Best Practice Risk Measurement in Emerging Markets: Empirical Test of Asymmetric Alternatives to CAPM

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Abstract

Downside and asymmtric risk measurement lends itself naturally to emerging equity markets, and offer an attractive alternative to traditional techniques.We investigate which of three models best fits the equity returns of emerging markets: CAPM, the Lower Partial Moment CAPM (LPM-CAPM), and an Asymmetric Response Model (ARM), and discuss implications for investment strategies and risk management. Using 10 years daily, weekly, and monthly returns of 690 MSCI Emerging Markets Free constituents, CAPM is not rejected for daily returns in 55% of cases, whilst for monthly returns, on average 80% of emerging market stocks are as well explained by CAPM as with asymmetric alternatives; in general, these are comparable to results for small UK companies. Our results reveal a strong 'regional effect', which we explore in more details, with reference to economic and political crisis. A clear conclusion of our analysis is that best practice risk and asset management involves customised approaches to quantitative economic analysis across geographies, and that one needs to take great care when recalibrating models, especially in more volatile periods.

JEL Classifications: C10, G12

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1 Introduction

An appropriate measure of risk is essential for decision-making in Finance. One of, if not, the most widely used risk measure is the systemic market risk, or "beta", of the mean-variance CAPM of Sharpe (1963 and 1964), Lintner (1965) and Mossin (1969). However, during the last couple of decades we have seen continuing theoretical and empirical criticism levelled against beta, an extensive bibliography on which can be found in Jagannathan and McGratten (1995). Such criticism has been particularly sharp in the field of emerging markets, where specific arguments have been put forward to challenge the use of CAPM (see, for instance, Harvey (1995), Godfrey and Espinosa (1996), Erb, Harvey, and Viskanta (1995, 1996) and Diamonte, Liew, and Stevens (1996) and Estrada (2000)). Most notably, the lack of an empirical relationship between beta and stock returns have driven this research, and obviously carried immense consequences for usage of CAPM in emerging markets asset pricing, discount rate measurement and risk management.

A useful class of models with which to address this issue are equilibrium models based on downside and/or asymmetric risk measures, which have been actively used in risk management in other areas of Finance. These were furthermore strongly supported in Estrada (2000), who documented their superior power of explaining risk in emerging market stock returns. In this study we shall consider in particular the Lower Partial Moment Capital Asset Pricing Model (LPM-CAPM) of Bawa and Lindenberg (1977) and a more general data-generating model - the Asymmetric Response Model (ARM) - first introduced in Bawa, Brown and Klein (1981). Asymmetric and downside risk models do not depend on mean-variance rules and imply the use of alternative systemic risk and performance measures, which complement or generalise the traditional trio associated with CAPM (introduced in Treynor (1965), Sharpe (1966) and Jensen (1972)). The LPM-CAPM and the ARM are suitable for non-normal returns and illiquid markets - and thus emerging stock returns - and their properties were examined in Pedersen and Satchell (2002). However, the extent to which such asymmetric equilibrium risk measures capture risk in emerging markets better than CAPM have not yet been quantified, and is obviously crucial to examine before one embarks upon a potential change in best practice modelling and risk/investment management methodologies.

In this study we investigate empirically under which conditions CAPM is as or less preferable to these general models for emerging markets, using an approach applied to mature markets in Pedersen and Hwang (2002), which in turn built on a procedure pioneered by Harlow and Rao (1989) and Eftekhari and Satchell (1996). This nests the three models (CAPM, LPM-CAPM and ARM) in each other and thus gives a statistical test of which model is preferred based on conventional econometric assumptions. Our empirical results suggest that on the whole, the applicability of CAPM is not more restricted for emerging markets than for small companies such as the FTSE250 or FTSE SmallCap constituents analysed in Pedersen and Hwang (2002). Moreover, the choice of risk measures varies greatly across different regions and time periods. For instance, in the case of Eastern Asia the proportion of CAPM is in convergence with that of the Western Economies, whereas Africa shows the highest tendency towards use of the ARM. More generally, our results suggest best practice risk measurement and management should include highly customised approaches across geographical regions, which are driven by occurrence of large political and economic 'events'.

The paper is organised as follows: in the next section, we discuss the issue of CAPM and emerging markets risk measurement and present the models. Section 3 briefly introduces the test procedure and the details of the market portfolio, whilst Section 4 describes the portfolio data. Results are presented in Section 5 and Section 6 is reserved for our conclusions.

2 The Problem with CAPM for Emerging Markets

CAPM relies upon the underlying assumption that investors have mean-variance preferences which - in turn - implicitly assumes that either (a) Investors care only about the first two moments of the returns distribution or (b) Return distributions are jointly spherically symmetric (e.g. normal, t-distribution etc.). The first of these implies a quadratic utility function with its well-documented empirical weaknesses (existence of a bliss point, symmetry and decreasing risk aversion etc.), whilst the latter has been fundamentally rejected in numerous financial settings, especially in thinly traded or default-driven markets, such as for small companies, credit portfolios and - indeed - emerging markets. The excellent and extensive survey by Jagannathan and McGrattan (1995) contains the general arguments this debate and we refer the reader to their work for details.

More specific problems with the poor empirical performance of beta are well documented in the studies of emerging markets. Firstly, the CAPM implicitly assumes that emerging markets are fully integrated with the world market. However, the assumption is not well supported by empirical evidence and beta and equity returns are far less correlated.[1] Harvey (1995) showed that as a result estimated betas in emerging markets are too low to explain the high cost of equity in these markets, a result confirmed in numerous future studies. Several studies attempted to explain the difference between beta and the cost of equity. Godfrey and Espinosa (1996), for example, preferred to directly adjust beta, whilst Erb, Harvey, and Viskanta (1995, 1996) and Diamonte, Liew, and Stevens (1996) proposed a method based on credit ratings. Whilst these have produced valuable insights into the economics of emerging markets, they are either less theoretically robust or hard to directly compare with CAPM from an empirical performance perspective.

Recently, Estrada (2000), motivated by the belief that risk is ultimately related to shortfall rather than volatility, proposed a downside risk model for the explanation of the cost of equity in emerging markets. Thus, the reason for the observed beta being too small may not lie just with the lack of market integration. There may be a case for the underlying risk measure and data generating functions of the CAPM not being appropriate in the emerging markets environment so that other approaches may produce better - and more accurate and realistic - results. Specifically, Estrada (2000) suggests using the semi-standard deviation

$$\sum_{i=1}^{n} (\tau - R_i(t))^2 \qquad \text{where } R_i(t) < \tau \tag{1}$$

in place of variance as a risk measure. Here, τ is a target return, typically set at a risk-free rate or another external benchmark. This, and related measures, has received considerable support from a number of practitioners (see Sortino and Price (1994), Sortino and Van Der Meer (1991), Efthekari and Satchell (1996)) and has a sound theoretical foundation in Microeconomics, Decision Theory and Psychology (see Pedersen and Satchell (1998) for

[1]See Harvey (1995), Bekaert (1995), Bekaert and Harvey (1995), Korajczyk (1996), and Bekaert, Harvey and Lumsdaine (2002) for example.

an extensive survey and references). Estrada (2000) confirms this choice of measure by demonstrating that it explains a larger part of the risk in emerging markets stock returns than beta, Value-at-Risk (VaR), idiosyncratic risk and size, as measured by log(market value). One of the models against which we test the CAPM, presented in the next section, is built by accepting all the assumptions of CAPM but replacing variance by (1) as risk measure, thus allowing for asymmetric features of the returns data - frequently observed in emerging markets - to contribute to risk measurement.

3 Test Procedure

In this section, we briefly discuss the test procedure used - details can be found in our previous paper, Pedersen and Hwang (2002). The most general model we use in this study was first introduced by Bawa, Brown, and Klein (1981). The key point of the model is to divide the excess market returns into two groups, positive and negative, in order to capture asymmetric responses of portfolio returns to changes in market conditions. The model - labelled the Asymmetric Response Model (ARM) - is defined by

$$R_i(t) - R_f(t) = \beta_{i1} R_m^-(t) + \beta_{i2} R_m^+(t) + \pi\delta(t) + \varepsilon_i(t) \tag{2}$$

where $R_m^-(t) = R_m(t) - R_f(t)$ when $R_m(t) < R_f(t)$ and zero otherwise, $R_m^+(t) = R_m(t) - R_f(t)$ when $R_m(t) > R_f(t)$ and zero otherwise, and $\delta(t)$ is an index function which is one when $R_m(t) > R_f(t)$ and zero otherwise. The disturbances, $\varepsilon_i(t)$, are serially uncorrelated, independent of all other variables, and have mean zero. This model has since been adapted to testing for the appropriateness of CAPM in several markets by Harlow and Rao (1989), Eftekhari and Satchell (1996), Pedersen (1998) and Hwang and Pedersen (2002). Moreover, a separate strand of literature has applied an identical data generating function when testing for asymmetries in market timing performance in Bull and Bear markets (see, for instance, Fabozzi and Francis (1977 and 1979), Kim and Zumwalt (1979), Chen (1982), Henriksson (1984) and Henriksson and Merton (1981)).

Indeed (2) is an ideal starting point for the modelling of emerging markets returns and testing the statistical validity of the CAPM and LPM-CAPM in providing 'best practice' risk and performance measures. To see this, note first that by letting $\pi = \phi\left(\beta_{i1} - \beta_{i2}\right)$ in

(2), where ϕ is the conditional expectation of $R_m(t)$ given that $R_m(t) > R_f(t)$, i.e.

$$\phi = E\left[R_m(t) - R_f(t)\,|R_m(t) > R_f(t)\right] = \frac{E\left[R_m^+(t)\right]}{\Pr(R_m(t) > R_f(t))} \tag{3}$$

and taking expectations, it can be shown that (2) reduces to the LPM-CAPM equation in Bawa and Lindenberg (1977) and

$$\beta_{i1} = \frac{E\left[(R_i(t) - R_f(t))\min\left(0, R_m(t) - R_f(t)\right)\right]}{E\left[\min\left(0, R_m(t) - R_f(t)\right)^2\right]} \tag{4}$$

which is the 'LPM-beta'. Hence, this gives the equilibrium risk measure of a model where all assumptions are the same as CAPM but variance is replaced by (1) as risk measure and the target return is the risk-free rate, $R_f(t)$. The linear models relating cost of equity, expected returns and risk premia are thus all preserved except that (4) replaces the traditional CAPM beta, whilst capturing only downside effects in returns. Moreover, the risk-return frontier conveniently remains two-dimensional and thus easy to analyse and present, despite higher moments affecting risk. Under this restriction, β_{i2} can be interpreted as the response of the portfolio to upside market returns. If one further imposes $\beta_{i1} = \beta_{i2}$ (and so by (3) also $\pi = 0$) in (2) and take expectations, one gets the traditional CAPM equation and

$$\beta_{i1} = \beta_{CAPM} = \frac{E[(R_i(t) - R_f(t))\,(R_m(t) - R_f(t))]}{E[(R_m(t) - R_f(t))^2]}. \tag{5}$$

Hence, in order to test for the differences between the three models, which can handle increasingly asymmetric returns data, we start with the general case (2) and then derive a test for

$$H_1 : \pi = \phi\,(\beta_{i1} - \beta_{i2}) \tag{6}$$

against

$$H_{1A} : \pi \neq \phi\,(\beta_{i1} - \beta_{i2}) \tag{7}$$

A rejection of H_1 implies that the data is not well-described by either LPM-CAPM or CAPM. This speaks in favour of modelling emerging market risk via the general asymmetric model (2) and it's empirical implications for risk and performance measurement, which were introduced in Pedersen and Satchell (2000). If we do not reject H_1, we test

$$H_2 : \beta_{i1} = \beta_{i2} \tag{8}$$

against

$$H_{2A} : \beta_{i1} \neq \beta_{i2} \tag{9}$$

which allows us to distinguish between CAPM being optimal (if we do not reject H_2) and LPM-CAPM (if we reject H_2). We have hence described a nested test which allows a direct comparison between the models, thus offering a statistically rigorous basis upon which to decide the suitability of one over the other for different markets, geographies and time periods.

3.1 S&P500: Excess Returns on the Market Portfolio

We now analyse the particular features of the choice of market portfolio in the empirical analysis and discuss some key assumptions on the distribution of excess market returns required to derive the testing equations for the above hypotheses. We need the full joint likelihood of $R_i(t), R_m^-(t), R_m^+(t), \delta(t)$, which we get from the decomposition

$$pdf\left(R_i(t), R_m^-(t),\ R_m^+(t), \delta(t)\right) = pdf\left(R_i(t)|R_m^-(t),\ R_m^+(t), \delta(t)\right) \times pdf\left(R_m^-(t),\ R_m^+(t), \delta(t)\right)$$

We know that the first conditional term is given by (2) and if the error $\varepsilon_i(t)$ is assumed to be distributed as a normal variable, this is given as

$$pdf\left(R_i(t)|R_m^-(t),\ R_m^+(t), \delta(t)\right) = \frac{1}{\sigma\sqrt{2\pi}} \exp\left[-\frac{1}{2\sigma^2}\left(R_i(t) - \beta_{i1}R_m^-(t) - \beta_{i2}R_m^+(t) - \pi\ \delta(t)\right)^2\right] \tag{10}$$

The second term, $pdf\left(R_m^-(t),\ R_m^+(t), \delta(t)\right)$, needs an appropriate assumption based on the observed excess market returns. For our empirical analysis, we use daily, weekly and monthly emerging market equity returns over the period from 1 April 1992 to 31 March 2002. The two sub-periods, discussed in more detail later, are from 1 April 1992 to 31 March 1997 and 1 April 1998 to 31 March 2002. Since we take the perspective of US investors, the S&P500 index and a three-month US Treasury Bill are used to calculate market returns and the risk-free rate. The summary statistics of the returns on the S&P500 are given in Table 1. The results indicate that the normal distribution may not be suitable for the daily, weekly and monthly market returns for the entire sample period. However, for the two sub-periods, weekly and monthly S&P500 returns of the sub-periods are normal, whilst - not unexpectedly - the Bera-Jarque test rejects normality for the daily returns. The non-normality of weekly and monthly market returns during the entire sample period reflects the extreme equity price movements during the Asian Crisis of 1997.

The empirical results in Table 1 hence suggest that we need a probability density function which is flexible enough to explain both normality and non-normality of market equity returns. In this study, we use the Mixed Gamma (MG) proposed by Knight, Satchell, and Tran (1995), which is designed to capture the asymmetry in upward and downward asset returns[2]. The distribution assumes that both $R_m^+(t)$ and $-R_m^-(t)$ are described by Gamma distributions

$$pdf(x) = \begin{cases} \frac{\lambda^\alpha x^{\alpha-1}\exp(-\lambda x)}{\Gamma(\alpha)} & x > 0 \\ 0 & \text{otherwise} \end{cases} \tag{11}$$

in which Γ denotes the Gamma function, $\alpha > 0$ and $\lambda > 0$. Under these assumptions, Knight, Satchell, Tran (1995) show that the joint likelihood of $R_m^+(t)$, $R_m^-(t)$ and $\delta(t)$ can be given as

$$\begin{aligned} pdf\left(R_m^-(t),\ R_m^+(t), \delta(t)\right) &= \left[pdf(R_m^-(t))p\right]^{\delta(t)} \left[pdf(R_m^+(t))(1-p)\right]^{1-\delta(t)} \\ = \left[\frac{p\lambda_1^{\alpha_1}\left[R_m^+(t)\right]^{\alpha_1-1}\exp\left[-\lambda_1 R_m^+(t)\right]}{\Gamma(\alpha_1)}\right]^{\delta(t)} &\times \left[\frac{(1-p)\,\lambda_2^{\alpha_2}\left[-R_m^-(t)\right]^{\alpha_2-1}\exp\left[-\lambda_2(-R_m^-(t))\right]}{\Gamma(\alpha_2)}\right]^{1-\delta(t)} \end{aligned} \tag{12}$$

where the parameters (α_1, λ_1) are from the Gamma distribution for $R_m^+(t)$, (α_2, λ_2) from the Gamma distribution modelling $-R_m^-(t)$, and p is the probability of $\delta(t)$ being one.

The result of fitting the MG distribution to the market excess returns is given in Table 2. All estimates are significantly different from zero and for monthly returns the results are similar to those reported in Hwang and Satchell (2001) and Pedersen and Hwang (2002); large values of λ_1 and λ_2 whilst $\alpha_1 > 1$ and $\alpha_2 > 1$. The density has maximum value (i.e. mode) at $(\alpha_i - 1)/\lambda_i$ when $\alpha_i > 1$; for example, for the monthly returns of the entire sample period, the conditional densities for positive and negative excess returns have maximum value at $(\widehat{\alpha}_1 - 1)/\widehat{\lambda}_1 = (1.3615 - 1)/44.4729 = 0.0081$, and $-(\widehat{\alpha}_2 - 1)/\widehat{\lambda}_2 =$

[2]We also used the continuous mixed truncated normal density function as in Pedersen and Hwang (2002), but as in that study, the selection of the three models with the density function is not different from the selection with the MG density function. The results with the continuous mixed truncated normal density function can be obtained from the authors.

$-(1.4762 - 1)/40.7748 = -0.0117$, respectively. Likewise, ϕ is easily deduced from model parameters. Since the expectation of a Gamma distribution (11) is $\frac{\alpha}{\lambda}$, $\phi = \frac{\alpha_1}{\lambda_1}$ and $E\left[R_m(t) - R_f(t) \,|R_m(t) < R_f(t)\right] = -\frac{\alpha_2}{\lambda_2}$. The probability of returns being below the risk-free rate is explicitly measured via the parameter estimation of p. Thus, for instance for the daily data during the entire sample period, since $\phi = 1.0799/152.4150 = 0.71\%$, $p = 0.5276$, and $E\left[R_m(t) - R_f(t) \,|R_m(t) < R_f(t)\right] = -0.71\%$, we have $E\left[R_m(t) - R_f(t)\right] = 0.5276(0.71\%) + 0.4724(-0.71\%) = 0.04\%$, indicating a 4 basis point 'daily market risk premium'.

We also report the maximum log-likelihood (LL) values and Akaike Information Criteria[3] (AIC) of the fitted models in Table 3. When the excess market returns are non-normal, the MG works well since LL values and AIC are much larger than those obtained with the normal distribution. However, when the excess market returns are normal, LL values obtained with the assumption of the MG are not very different from those obtained with the normality, and thus AIC with the MG is smaller, since it has more parameters. All in all, the results in Table 3 confirm that the MG density function allows more flexibility than the normal distribution across several data sets and is not significantly outperformed in any area. As we seek consistency in the analysis across geographies, time periods and frequencies, and MG is needed in all non-normal cases, it is thus - like we found for the UK FTSE All -Share in Pedersen and Hwang (2002) - an appropriate distribution to use for this purpose.

To complete the test derivation, with the marginal distribution for the excess market returns just described in (12) and conditional distribution given by (10), we generate three relevant total likelihood functions for the joint returns distribution; 1) the likelihood function of $\{R_i(t), R_m^-(t),\ R_m^+(t), \delta(t)\}$ without any parameter restriction as in (2); 2) after imposing (6); and 3) after imposing both (6) and (8). Standard Likelihood Ratio (LR) tests are then easily be constructed, by comparing the resulting maximum likelihood values and the hypothesis tested. The relevant equations are given in the Appendix.

[3]The AIC is a standard model selection criteria and defined as

$$\mathsf{AIC} = 2 * (\mathsf{LL} - \mathsf{N})$$

where LL is log-likelihood and N denotes number of parameters. This was introduced in Akaike (1973).

4 Returns Data and Summary Statistics

We use all of the 690 stocks included in the MSCI emerging market free (EMF) index[4], which are available for our various sample periods. The full sample period is 10 years from 1 April 1992 to 31 March 2002. The period is divided into two sub-periods to investigate if there were changes in the risk measures before and after the Asian Crisis of 1997, namely 1 April 1992 to 31 March 1997 and 1 April 1998 to 31 March 2002. As explained in the previous section, the S&P500 index and a three-month US Treasury Bill are used to calculate excess market returns and the MG density function employed for the joint pdf of $R_m^+(t)$, $R_m^-(t)$ and $\delta(t)$. We use three different frequency of data; daily, weekly and monthly returns. We note that the daily case should be interpreted with slight caution since emerging markets and the US market do not open and close at the same time in a day and have different holidays, although this does not have significant impact on lower frequency data. We also recognise that there is likely to be some survivorship bias from excluding stocks without a long enough return history, since the more established firms are likely to have more robust track records and thus more stable and 'normal' returns. As we focus on choice of model, where insufficient data means the stock leaves our 'universe' in the first place, one could argue that our conclusions are unaffected. However, we believe that as emerging markets data collection improves to cover smaller and newer firms, with higher bankruptcy and product concentration risk, a rerun of our analysis would likely reveal more returns featuring asymmetries and less firm evidence for CAPM.

We also group the emerging market stocks into six groups on regional basis as follows; South Asia (India and Pakistan), East Asia (Indonesia, Taiwan, Hong Kong, Thailand, South Korea, Philippine, Malaysia), Eastern Europe (Czech Republic, Hungary, Poland), Latin America (Argentina, Brazil, Chile, Colombia, Mexico, Peru, Venezuela), Middle East (Egypt, Israel, Turkey), and Africa (Morocco, South Africa). Hwang and Satchell (1999b) showed that there are common factors in emerging markets based on region, and possibly a similar level of integration and 'optimal' risk measure may consequently be

[4]The MSCI EMF Index consists of the following 26 emerging market country indices at May 2002: Argentina, Brazil, Chile, China, Colombia, Czech, Egypt, Hungary, India, Indonesia, Israel, Jordan, Korea, Malaysia, Mexico, Morocco, Pakistan, Peru, Philippines, Poland, Russia, South Africa, Taiwan, Thailand, Turkey and Venezuela.

found. Strong 'regional effects' indicate that one needs to customise quantitative analysis of data in alternative emerging markets regions, to accompany due diligence investigations, with obvious implications for pricing, investment and risk management.

Table 4 reports summary statistics of the daily, weekly and monthly returns for the emerging market stocks. As expected, all daily returns reject normality for the entire sample period and both sub-periods. However, as the data frequency decreases, the proportion of normality increases, and around 23% of monthly returns do not reject normality at the 5% level. The results of the UK market during a similar sample period reported in Pedersen and Hwang (2002) show that 100% of daily and weekly returns are non-normal, whilst 61%, 62% and 77% of monthly returns of the FTSE100, FTSE250, and FTSE SmallCap constituents are non-normal, respectively. In aggregate, emerging market stocks appear to display similar levels of non-normality to the smaller stocks in the UK. We find this very surprising given the fact the Asian Crisis data is included in this sample, and it indicates that investor perception (i.e. that part of the valuation pattern not explained by fundamental data analysis) of emerging markets may be slightly skewed towards the negative.

The proportion of non-normality drops further for the two sub-periods as the Asian Crisis data is removed. In monthly returns, 45% and 33% of stock returns are non-normal, respectively, which are far less than 77% of the entire sample period[5]. The increase over in normality over time may reflect that markets are maturing and - potentially - a toughening of the market to absorb responses to larger political and socio-economic 'events'. We discuss this in more details for the different regions in the next section.

The averaged statistics aggregated across the six different regions are also given in Table 4. Weekly and monthly returns show that Middle East has the highest proportion of normality and thus appears most 'stable' during our period, reflecting the period of relative stability generated by the increased diplomatic process following the 1990-1991

[5] As an aside, the results indirectly indicate that during the Asian Crisis, emerging market returns became extreme to the extent that use of linear data generating functions becomes unattractive. However, one should bear in mind that at the stage where a country is in danger of defaulting, analysis associated with credit risk in debt markets (default prediction using key macroeconomic drivers, contagion impacts etc.) should pick up such extreme impact. Hence, best practice risk management should involve enough flexibility to optimally link equity and fixed income research at country level.

Gulf War. On the other hand, Latin America and Eastern Europe show high non-normality during the first sub-period and the second sub-period, respectively, which are most likely primarily caused by the Latin American Crisis in 1994 and the contagion from the Russian Crisis in 1998. Eastern Asian countries, which constitute the largest proportion of our sample stocks (see panel C of table 4) show that more than 70% of stocks are normal in monthly returns during the second sub-period. This is very high - indeed comparable to UK data observed in Pedersen and Hwang (2002) - and indicates that these markets are fast maturing towards a stage where conventional tools used for analysing fully developed markets may be appropriate. Of course, this was also the region most affected by the Asian Crisis and the one which has learned the most valuable lessons. The impact of the Asian Crisis during 1997 is clear when the proportion of non-normality during the entire sample period is compared with those of the sub-periods. The proportion of non-normality in monthly returns during the entire sample period are as high as 90% for some of the countries that directly suffered the Asian Crisis of 1997 - such as South Korea, Thailand, and Malaysia[6]. Even accounting for some selection bias, these are striking results.

5 Comparison of Risk Measurement Models

The results of the tests of the main hypotheses (6) and (8) distinguishing between the risk measurement models proposed are reported in Table 5 which summarises the number of rejections at the 10% significance level. These are broadly consistent with the results of non-normality reported in Table 4. As in Pedersen and Hwang (2002), for higher frequency returns which are highly non-normal, the ARM or LPM-CAPM is often chosen instead of the conventional CAPM. To see this, we first compare the results for the three different frequencies for the entire sample period. The daily returns, all of which are non-normal, are explained by CAPM only in 55% of cases. On the other hand, the weekly and monthly returns are explained with CAPM in around 80% of cases. When we compare these with those of the UK market reported in Pedersen and Hwang (2002), we find that the FTSE250 and FTSE SmallCap constituents show similar patterns, but not the FTSE100. A slight

[6]For reasons of space, these particular results are not reported. However, country-specific results are available from the authors.

difference between the emerging markets and the UK market is that the choice of the ARM relative to LPM-CAPM in emerging markets are relatively higher than those in the UK market, perhaps reflecting a few more cases of extreme asymmetry in the emerging markets.

Moving towards the results of the sub-periods (i.e. with the Asian Crisis data removed) we expect that more stocks are explained as well by CAPM as the other models, because returns are more normal. This is true for daily returns; 81% (first sub-period) and 72% (second sub-period) of stocks compared with 55% for entire sample period. However, for the other two frequencies, weekly and monthly, this pattern is not repeated. For these, during the second sub-period, fewer stocks support use of CAPM, whilst more select LPM-CAPM over ARM. In all, on average 20% of stock are not explained well by CAPM, which - as Figure 1 shows - does not appear to change significantly over different sub-periods. This frequency effect may reflect the possibility that intra-day volatilities were much higher than monthly return volatility during the Asian Crisis. However, the slight discrepancy between our preliminary observations on the sample properties of the underlying data in the last section, and results on CAPM-usage presented here, most possible are explained by the fact that although normality of portfolio returns is an established guide for CAPM, it is not necessary (i.e. other symmetric distributions may work) nor sufficient (the formal requirement is spherical symmetry in the joint distribution of the stock and market portfolios).

The pattern described above changes dramatically when addressing different regions in isolation, as illustrated in Table 5 and Figure 2. For the whole sample period, South and East Asia seem to be explained well by CAPM (86% and 84% of stocks respectively). Indeed, these are quite similar characteristics to small and medium stocks in the UK studied in Pedersen and Hwang (2002), although slight differences in sample periods make precise comparison levels hard to make. In particular, after the Asian Crisis, CAPM is chosen for about 94% of stocks in Eastern Asia, which appears to be displaying strong signs of maturing. At the other end of the spectrum, the Asymmetric Response Model (ARM) sees highest demand from African stock returns (25% of cases). This, together with Latin America in the second sub-period, indicates areas where mis-modelling risk is likely to be greatest if one applies the standard equilibrium models for market risk measurement and stock pricing[7]. In between these two cases lie the other regions studied. The Middle East saw relative stability in the post-Gulf War years and has the highest proportion of monthly stocks returns not rejecting CAPM in the first sub-period (91%). Indeed, during this period, all stocks conformed with one of the two theoretical risk measurement models, as LPM-CAPM was never rejected in favour of ARM. However, with the Israeli-Palestinian peace talks stalling, this stability deteriorated somewhat, which is reflected in CAPM being only selected in 65% of cases in sub-period 2, whereas the LPM-CAPM increased to 26%. This is a classic illustration of how one needs to not only keep up to date with developments, but ensure that models are recalibrated regularly, so that estimation errors and model risk is kept to a minimum. With the Middle East in particular, this is likely to remain a key factor given the further political deterioration in the region.

A similar pattern is observed for Latin America and Eastern Europe[8]. Again, for the former during the first sub-period, CAPM was chosen in 82% of the cases and remarkably, no stocks reject LPM-CAPM in favour of the ARM. Amongst notable events which may have yielded stability this was Mexico joining NAFTA, and the 1995 US bail-out of Mexico's private banks in return for a veto over the country's economic policy. Further, Colombia made serious progress on prosecuting drug cartels in the early 1990's, which meant better relations with the US. The major negative event for the countries studied, was the worsening economic conditions in Venezuela following a change of government in December 1993, which did not spread and affect neighbours via the strong contagion effect previously observed in the region. however, following the Asian Crisis, which arrived in Latin America in a year where El Nino also devastated crops in the region, the picture changed a lot. The biggest economy, Brazil, was bailed out by $42bn from the IMF in 1998 following a devaluation of the Real. However, the president (Fernando Cardosa) was credited with turning the economy around quickly in the next 12 months, returning stability. This pattern was copied to smaller or larger extent by Brazil's smaller neighbours, which have recently been further ravaged by contagion from the ongoing Argentinian cri-

[7]Note that most of the relevant African stocks are from South Africa, rather than Morocco, where the LPM-CAPM explains more than the ARM.

[8]The number of stocks for the entire sample period and the first sub-period of Eastern Europe is two, which is too small to make firm statements.

sis[9]. Hence, large stock price moves occurred in both directions, significantly affecting return volatility and skew towards the end of our sample period.

Finally, we also report the results of three individual countries whose numbers of stocks are reasonably large; South Africa, South Korea and Taiwan. We choose these countries because the first one is far away from the Asian Crisis in 1997, the second directly suffered it, and the third is in the region but did not experience it fully, respectively. Figures 3A, 3D, and 3G show that there are significant differences in the choices of risk measures. The monthly returns of the South Korean stocks are well explained by CAPM, i.e., 96% of stocks. However, as explained above the South African stocks are not well explained by CAPM; only 52% of stocks are explained by CAPM and 27% and 21% of them are explained by the asymmetric model and LPM-CAPM, respectively. The Taiwanese market is in the middle of the two; 78% of stocks are explained by CAPM. These results clearly show that the risk measures are different for different countries as well as for different regions[10]. The second interesting result is that Taiwanese market are explained very well by CAPM after the Asian Crisis; the proportion is 96%. Interestingly, before the Asian Crisis the South Korean and Taiwanese markets are explained by CAPM and LPM-CAPM, but not the asymmetric model. After the Asian Crisis, the proportion of the asymmetric model in the South Korean market increased. We guess that this result comes from large negative/positive returns of companies from continuous restructuring in South Korea after the crisis. Apart from this observation, in general CAPM appears to be the appropriate model for the two Asian countries in the post-crisis period. The ARM model appears most useful for the South African market, for which CAPM should not ideally be used without

[9] Political scandals and disruption in Chile (Pinochet 1998), Peru (Fujimori 2000) and Venezuela (debacle as Chavez rose to power in 1999) coupled with the ongoing drugs-related political issues in Colombia also left their mark on the regions stock markets.

[10] Politically destabilising troubles of the early 1990's in South Africa such as the violence at ANC demonstrations in 1992 and assassination of the secretary-general of the Communist Party in 1993, which marred the build-up to Nelson Mandela becoming president in April 1994, and the subsequent positive 'feel' in the coming 2-3 years account for the extreme behaviour of some stocks in Sub-period 1. The economic woes of the late 1990's, including high crime rates periods of labour unrest, coupled with the much-publicised brain-drain and devastating effects of AIDS, have also fed through to the second sub-period returns. South Africa thus remains an area for which quantitative economic analysis should be conducted and interpreted with extreme caution.

some note of caution when interpreting results. The proportions for the first and second sub-periods are 24% and 29%, respectively, which are much larger than the proportion of the LPM-CAPM.

6 Conclusion

Risk measurement in emerging markets is an ongoing debate which have attracted interest from both eminent academics and practitioners in leading financial institutions. Numerous differing views exist on 'best practice' in risk measurement and asset pricing for this particular asset class. With improvements in data discipline and increasingly maturing markets in developing countries, the potential for more robust quantitative analysis is set to increase. At the same time, a debate within the broader financial community - which has centered around the 'right' way to measure risk, and highlighted inherent weaknesses in CAPM - has proposed several models which are able to more effectively capture the observed asymmetry and fat-tails in emerging markets equity returns data, whilst preserving plausible theoretical assumption and the convenience of a two-dimensional risk-return frontier. Our work indicates that such models give a useful - and in some cases necessary - alternative for risk measurement in (regions of) developing countries. Moreover, with data on smaller stocks increasingly being collected, we expect these to become more frequently preferred as the selection bias reduces. An optimal strategy for quantitative risk management and asset pricing for emerging markets for the future should most likely develop a mixture of approaches depending upon current state of the region studied and historical price movements.

Naturally, downside risk models and asymmetric data generating functions are not the only alternative to CAPM, nor do they indeed solve all the related problems cited in this field. For instance, although the correlation between stock price and risk measure can be improved, other models such a higher-moment modelling (see Hwang and Satchell (1999a) for analytics and references) may also be favourable in certain circumstances. Finally, other assumptions in the international CAPM still need to be further challenged, such as the assumption of markets being integrated. Lack of integration will imply that some measures of risk will continue to be underestimated with LPM-CAPM - however, the

ARM is free of any such equilibrium assumptions and appears to prove most effective in precisely those areas (most notably Africa, and to a lesser extent Latin America) where markets are least developed. Future research along the lines presented in this paper and with comparison to those cited in the Introduction should further knowledge in this field and bring the community closer to consensus on practical and theoretical approaches to the best practice risk measurement in emerging markets.

7 Appendix

Likelihood Functions for the Test our Main Hypotheses

The joint likelihood function for $\{R_p(t), R_m^+(t), R_m^-(t), \delta(t)\}$ at time t is the product of the marginal likelihood (12) and conditional likelihood (10). By taking logarithms of this product, summing over a sample of size T, we have a log-likelihood of

$$
\begin{gathered}
-T\ln\sqrt{2\pi} - T\ln\sigma - \frac{1}{2\sigma^2}\sum_{t=1}^{T}\left(R_i(t) - \beta_{i1}R_m^-(t) - \beta_{i2}R_m^+(t) - \pi\delta(t)\right)^2 \\
+T_1\ln p + T_1\alpha_1\ln\lambda_1 + (\alpha_1 - 1)\sum_{t=1}^{T}\delta(t)\ln R_m^+(t) \\
-\lambda_1\sum_{t=1}^{T}\delta(t)R_m^+(t) - T_1\ln(\Gamma(\alpha_1)) + T_2\ln(1-p) + T_2\alpha_2\ln\lambda_2 \\
+(\alpha_2 - 1)\sum_{t=1}^{T}[1-\delta(t)]\ln\left[-R_m^-(t)\right] - \lambda_2\sum_{t=1}^{T}[1-\delta(t)]\left[-R_m^-(t)\right] - T_2\ln(\Gamma(\alpha_2))
\end{gathered}
\qquad (13)
$$

which is the unrestricted model corresponding to the Asymmetric Response Model (ARM) given by (2). Since, for a Gamma function, $E\left[R_m^+(t)\,|R_m^+(t) > 0\right] = \frac{\alpha_1}{\lambda_1}$,the test of LPM-CAPM versus the general asymmetric model (2) defined by (6) - becomes

$$H_1 : \pi = \frac{\alpha_1}{\lambda_1}\left(\beta_{i1} - \beta_{i2}\right) \qquad (14)$$

which is tested against

$$H_{1A} : \pi \neq \frac{\alpha_1}{\lambda_1}\left(\beta_{i1} - \beta_{i2}\right). \qquad (15)$$

The restricted likelihood under H_1 is thus given by substituting (14) into (13), thus

$$-T\ln\sqrt{2\pi} - T\ln\sigma - \frac{1}{2\sigma^2}\sum_{t=1}^{T}\left(R_i(t) - \beta_{i1}R_m^-(t) - \beta_{i2}R_m^+(t) - \frac{\alpha_1}{\lambda_1}\left(\beta_{i1} - \beta_{i2}\right)\delta(t)\right)^2$$

$$+T_1\ln p + T_1\alpha_1\ln\lambda_1 + (\alpha_1 - 1)\sum_{t=1}^{T}\delta(t)\ln R_m^+(t)$$

$$-\lambda_1\sum_{t=1}^{T}\delta(t)R_m^+(t) - T_1\ln(\Gamma(\alpha_1)) + T_2\ln(1-p) + T_2\alpha_2\ln\lambda_2$$

$$+(\alpha_2 - 1)\sum_{t=1}^{T}[1-\delta(t)]\ln\left[-R_m^-(t)\right] - \lambda_2\sum_{t=1}^{T}[1-\delta(t)]\left[-R_m^-(t)\right] - T_2\ln(\Gamma(\alpha_2)) \qquad (16)$$

If we reject (14), the data do not support an equilibrium model (i.e. LPM-CAPM or CAPM), but favour the general asymmetric model (2). If (14) is not rejected, we test LPM-CAPM against CAPM by considering $H_2 : \beta_{i1} = \beta_{i2}$ using the Likelihood Ratio test where (16) is the unrestricted likelihood, and the restricted likelihood, obtained by substituting $\beta_{i1} = \beta_{i2}$ in (16), is

$$-T\ln\sqrt{2\pi} - T\ln\sigma - \frac{1}{2\sigma^2}\sum_{t=1}^{T}\left(R_i(t) - \beta_{i1}\left[R_m(t) - R_f(t)\right]\right)^2$$

$$+T_1\ln p + T_1\alpha_1\ln\lambda_1 + (\alpha_1 - 1)\sum_{t=1}^{T}\delta(t)\ln R_m^+(t) - \lambda_1\sum_{t=1}^{T}\delta(t)R_m^+(t)$$

$$-T_1\ln(\Gamma(\alpha_1)) + T_2\ln(1-p) + T_2\alpha_2\ln\lambda_2 +$$

$$(\alpha_2 - 1)\sum_{t=1}^{T}[1-\delta(t)]\ln\left[-R_m^-(t)\right] - \lambda_2\sum_{t=1}^{T}[1-\delta(t)]\left[-R_m^-(t)\right] - T_2\ln(\Gamma(\alpha_2)) \qquad (17)$$

If H_2 is rejected, we can then conclude that the most suitable model describing the data is LPM-CAPM and therefore β_{i1} is the "correct" risk measure. If H_2 is not rejected, we have illustrated strong support for CAPM.

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Table 1 Properties of S&P500 Index Returns

Frequency	Parameter	Entire Sample Period 1/04/1992 - 31/03/2002	Sub-period 1 1/04/1992 - 31/03/1997	Sub-period 2 1/04/1998 - 31/03/2002
Daily	Number of Daily Observations	2519	1263	1003
	Mean	0.0005	0.0006	0.0001
	Standard Deviation	0.0100	0.0062	0.0131
	Skewness	-0.3045	-0.3678	-0.1320
	Excess Kurtosis	4.6119	1.6513	1.9131
	Jarque-Bera	2271.3315	171.9768	155.8687
Weekly	Number of Weekly Observations	561	261	208
	Mean	0.0024	0.0029	0.0004
	Standard Deviation	0.0208	0.0143	0.0272
	Skewness	-0.3174	-0.2609	-0.1313
	Excess Kurtosis	1.6628	0.3434	0.4512
	Jarque-Bera	68.7701	4.2422	2.3625
Monthly	Number of Monthly Observations	120	60	48
	Mean	0.0104	0.0127	0.0019
	Standard Deviation	0.0407	0.0260	0.0523
	Skewness	-0.8134	-0.3812	-0.5388
	Excess Kurtosis	1.4286	-0.2176	0.1338
	Jarque-Bera	23.4386	1.5716	2.3581

Notes: The above tables is a summary of the S&P500 index returns for the three frequencies.
The Jarque-Bera statistic is asymtotically distributed as Chi-square with the 2 degrees of freedom whose critical value is 5.99 at 5% sigificance level.

Table 2 Maximum Likelihood Estimates of Mixed Gamma Distribution on the Excess Market Returns

Frequency	Parameter	Entire Sample Period 1/04/1992 - 31/03/2002		Sub-period 1 1/04/1992 - 31/03/1997		Sub-period 2 1/04/1998 - 31/03/2002	
		Estimate	Std	Estimate	Std	Estimate	Std
Daily	p	0.5276	0.0099	0.5432	0.0140	0.4985	0.0158
	α_1	1.0799	0.0371	1.1243	0.0540	1.2804	0.0728
	λ_1	152.4150	6.6079	237.7813	14.2744	129.6758	8.9810
	α_2	1.0218	0.0370	1.0436	0.0543	1.2184	0.0688
	λ_2	143.4181	6.6198	228.7667	15.1204	123.3745	8.5657
Weekly	p	0.5797	0.0216	0.5900	0.0304	0.5385	0.0346
	α_1	1.2755	0.0933	1.3079	0.1343	1.3557	0.1636
	λ_1	85.2175	7.5977	115.9301	14.4338	68.8621	10.0161
	α_2	1.1391	0.0969	1.0674	0.1292	1.6800	0.2226
	λ_2	66.8821	7.0944	95.9167	14.6750	70.1443	10.8122
Monthly	p	0.6417	0.0438	0.7167	0.0582	0.5000	0.0722
	α_1	1.3615	0.1983	1.5658	0.3084	1.2564	0.3256
	λ_1	44.4729	7.7978	70.9932	16.4433	31.1658	9.8722
	α_2	1.4762	0.2895	1.2888	0.3977	1.9204	0.5135
	λ_2	40.7748	9.4941	54.2251	20.3519	43.7853	13.3667

Notes: The excess market returns are calculated using the S&P500 Index and US 3 Month Treasury Bill rate.

Table 3 Summary of Fits to the Excess Market Returns

Frequency	Distribution	Entire Sample Period 1/04/1992 - 31/03/2002		Sub-period 1 1/04/1992 - 31/03/1997		Sub-period 2 1/04/1998 - 31/03/2002	
		Log-Likelihood Value	AIC	Log-Likelihood Value	AIC	Log-Likelihood Value	AIC
Daily	Normal	8019.06	16034.12	4618.76	9233.52	2928.09	5852.18
	Mixed Gamma	8203.17	16396.34	4652.54	9295.09	2948.03	5886.06
Weekly	Normal	1278.19	2552.38	739.71	1475.41	455.16	906.31
	Mixed Gamma	1291.71	2573.42	737.60	1465.20	456.21	902.41
Monthly	Normal	214.54	425.08	134.81	265.63	73.95	143.89
	Mixed Gamma	216.69	423.38	134.43	258.86	73.71	137.41

Notes: The excess market returns are calculated using the S&P500 Index and US 3 Month Treasury Bill rate.

Table 4 Average Values of Statistics of MSCI Emerging Market Constituents

A. Daily Returns

		Entire Sample Period 1/04/1992 - 31/03/2002 2519 Observations	Subperiod 1 1/04/1992 - 31/03/1997 1263 Observations	Subperiod 2 1/04/1998 - 31/03/2002 1003 Observations
Entire Stocks (24 Emerging Markets)	Number of Stocks	324	324	605
	Mean	0.000	0.001	0.000
	Standard Deviation	0.033	0.027	0.036
	Skewness	0.337	0.460	0.009
	Excess Kurtosis	21.196	21.374	10.489
	Bera-Jarque	1236300	460591	41757
	(Significance at 5%)	100%	100%	100%
Southern Asia (India, Parkinstan)	Number of Stocks	37	37	64
	Mean	0.000	0.000	0.000
	Standard Deviation	0.030	0.028	0.034
	Skewness	0.030	-0.083	-0.035
	Excess Kurtosis	12.785	18.123	4.471
	Bera-Jarque	60680	46583	1737
	(Significance at 5%)	100%	100%	100%
Eastern Asia (Indonesia, Taiwan, Hong Kong, Thai, South Korea, Philippine, Malaysia)	Number of Stocks	190	190	297
	Mean	0.000	0.001	0.000
	Standard Deviation	0.034	0.024	0.038
	Skewness	0.254	0.448	0.158
	Excess Kurtosis	9.163	6.546	5.908
	Bera-Jarque	15244	9186	3969
	(Significance at 5%)	100%	100%	100%
Eastern Europe (Czech, Hungrary, Poland)	Number of Stocks	2	2	23
	Mean	0.000	0.002	0.000
	Standard Deviation	0.038	0.038	0.033
	Skewness	-0.272	0.004	-0.160
	Excess Kurtosis	22.269	30.475	12.362
	Bera-Jarque	84713.103	90640.658	29189
	(Significance at 5%)	100%	100%	100%
Latin America (Argentina, Brazil, Chile, Colombia, Mexico, Peru, Venezuela)	Number of Stocks	39	39	96
	Mean	0.000	0.000	0.000
	Standard Deviation	0.029	0.029	0.031
	Skewness	0.780	0.535	-0.057
	Excess Kurtosis	64.654	47.709	13.622
	Bera-Jarque	8666234	1638337	32402
	(Significance at 5%)	100%	100%	100%
Middle East (Egypt, Israel, Turkey)	Number of Stocks	23	23	54
	Mean	0.000	0.001	0.000
	Standard Deviation	0.047	0.047	0.037
	Skewness	1.269	1.692	-0.345
	Excess Kurtosis	42.693	45.543	20.327
	Bera-Jarque	1486921	827787	139555
	(Significance at 5%)	100%	100%	100%
Africa (Morocco, South Africa)	Number of Stocks	29	29	49
	Mean	0.000	0.001	-0.001
	Standard Deviation	0.027	0.021	0.030
	Skewness	0.055	0.225	0.274
	Excess Kurtosis	28.227	58.321	18.918
	Bera-Jarque	560716	1973392	171655
	(Significance at 5%)	100%	100%	100%

Notes: The table reports average values of individual stocks' means, standard deviations, skewnesses, excess kurtoses, and Bera-Jarque statistics. Significance of Bera-Jarque statistics reports the proportion of non-normality of individual stocks.

B. Weekly Returns

		Entire Sample Period 7/4/1992 - 26/3/2002 561 Observations	Subperiod 1 7/4/1992 - 1/4/1997 261 Observations	Subperiod 2 7/4/1998 - 26/3/2002 208 Observations
Entire Stocks (24 Emerging Markets)	Number of Stocks	322	322	601
	Mean	0.0007	0.0027	-0.0003
	Standard Deviation	0.076	0.060	0.082
	Skewness	0.128	0.299	0.052
	Excess Kurtosis	6.600	5.440	3.624
	Bera-Jarque	10532	3672	516
	(Significance at 5%)	100%	94%	84%
Southern Asia (India, Parkinstan)	Number of Stocks	37	37	64
	Mean	0.000	0.000	0.000
	Standard Deviation	0.070	0.066	0.083
	Skewness	0.015	-0.099	0.032
	Excess Kurtosis	4.376	5.781	1.754
	Bera-Jarque	776	628	45
	(Significance at 5%)	100%	100%	80%
Eastern Asia (Indonesia, Taiwan, Hong Kong, Thai, South Korea, Philippine, Malaysia)	Number of Stocks	189	189	295
	Mean	0.001	0.003	0.001
	Standard Deviation	0.078	0.054	0.088
	Skewness	0.115	0.336	0.183
	Excess Kurtosis	5.083	2.940	3.173
	Bera-Jarque	786	228	224
	(Significance at 5%)	100%	92%	86%
Eastern Europe (Czech, Hungary, Poland)	Number of Stocks	2	2	23
	Mean	0.000	0.008	-0.002
	Standard Deviation	0.083	0.078	0.077
	Skewness	-0.443	0.092	-0.382
	Excess Kurtosis	3.892	2.899	6.244
	Bera-Jarque	353.967	143.221	744
	(Significance at 5%)	100%	50%	87%
Latin America (Argentina, Brazil, Chile, Colombia, Mexico, Peru, Venezuela)	Number of Stocks	39	39	92
	Mean	0.000	0.002	-0.002
	Standard Deviation	0.067	0.067	0.070
	Skewness	0.348	0.313	-0.004
	Excess Kurtosis	14.820	10.922	4.323
	Bera-Jarque	74202	13537	518
	(Significance at 5%)	100%	100%	87%
Middle East (Egypt, Israel, Turkey)	Number of Stocks	23	23	53
	Mean	0.002	0.004	-0.001
	Standard Deviation	0.106	0.106	0.082
	Skewness	0.466	0.822	-0.187
	Excess Kurtosis	7.705	9.047	1.921
	Bera-Jarque	8039	5668	170
	(Significance at 5%)	100%	100%	58%
Africa (Morocco, South Africa)	Number of Stocks	17	17	34
	Mean	0.001	0.004	-0.003
	Standard Deviation	0.063	0.051	0.062
	Skewness	-0.047	0.744	0.114
	Excess Kurtosis	7.604	6.488	7.204
	Bera-Jarque	4558	3849	3380
	(Significance at 5%)	100%	88%	91%

Notes: The table reports average values of individual stocks' means, standard deviations, skewnesses, excess kurtoses, and Bera-Jarque statistics. Significance of Bera-Jarque statistics reports the proportion of non-normality of individual stocks.

C. Monthly Returns

		Entire Sample Period 30/4/1992 - 31/3/2002 120 Observations	Subperiod 1 30/4/1992 - 31/3/1997 60 Observations	Subperiod 2 30/4/1998 - 31/3/2002 48 Observations
Entire Stocks (24 Emerging Markets)	Number of Stocks	324	324	605
	Mean	0.0027	0.0113	-0.0021
	Standard Deviation	0.162	0.127	0.177
	Skewness	0.108	0.349	-0.010
	Excess Kurtosis	2.785	1.647	1.127
	Bera-Jarque	176	52	15
	(Significance at 5%)	77%	45%	33%
Southern Asia (India, Parkinstan)	Number of Stocks	37	37	64
	Mean	0.002	-0.001	0.002
	Standard Deviation	0.141	0.133	0.166
	Skewness	0.070	0.056	0.054
	Excess Kurtosis	1.999	1.852	0.492
	Bera-Jarque	94	39	4
	(Significance at 5%)	62%	51%	20%
Eastern Asia (Indonesia, Taiwan, Hong Kong, Thai, South Korea, Philippine, Malaysia)	Number of Stocks	190	190	297
	Mean	0.003	0.012	0.003
	Standard Deviation	0.167	0.115	0.189
	Skewness	0.235	0.483	0.236
	Excess Kurtosis	2.693	1.411	0.926
	Bera-Jarque	64	24	12
	(Significance at 5%)	80%	45%	29%
Eastern Europe (Czech, Hungrary, Poland)	Number of Stocks	2	2	23
	Mean	0.001	0.036	-0.009
	Standard Deviation	0.184	0.182	0.158
	Skewness	-0.264	0.795	-0.837
	Excess Kurtosis	3.886	1.561	2.559
	Bera-Jarque	96.823	15.952	42
	(Significance at 5%)	100%	100%	61%
Latin America (Argentina, Brazil, Chile, Colombia, Mexico, Peru, Venezuela)	Number of Stocks	39	39	96
	Mean	-0.001	0.009	-0.009
	Standard Deviation	0.141	0.134	0.156
	Skewness	-0.100	0.066	-0.294
	Excess Kurtosis	4.349	2.351	1.700
	Bera-Jarque	934	156	18
	(Significance at 5%)	79%	54%	48%
Middle East (Egypt, Israel, Turkey)	Number of Stocks	23	23	54
	Mean	0.010	0.020	-0.006
	Standard Deviation	0.224	0.227	0.177
	Skewness	0.179	0.483	-0.253
	Excess Kurtosis	2.002	1.965	0.720
	Bera-Jarque	95	52	8
	(Significance at 5%)	57%	39%	19%
Africa (Morocco, South Africa)	Number of Stocks	29	29	49
	Mean	0.003	0.016	-0.016
	Standard Deviation	0.131	0.104	0.142
	Skewness	-0.453	0.121	-0.250
	Excess Kurtosis	2.984	1.819	1.586
	Bera-Jarque	87	123	30
	(Significance at 5%)	86%	28%	41%

Notes: The table reports average values of individual stocks' means, standard deviations, skewnesses, excess kurtoses, and Bera-Jarque statistics. Significance of Bera-Jarque statistics reports the proportion of non-normality of individual stocks.

Table 5 The Choice of Risk Measures for Emerging Market Stocks

A. Daily Returns

Region	Jarque-Bera Normality	Entire Sample Period: 1/04/1992 - 31/03/2002							Subperiod 1: 1/04/1992 - 31/03/1997							Subperiod 2: 1/04/1998 - 31/03/2002						
		Jarque -Bear	H1 Rejected Asymmetric		H1 not rejected H2 rejected: LPM-CAPM		H1 not rejected: H2 not rejected CAPM		Jarque -Bear	H1 Rejected Asymmetric		H1 not rejected H2 rejected: LPM-CAPM		H1 not rejected: H2 not rejected CAPM		Jarque -Bear	H1 Rejected Asymmetric		H1 not rejected H2 rejected: LPM-CAPM		H1 not rejected: H2 not rejected CAPM	
Entire Stocks	Rejected	324	74	23%	71	22%	179	55%	324	37	11%	26	8%	261	81%	604	74	12%	97	16%	433	72%
	Not Rejected	0	0	0%	0	0%	0	0%	0	0	0%	0	0%	0	0%	1	0	0%	1	100%	0	0%
	Total	324	74	23%	71	22%	179	55%	324	37	11%	26	8%	261	81%	605	74	12%	98	16%	433	72%
Southern Asia	Rejected	37	13	35%	6	16%	18	49%	37	1	3%	1	3%	35	95%	64	12	19%	10	16%	42	66%
	Not Rejected	0	0	0%	0	0%	0	0%	0	0	0%	0	0%	0	0%	0	0	0%	0	0%	0	0%
	Total	37	13	35%	6	16%	18	49%	37	1	3%	1	3%	35	95%	64	12	19%	10	16%	42	66%
Eastern Asia	Rejected	190	29	15%	44	23%	117	62%	190	21	11%	16	0%	153	81%	296	22	7%	61	21%	213	72%
	Not Rejected	0	0	0%	0	0%	0	0%	0	0	0%	0	0%	0	0%	1	0	0%	1	100%	0	0%
	Total	190	29	15%	44	23%	117	62%	190	21	11%	16	8%	153	81%	297	22	7%	62	21%	213	72%
Eastern Europe	Rejected	2	0	0%	1	50%	1	50%	2	0	0%	0	0%	2	100%	23	3	13%	0	0%	20	87%
	Not Rejected	0	0	0%	0	0%	0	0%	0	0	0%	0	0%	0	0%	0	0	0%	0	0%	0	0%
	Total	2	0	0%	1	50%	1	50%	2	0	0%	0	0%	2	100%	23	3	13%	0	0%	20	87%
Latin America	Rejected	39	15	38%	5	13%	19	49%	39	4	10%	8	0%	27	69%	96	13	14%	17	18%	66	69%
	Not Rejected	0	0	0%	0	0%	0	0%	0	0	0%	0	0%	0	0%	0	0	0%	0	0%	0	0%
	Total	39	15	38%	5	13%	19	49%	39	4	10%	8	21%	27	69%	96	13	14%	17	18%	66	69%
Middle East	Rejected	23	0	0%	8	35%	15	65%	23	2	9%	1	0%	20	87%	54	5	9%	1	2%	48	89%
	Not Rejected	0	0	0%	0	0%	0	0%	0	0	0%	0	0%	0	0%	0	0	0%	0	0%	0	0%
	Total	23	0	0%	8	35%	15	65%	23	2	9%	1	4%	20	87%	54	5	9%	1	2%	48	89%
Africa	Rejected	29	14	48%	7	24%	8	28%	29	9	31%	0	0%	20	69%	49	17	35%	5	10%	27	55%
	Not Rejected	0	0	0%	0	0%	0	0%	0	0	0%	0	0%	0	0%	0	0	0%	0	0%	0	0%
	Total	29	14	48%	7	24%	8	28%	29	9	31%	0	0%	20	69%	49	17	35%	5	10%	27	55%

Notes: The numbers of rejections of H1 and H2 above are counted at the 10% significance level.

B. Weekly Returns

Region	Jarque-Bera Normality	Entire Sample Period: 1/04/1992 - 31/03/2002							Subperiod 1: 1/04/1992 - 31/03/1997							Subperiod 2: 1/04/1998 - 31/03/2002						
		Jarque -Bear	H1 Rejected Asymmetric		H1 not rejected H2 rejected: LPM-CAPM		H1 not rejected H2 not rejected CAPM		Jarque -Bear	H1 Rejected Asymmetric		H1 not rejected H2 rejected: LPM-CAPM		H1 not rejected: H2 not rejected CAPM		Jarque -Bear	H1 Rejected Asymmetric		H1 not rejected H2 rejected: LPM-CAPM		H1 not rejected: H2 not rejected CAPM	
Entire Stocks	Rejected	322	21	7%	34	11%	267	83%	308	30	10%	28	9%	250	81%	528	36	7%	96	18%	396	75%
	Not Rejected	0	0	0%	0	0%	0	0%	14	0	0%	2	14%	12	86%	73	2	3%	13	18%	58	79%
	Total	322	21	7%	34	11%	267	83%	322	30	9%	30	9%	262	81%	601	38	6%	109	18%	454	76%
Southern Asia	Rejected	37	0	0%	15	41%	22	59%	37	1	3%	2	5%	34	92%	54	0	0%	25	46%	29	54%
	Not Rejected	0	0	0%	0	0%	0	0%	0	0	0%	0	0%	0	0%	10	0	0%	5	50%	5	50%
	Total	37	0	0%	15	41%	22	59%	37	1	3%	2	5%	34	92%	64	0	0%	30	47%	34	53%
Eastern Asia	Rejected	189	9	5%	9	5%	171	90%	178	22	12%	15	0%	141	79%	263	13	5%	30	11%	220	84%
	Not Rejected	0	0	0%	0	0%	0	0%	11	0	0%	2	0%	9	82%	32	1	3%	1	3%	30	94%
	Total	189	9	5%	9	5%	171	90%	189	22	12%	17	9%	150	79%	295	14	5%	31	11%	250	85%
Eastern Europe	Rejected	2	1	50%	0	0%	1	50%	2	0	0%	0	0%	2	100%	22	3	14%	4	18%	15	68%
	Not Rejected	0	0	0%	0	0%	0	0%	0	0	0%	0	0%	0	0%	1	0	0%	0	0%	1	100%
	Total	2	1	50%	0	0%	1	50%	2	0	0%	0	0%	2	100%	23	3	13%	4	17%	16	70%
Latin America	Rejected	39	4	10%	0	0%	35	90%	39	0	0%	9	0%	30	77%	83	3	4%	6	7%	74	89%
	Not Rejected	0	0	0%	0	0%	0	0%	0	0	0%	0	0%	0	0%	9	0	0%	0	0%	9	100%
	Total	39	4	10%	0	0%	35	90%	39	0	0%	9	23%	30	77%	92	3	3%	6	7%	83	90%
Middle East	Rejected	23	1	4%	4	17%	18	78%	23	0	0%	2	0%	21	91%	36	4	11%	14	39%	18	50%
	Not Rejected	0	0	0%	0	0%	0	0%	0	0	0%	0	0%	0	0%	17	1	6%	7	41%	9	53%
	Total	23	1	4%	4	17%	18	78%	23	0	0%	2	9%	21	91%	53	5	9%	21	40%	27	51%
Africa	Rejected	17	3	18%	3	18%	11	65%	16	3	19%	0	0%	13	81%	31	10	32%	6	19%	15	48%
	Not Rejected	0	0	0%	0	0%	0	0%	1	0	0%	0	0%	1	100%	3	0	0%	0	0%	3	100%
	Total	17	3	18%	3	18%	11	65%	17	3	18%	0	0%	14	82%	34	10	29%	6	18%	18	53%

Notes: The numbers of rejections of H1 and H2 above are counted at the 10% significance level.

C. Monthly Returns

Region	Jarque-Bera Normality	Entire Sample Period: 1/04/1992 - 31/03/2002							Subperiod 1: 1/04/1992 - 31/03/1997							Subperiod 2: 1/04/1998 - 31/03/2002						
		Jarque -Bear	H1 Rejected Asymmetric		H1 not rejected H2 rejected: LPM-CAPM		H1 not rejected: H2 not rejected CAPM		Jarque -Bear	H1 Rejected Asymmetric		H1 not rejected H2 rejected: LPM-CAPM		H1 not rejected: H2 not rejected CAPM		Jarque -Bear	H1 Rejected Asymmetric		H1 not rejected H2 rejected: LPM-CAPM		H1 not rejected: H2 not rejected CAPM	
Entire Stocks	Rejected	263	32	12%	31	12%	200	76%	157	6	4%	32	20%	119	76%	226	25	11%	23	10%	178	79%
	Not Rejected	61	7	11%	6	10%	48	79%	167	8	5%	22	13%	137	82%	379	24	6%	45	12%	310	82%
	Total	324	39	12%	37	11%	248	77%	324	14	4%	54	17%	256	79%	605	49	8%	68	11%	488	81%
Southern Asia	Rejected	24	1	4%	1	4%	22	92%	22	3	14%	1	5%	18	82%	15	0	0%	1	7%	14	93%
	Not Rejected	13	3	23%	0	0%	10	77%	15	1	7%	1	7%	13	87%	49	1	2%	8	16%	40	82%
	Total	37	4	11%	1	3%	32	86%	37	4	11%	2	5%	31	84%	64	1	2%	9	14%	54	84%
Eastern Asia	Rejected	164	8	5%	16	10%	140	85%	91	2	2%	28	31%	61	67%	102	2	2%	3	3%	97	95%
	Not Rejected	26	2	8%	3	12%	21	81%	99	1	1%	14	14%	84	85%	195	10	5%	4	2%	181	93%
	Total	190	10	5%	19	10%	161	85%	190	3	2%	42	22%	145	76%	297	12	4%	7	2%	278	94%
Eastern Europe	Rejected	2	1	50%	0	0%	1	50%	2	0	0%	0	0%	2	100%	14	3	21%	5	36%	6	43%
	Not Rejected	0	0	0%	0	0%	0	0%	0	0	0%	0	0%	0	0%	9	1	11%	4	44%	4	44%
	Total	2	1	50%	0	0%	1	50%	2	0	0%	0	0%	2	100%	23	4	17%	9	39%	10	43%
Latin America	Rejected	32	10	31%	7	22%	15	47%	21	0	0%	1	5%	20	95%	50	8	16%	10	20%	32	64%
	Not Rejected	7	0	0%	2	29%	5	71%	18	0	0%	6	33%	12	67%	46	7	15%	13	28%	26	57%
	Total	39	10	26%	9	23%	20	51%	39	0	0%	7	18%	32	82%	96	15	16%	23	24%	58	60%
Middle East	Rejected	14	3	21%	2	14%	9	64%	11	0	0%	2	18%	9	82%	11	4	36%	3	27%	4	36%
	Not Rejected	9	1	11%	0	0%	8	89%	12	0	0%	0	0%	12	100%	43	1	2%	11	26%	31	72%
	Total	23	4	17%	2	9%	17	74%	23	0	0%	2	9%	21	91%	54	5	9%	14	26%	35	65%
Africa	Rejected	25	8	32%	5	20%	12	48%	9	1	11%	0	0%	8	89%	22	7	32%	1	5%	14	64%
	Not Rejected	4	0	0%	1	25%	3	75%	20	6	30%	1	5%	13	65%	27	4	15%	3	11%	20	74%
	Total	29	8	28%	6	21%	15	52%	29	7	24%	1	3%	21	72%	49	11	22%	4	8%	34	69%

Notes: The numbers of rejections of H1 and H2 above are counted at the 10% significance level.

Figure 1A Percent of the Three Models for Daily Returns: Entire Sample Period

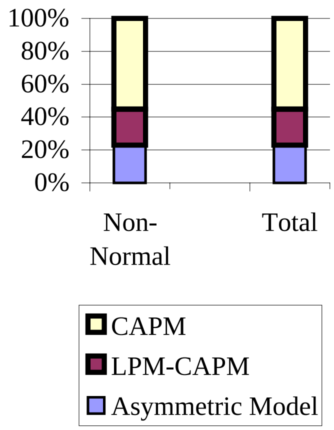


Figure 1B Percent of the Three Models for Daily Returns: Sub-period 1

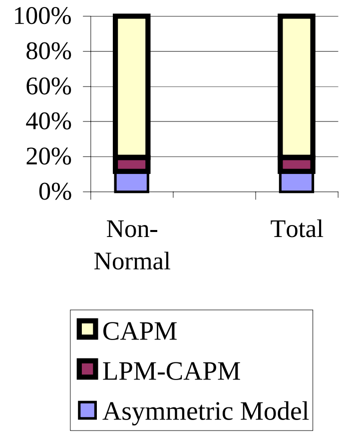


Figure 1C Percent of the Three Models for Daily Returns: Sub-period 2

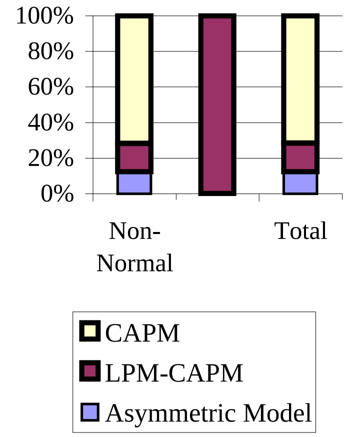


Figure 1D Percent of the Three Models for Weekly Returns: Entire Sample Period

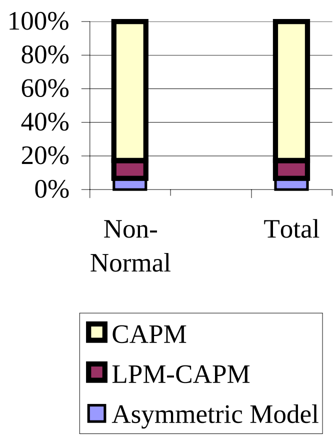


Figure 1E Percent of the Three Models for Weekly Returns: Sub-period 1

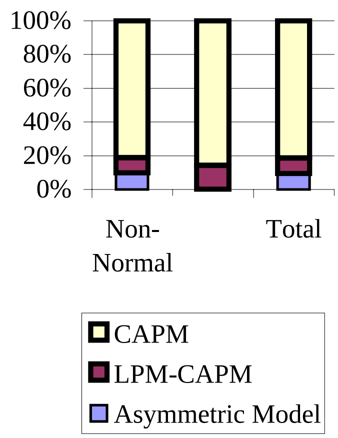


Figure 1F Percent of the Three Models for Weekly Returns: Sub-period 2

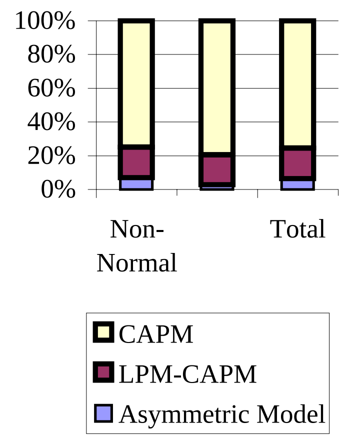


Figure 1G Percent of the Three Models for Monthly Returns: Entire Sample Period

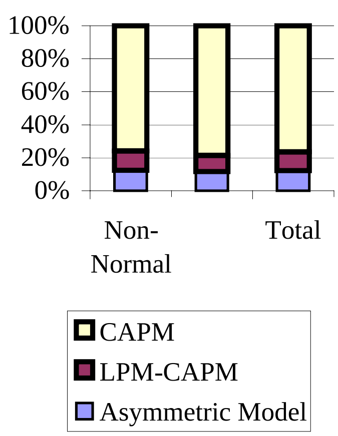


Figure 1H Percent of the Three Models for Monthy Returns: Sub-period 1

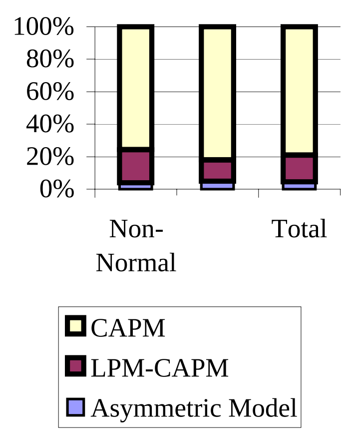
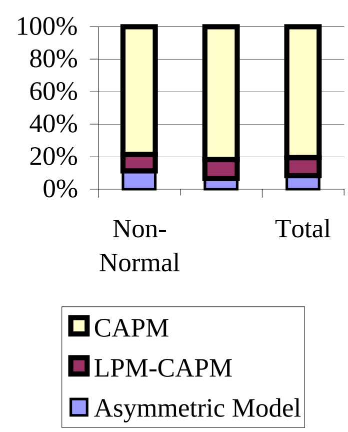


Figure 1I Percent of the Three Models for Monthly Returns: Sub-period 2



Notes: We have only one stock which shows normal daily returns during the second sub-period in figure 1C.

Figure 2A Percent of the Three Models for Monthly Returns: Entire Sample Period

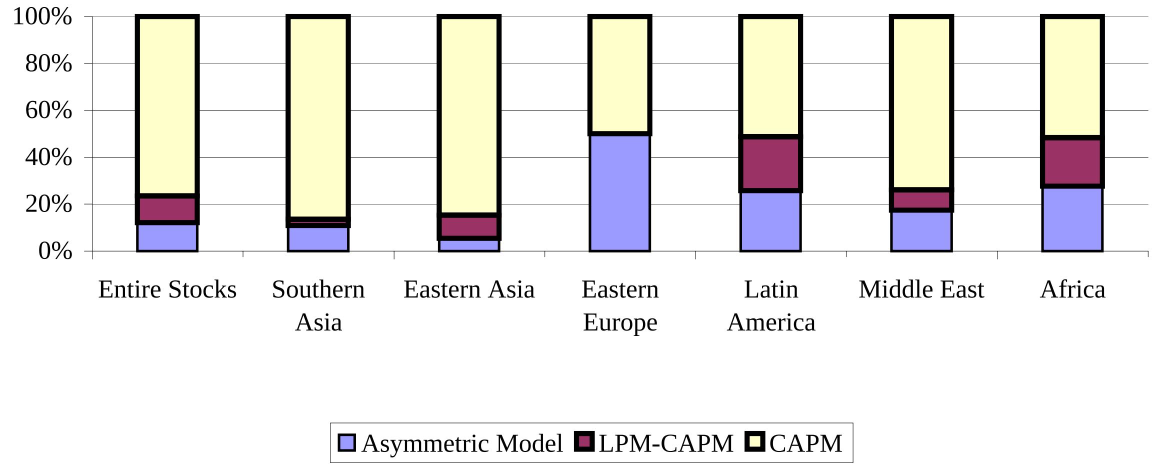


Figure 2B Percent of the Three Models for Monthly Returns: Sub-period 1

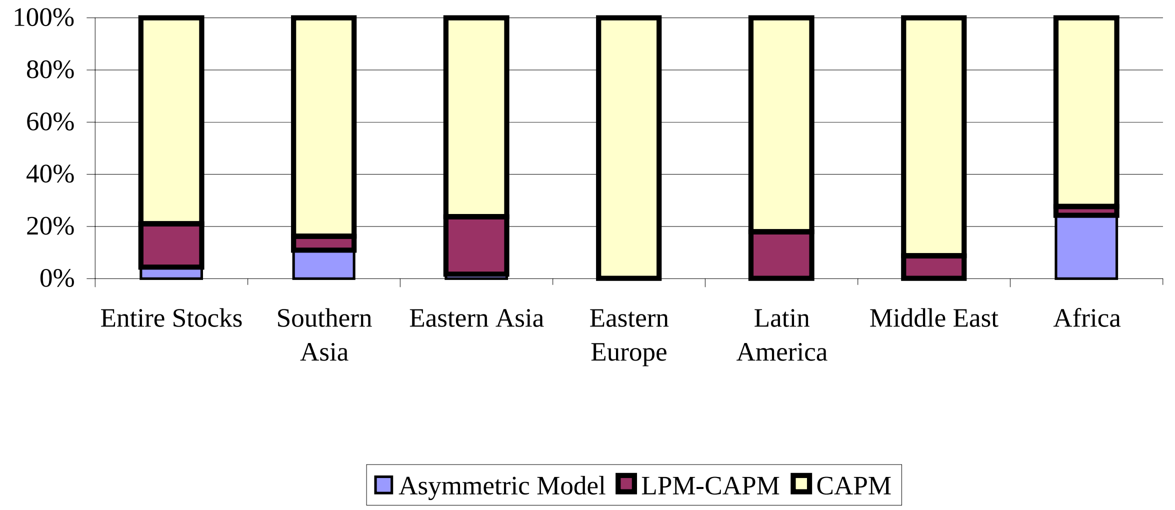


Figure 2C Percent of the Three Models for Monthly Returns: Sub-period 2

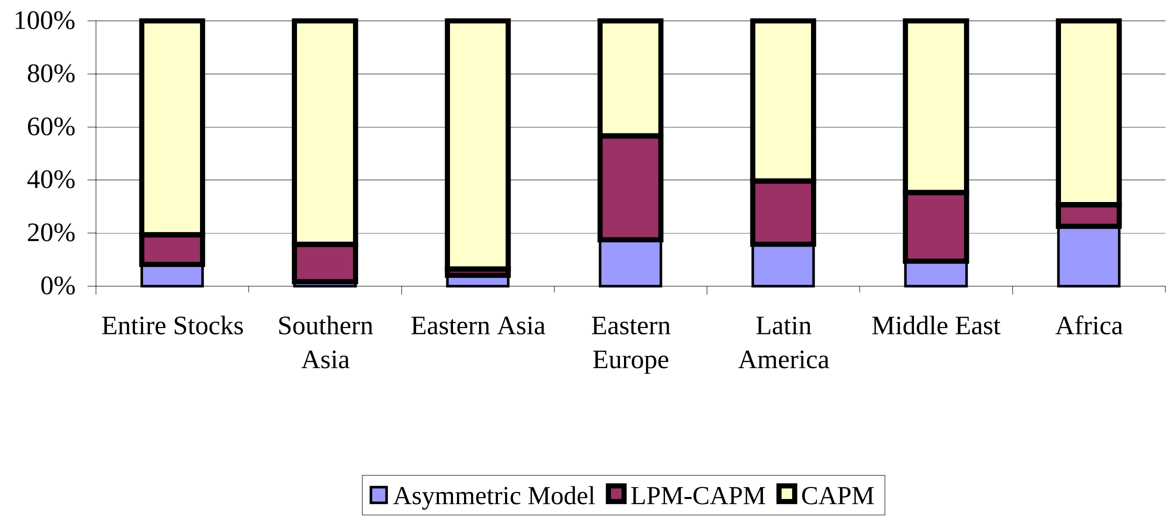


Figure 3A Percent of the Three Models for the Monthly Returns of South Africa: Entire Period

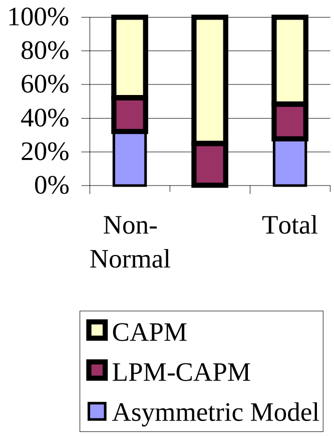


Figure 3B Percent of the Three Models for the Monthly Returns of South Africa: Sub-period 1

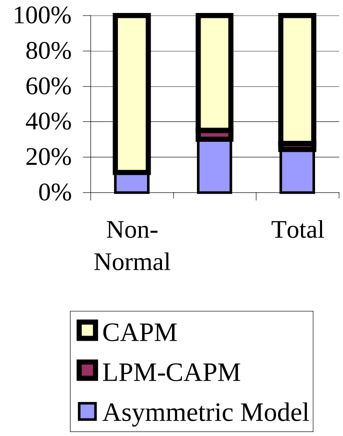


Figure 3C Percent of the Three Models for the Monthly Returns of South Africa: Sub-period 2

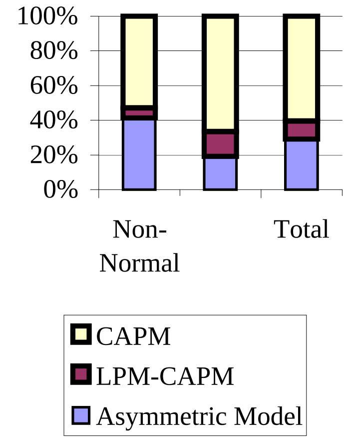


Figure 3D Percent of the Three Models for the Monthly Returns of South Korea: Entire Period

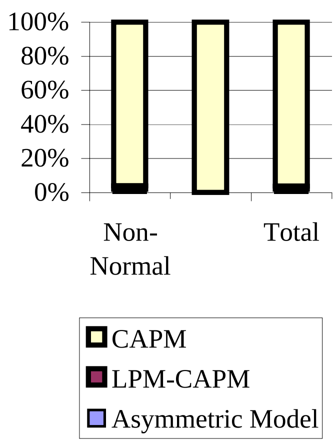


Figure 3E Percent of the Three Models for the Monthly Returns of South Korea: Sub-period 1

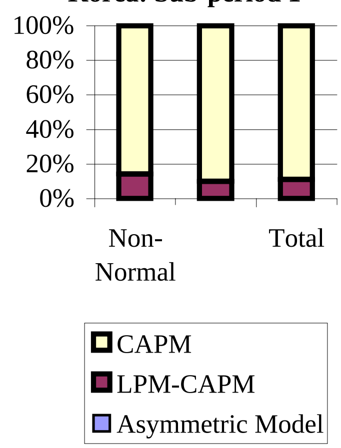


Figure 3F Percent of the Three Models for the Monthly Returns of South Korea: Sub-period 2

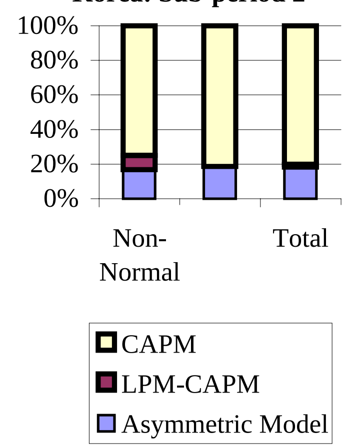


Figure 3G Percent of the Three Models for the Monthly Returns of Taiwan: Entire Period

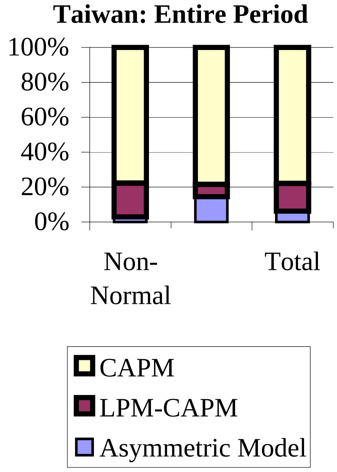


Figure 3H Percent of the Three Models for the Monthly Returns of Taiwan: Sub-period 1

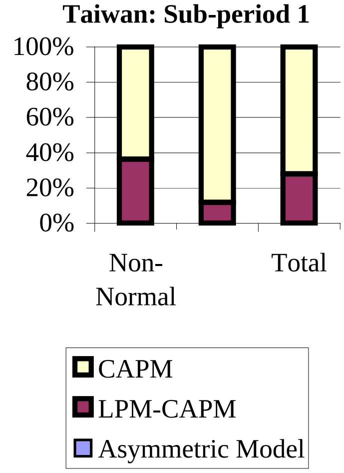


Figure 3I Percent of the Three Models for the Monthly Returns of Taiwan: Sub-period 2