{\sqrt{\frac{\alpha}{\alpha-2}}}. \quad (10)$$

The variable θ therefore replaces the standard deviate as the risk measure in Eq. (5), and S^* is our desired cut off point on the distribution. This then gives us the required return R^* under the VaR-x formulation as:

$$R^* = -S^*\theta + \mu. \quad (11)$$

We now need only substitute this value for R^* into Eq. (4) to give us the relative VaR-x, equal to $W_0 S^* \theta$. The formulation allows for the conditional or unconditional estimation of the parameters.

In order to see how the VaR-x approach works in practice, we undergo the same sample test as we did for the parametric-normal approach earlier. In Figs. 3 and 4 we have plotted the unconditional and conditional forecasts using the VaR-x methodology alongside those generated from the assumption of normally, and conditionally normally distributed returns. We see that the VaR-x approach is able to capture some of the additional downside risk faced in the more volatile periods, beyond that from the use of the standard deviation alone. This is exemplified by the fact that the 99% boundary lies below that from the parametric-normal approach. During the financial crises the VaR-x approach provides a 99% boundary even further below that from the assumption of normality, with the difference becoming greater through the use of conditional volatility. In both cases the VaR-x approach provides consistently

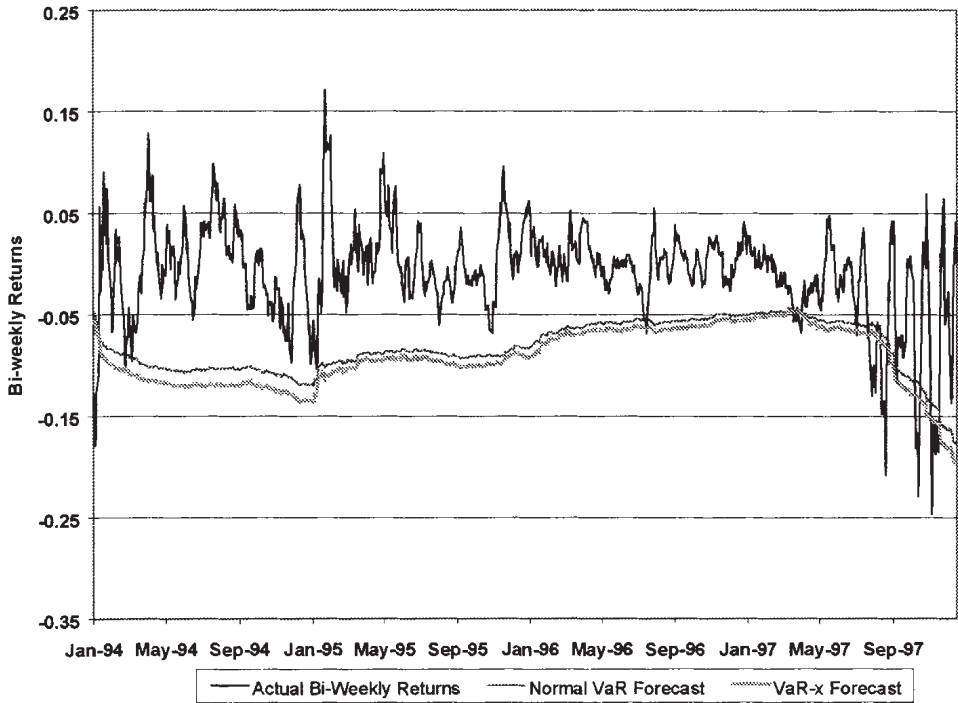


Fig. 3. Rolling VaR-x and Parametric-Normal VaR estimates. The graph depicts how the forecasts of the VaR-x estimates, using the Student-t distribution, compare to forecasts from using the Parametric-Normal VaR approach for the Asia 50 Index. We have used rolling observations of daily data, over the period January 1993 until January 1998 using 1,302 rolling Bi-Weekly total returns, to provide forecasts of the Value-at-Risk at the 99% confidence level. The forecasts are based on yearly samples of daily data, and the alpha estimate is calculated for the left tail using a modified version of the Hill estimator.

more accurate forecasts of the VaR than the parametric-normal approach. The number of exceedances and the percentages, compared to their theoretical values are presented in Table 5.

Since conditional estimation of VaR is better able to capture external shocks to volatility during periods of greater turmoil in financial markets, it would seem more appropriate to use a conditional approach to forecasting VaR. The evidence that estimating volatility unconditionally provides more robust forecasts over the entire sample lends itself to the notion that the decay factor in the conditional approach is too low, with the effect of the persistence of a shock dying out too fast. The IGARCH model using a higher decay factor, and hence allowing for external shocks to volatility to persist for longer may therefore be more appropriate.

Of crucial importance through, is that the use of an additional parameter in the VaR-x methodology, to capture the additional downside risk resulting from non-normality, results in more accurate VaR estimates than the from the assumption of conditional normality. When adopting conditional volatility into the VaR-x approach, using the same decay factor for the IGARCH(1,1) model for conditional volatility,

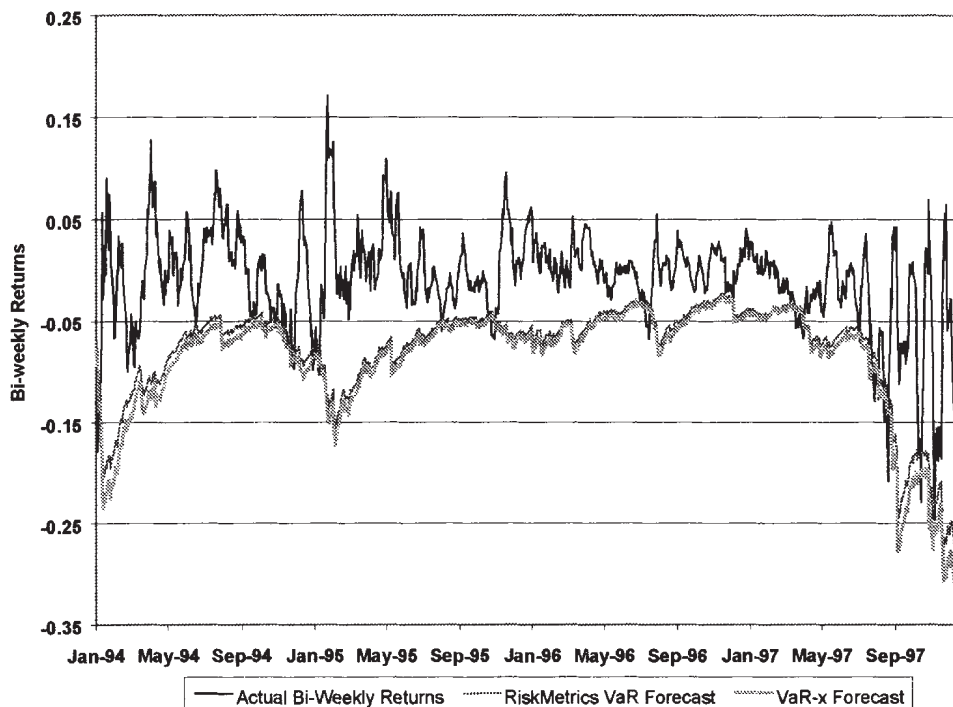


Fig. 4. Rolling VaR-x and RiskMetrics™ estimates. The graph depicts how the forecasts of the VaR-x estimates, using the Student-t distribution, compare to forecasts from using the RiskMetrics™ approach of conditional Parametric-Normal VaR for the Asia 50 Index. We have used rolling observations of daily data, over the period January 1993 until January 1998 using 1,302 rolling Bi-Weekly total returns, to provide forecasts of the Value-at-Risk at the 99% confidence level. The forecasts are based on yearly samples of daily data. The conditional volatility is estimated using an IGARCH(1,1) model with a decay factor of 0.94 for the daily data. The alpha estimate is calculated for the left tail using a modified version of the Hill estimator.

we find that conditional VaR-x improves upon the RiskMetrics™ estimates by over 13% for the period of financial turmoil.¹² The improvement is even larger when looking at the period as a whole, as shown in Table 6, hence providing much more accurate forecasts of the true Value-at-Risk. It would appear that even though conditional VaR-x is an improvement over the RiskMetrics methodology, further research into additional risk factors is still needed to try and explain the deviations from the use of a conditional student-*t* distribution to the true distribution.

¹² Danielson and de Vries (1997) also use EVT to find a semi-parametric method for estimating VaR, and also find that RiskMetrics under-predicts the true VaR at the 99% level. Their approach however only performs better far out in the tails, and has the unfortunate drawback of requiring an extremely large sample of data, using 100 000 observations. Their approach is therefore only applicable when high frequency data are available.

Table 5
Number of Exceedances for Unconditional and Conditional VaR-x using Rolling Bi-Weekly Returns^a

| Exceedences of VaR-x At 99% Confidence Level | | | |
|--|----------------------------|-----------------------|-------------|
| | Theoretical | Number of Exceedences | |
| | | Unconditional | Conditional |
| Whole Sample | 10.33 | 53 | 55 |
| 1/1944-1/1997 | 7.73 | 9 | 29 |
| 1/1997-1/1998 | 2.60 | 44 | 26 |
| | Percentages Theoretical | Unconditional | Conditional |
| Whole Sample | 1.00% | 5.13 | 5.32 |
| 1/1994-1/1997 | 1.00% | 1.16 | 3.75 |
| 1/1997-1/1998 | 1.00% | 16.86 | 9.96 |

^a This table contains the statistics on the Asia 50 Price Index for the period January 1993 until January 1998 using 1293 rolling bi-Weekly total returns. The forecasts are based on yearly samples of daily data (260 returns), and a decay factor of 0.94 is used for the IGARCH(1,1) model for conditional volatility.

Table 6
Improvement of Conditional VaR-x over RiskMetricsTM^a

| Exceedences of VaR-x At 99% Confidence Level | |
|--|--|
| | Percentage Improvement from RiskMetrics TM to VaR-x |
| Whole Sample | 26.67% |
| 1/1994-1/1997 | 35.56% |
| 1/1997-1/1998 | 13.33% |

^a This table contains the percentage improvement from using conditional VaR-x over RiskMatericsTM for the Asia 50 Price Index for the period January 1993 until January 1998. We use 1293 rolling bi-Weekly total returns and the forecasts using the two approaches are on yearly samples of daily data (260 returns). For both approaches a decay factor of 0.94 is used for the IGARCH(1,1) model for conditional volatility.

5. Implications for asset allocation

Asian financial markets have been characterized as highly volatile, however they are attractive to international investors since they offer the possibility of achieving high returns with low correlation to developed countries' returns. The diversification benefits from investing in these markets are thought to be huge. In practise however, we have seen that investors have shied away from these diversification benefits with the potential to diversify having been severely underexploited. Assuming that investors behave rationally, then the lack of diversification can only be explained by assuming that the perceived risk from investing in emerging markets must be much higher than the standard measure of risk suggests. Our evidence that the downside risk involved from non-normality is an important additional risk factor may be of

significance when looking at risk premia. If the risk is higher than otherwise assumed under the use of volatility alone, then such a high risk aversion parameter would not be required to explain the huge tendency, shown by investors, towards favouring the home country when investing. The implications for including non-normality would therefore also have serious implications for both the equity premium puzzle, whereby the risk involved in holding equity may be much higher than originally perceived.

The importance of non-normalities is also underlined when observing how any tail fatness, as captured by the tail index, appears to dominate a portfolios distribution. This results in tail fatness becoming important in a portfolio context. We can see that the tail-index for the Asia 50 Index, when considering the whole sample as given in Table 4, is dominated by the severe deviations from normality occurring during the financial crises in 1997. This highlights the likely importance of additional downside risk in portfolio allocation.

6. Conclusions

The empirical evidence on Asian equity markets provides evidence that Asian financial markets have been experiencing more frequent extreme negative returns than suggested by conditional normality. Moreover the deviations tend to be significantly greater during periods of financial turmoil. Such large deviations from normality, whether occurring in response to external economic and political news, or from the presence of herd-like behavior by investors¹³, results in the true risk from exposure on Asian financial markets being underestimated. The implications have already been severely felt, and indeed pose an even more serious threat on the stability of the entire financial system, when considering the contagious nature of financial distress. In order to ensure a sound financial environment it is crucial that risk management techniques accurately reflect the risk from exposure to financial markets. It therefore is of vital importance that the effects from additional downside risk are included into risk management.

Our conditional VaR-x estimates more accurately capture the additional risk, reflected by increased tail fatness, particularly crucial in times of financial crises. This has been shown with respect to the RiskMetrics™ methodology, which on testing out of sample resulted in a significant improvement to accurately forecasting Value-at-Risk. Accurate measurement of this exposure is crucial for financial risk management, both from an institution's, and a regulator's point of view. Institutions should be required to hold more capital, and if insurance schemes are set up¹⁴, then the premium paid to regulators would need to be greater. Such measures should result

¹³ See Kaminsky and Schmukler (1998), for an interpretation on the causes leading to such extreme market returns in Asia.

¹⁴ A proposed International Credit Insurance Corporation for example, as proposed by George Sores (EIU, 1998a), would require the purchase of an option in the form of an option from the agency, with the greater the firm's risk exposure the greater the fee to be paid.

in greater financial stability, with fewer banking and security house failures within Asian markets. Indeed it has been shown that those firms that have had more conservative capital standards have been able to dodge major losses from the turmoil across Asia¹⁵.

Knowing the true importance of downside risk appears to play a crucial role in the improvement of risk management techniques, and the avoidance of further financial crises. Our VaR-x approach not only highlights the huge risks and potential danger from investing in Asian markets, but also directs attention towards the importance of deviations from normality in asset pricing theory. The additional risk faced by the investor may indeed be able to give a better understanding to the size of the risk premium. This points towards an explanation to both the high equity premium and home-country bias, without having to resort to excessive estimates of peoples risk aversion. The implications for portfolio management are therefore of particular interest for future research.

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References

- Basle Committee on Banking Supervision 1996. Ammendment to the Capital Accord to Incorporate Market Risks, Basle Report no. 24, BIS.
- Bekaert, G., Erb, C., Harvey C., Viskanta, T., 1998, Distributional characteristics of emerging market returns and asset allocation. *Journal of Portfolio Management*, winter 1998.
- Bekaert, G., Harvey, C., 1995. Time-varying world market integration. *Journal of Finance* 40 (2), 403–444.
- Bollerslev, T., 1986. Generalised autoregressive conditional heteroskedasticity. *Journal of Econometrics* 31, 307–327.
- Danielsson, J., de Vries, C., 1997. Value-at-Risk and Extreme Returns. LSE Working Paper.
- Economist Intelligence Unit, 1998a. Securing the downside: a proposal for solving financial crises. *Strategic Finance*, June–August 1998.
- Economist Intelligence Unit, 1998b. How firms are reacting to turmoil in Asia. *Strategic Finance*, June–August 1998.
- Engle, R., 1982. Autoregressive conditional heteroskedasticity with estimates of the variance of the United Kingdom inflation. *Econometrica* 50, 391–407.
- Fama, E.F., Roll, R., 1968. Some properties of symmetric stable distributions. *Journal of the American Statistical Association*, 63.
- Hill, B., 1975. A simple general approach to inference about the tail of a distribution. *Annals of Mathematical Statistics* 3, 1163–1174.
- Huisman, R., Koedijk, K.G., Kool, C., Palm, F., 1997. Fat Tails in Small Samples. LIFE Working Paper.
- Huisman, R., Koedijk, K.G., Kool, C., Palm, F., 1998. The Fat-Tailedness of FX Returns. LIFE Working Paper.

¹⁵ See EIU (1998b) for a detailed survey of the response of major international firms to financial turmoil in Asia.

- Huisman, R., Koedijk, K.G., Pownall, R.A., 1998. VaR-x: fat tails in financial risk management. *Journal of Risk*, fall 1998.
- Jorion, P., 1997. *Value at Risk: The New Benchmark for Controlling Derivatives Risk*. McGrawHill.
- J P Morgan Bank, 1996, *RiskMetrics Technical manual*, 4th ed. J P Morgan Bank, New York.
- Kaminsky, G.L., Schmukler, S.I., 1998. What Triggers market Jitters?: A Cronicle of the Asian Crises. World Bank Working Paper.
- Mandelbrot, B., 1963. The variation of certain speculative prices. *Journal of Business* 36, 394–419.
- Taylor, S., 1986. *Modeling Financial Time Series*. John Wiley & Sons Ltd.