The rare event risk in African emerging stock markets

Abstract

Purpose: To investigate the asymptotic distribution of the extreme daily stock returns in African stock markets over the period 1996 to 2007 and examine the implications for downside risk measurement.

Design/methodology/approach: Extreme Value Theory methods are used to model adequately the extreme minimum daily returns in a number of African emerging stock markets.

Findings: The empirical results indicate that the GL distribution best fitted the empirical data over the period of study.

Practical implications: Using the GEV and Normal distributions for risk assessment could lead to an underestimation of the likelihood of extreme share price declines which could potentially lead to inadequate protection against catastrophic losses.

Originality/value: To the best of my knowledge this is the first study to examine the lower tail distribution of daily returns for African emerging stock markets.

Keywords: African stock markets, Extreme share returns, risk measurement, Generalised Logistic distribution, Generalised Extreme Value distribution, L-moments.

Paper type: Research paper

1. Introduction

Research in emerging stock markets has suggested a number of empirical characteristics that international investors should be aware of. In particular, there is a growing body of evidence that emerging market securities tend to offer larger returns with higher volatility compared to developed stock markets (e.g. Harvey (1995), Bekaert et al. (1998), Bekaert and Harvey (1997) and De Santis and Improhoroglu (1997)). In addition, they show greater evidence of predictability (e.g. Harvey (1995), Claessens et al. (1993)) and lower correlation with developed stock market securities implying significant risk diversification opportunities for international portfolios (e.g. Bailey and Stulz (1990), Divecha et al. (1992), Harvey (1995) and Errunza (1988)). Although it is also argued that the behaviour of emerging markets is affected to a greater extent by local political, economic and social events rather than global events (e.g. Aggarwal et al (1999), Bekaert and Harvey (1997) and Susmel (1997)), more recent evidence has suggested that the diversification benefits of these markets have started to diminish because of changes in investment barriers for international investors (Errunza et al. (1999), Bekaert and Harvey, (1997)).

There is a vast amount of empirical evidence that the empirical distribution of asset returns is characterized by fatter tails relative to the normal distribution[1]. This empirical fact appears to be more pronounced in emerging than in developed markets possible due to liquidity problems, speculative attacks and other inefficiencies (Bekaert et al., 1998) which effectively increase the chances of large price movements[2]. Although these large price movements have almost zero probabilities of occurring according to the normal distribution, they tend to occur more often than the

[1] See, for example, Harris and Küçüközmen (2001) for a review of the relevant literature.

[2] In addition, there is evidence that the distribution of the empirical returns in emerging markets changes over time since research has indicated that there exist well defined structural breaks in the behaviour of return and volatility (Bekaert et al. (1997), Garcia and Ghysels (1997) and Bekaert et al. (2002)).

normal distribution would suggest sometimes with devastating consequences; for example, the stock market crash of October 1987. Unsurprisingly, investment managers and bankers have a keen interest in large price movements because these can erode the performance and value of an investment. The occurrence of extremes can also dramatically reduce the benefits of risk diversification because it is very difficult to diversify away the risk associated with extreme price movements since during a market crash all assets become highly correlated. Financial regulators like the Bank for International Settlements also have a keen interest in the chance of large financial losses. This is because large financial losses can endanger the stability of the financial system. For that reason, financial institutions must keep aside capital to cover any potential losses in the market place. The level of these capital requirements should be high enough to protect a financial institution and the financial system against the likelihood of large losses due to a rare but catastrophic event. In relation to the African emerging markets, the probability of occurrence of extremes can also have a large impact on economic development because stock markets are the main sources of finance for local businesses.

Extreme Value Theory (EVT) is a set of statistical techniques that has been used to analyse and model the tails of the empirical asset returns distribution. Longin (1996) defined a financial extreme as the minimum daily return (the minima) or the maximum daily return (the maxima) of a stock market index over a given period (the selection interval). He examined the distribution of the US extreme daily stock returns and found that it can be described by the Generalised Extreme Value (GEV) distribution; similar findings are reported in the literature for other stock markets and asset classes (e.g. Jansen and De Vries (1991) and Loretan and Phillips (1994)). It has also been argued that EVT methods can be useful in Value-at-Risk (VaR) and capital requirements calculations for security firms (e.g. Longin (2000), Pownall and Koedijk (1999) and Bali (2003)). Gettinby et al. (2006), however, found that the Generalised Logistic (GL) distribution characterized the extreme daily share returns in the US, UK and Japan better than the GEV. Recently, Tolikas (2008) and Tolikas and Gettinby (2009) documented further evidence of the ability of the GL distribution to fit extreme returns adequately; they illustrated that the GL can lead to more accurate VaR estimates compared to those based on the GEV or the normal distribution. Susmel (2001) was one of the first to examine the behaviour of extreme returns in emerging stock markets. He presented evidence that the empirical distribution of returns in Latin American stock markets had significantly fatter tails compared to their developed market counterparts. Indeed, he demonstrated that US investors could benefit by including Latin American equities in their portfolio. More recently, Jondeau and Rockinger (2003) used the GEV distribution to examine the tail behaviour in both emerging and developed stock markets. They found that the left and right tails acted rather similarly but that the behaviour of extreme returns different markedly between emerging and developed stock markets.

For many years international investors' have focused on Latin American and Asian countries, mainly because their stock markets have undertaken a number of steps towards financial liberalisation which made them more attractive to foreign and local investors. Consequently, they grew considerably in terms of size, trading volume and number of companies listed; they became important sources of capital for their local economies. On the other hand, the African stock markets remained small, unsophisticated and consequently insignificant for both the local economy and international investors; with the notable exception of South Africa. This was mainly due to political instability, poor economic conditions and restrictive regulations, especially for foreign investors,

The main aim of this paper is to identify the asymptotic distribution of the extreme stock returns in a group of African stock markets over the period 1996 to 2007. For that reason, a wide set of probability distributions including the Normal, Fréchet, Gumbel, Weibull, GEV and GL is considered. The empirical results provide evidence that both the GEV and GL distributions describe the lower tail of the empirical distribution of returns in the African stock markets better than the normal distribution. Although the fit that the GEV and GL provide to the data is rather comparable, examples are given where the superiority of the GL is illustrated. The remainder of this article is structured as follows. Section 2 briefly introduces the African stock markets under investigation and reviews the available literature, while section 3 describes the data and presents the methodology. Section 4 discusses the empirical results and section 5 outlines the implications of the findings for the practice of finance. Finally, section 6 summarises and concludes.

2. African Stock Markets

Smith et al. (2002) divided the African stock markets into four categories: (i) South Africa which is larger, more developed in terms of regulatory framework and more advanced in terms of technical infrastructure that its counterparts; (ii) medium sized markets which have been established for a long time, (e.g. Egypt, Nigeria and Morocco); (iii) small sized new market which have grown rapidly (e.g. Ghana Mauritius and Botswana); and (iv) small sized markets that are still at an early stage of development (e.g. Swaziland, Zambia and Malawi). However, most of the African stock markets are very small by world standards and of limited local interest.

Therefore the analysis is focused only on the four largest African stock markets in terms of market capitalization; this group comprises Egypt (Alexandria stock exchange, established in 1883 and Cairo stock exchange, established in 1903), Morocco (Casablanca stock exchange, established in 1929), Nigeria (Lagos stock exchange, established in 1960) and South Africa (Johannesburg stock exchange established in 1887). Although, these African stock markets have received limited attention by international investors, they have been established for a long time and have taken some steps towards development over the last decades[3].

Table 1 contains information for the four African stock markets over the period 1996 to 2007. It can be seen that the market capitalisation has significantly increased for all stock markets over the eleven year period. The ratio of market capitalisation to GDP has also risen for all these stock markets. However, with the exception of South Africa, the ratio takes values of less than 1 indicating that the Egyptian, Nigerian and Moroccan stock markets are rather under developed. The low values of the turnover ratio imply that liquidity is an important problem for all of the stock markets under investigation; typically developed markets tend to have turnover ratio values of over 100%. The number of listed companies has slightly increased for the Nigerian and Moroccan stock markets but decreased for the South African and

[3] In South Africa, for example an Insider Trading Law was introduced in 1989 while foreign banks were admitted as members in 1995. In 1996, electronic trading was implemented and in 2001 the Capital Gains Tax was introduced. In Egypt, in 1991, interest rates and foreign exchange controls were abolished, foreign investors were given full access to the stock market and an Insider Trading Law was introduced. In 1997 foreign investors were given the right to repatriate capital and profits generated in Egypt; further restrictions to foreign investors were removed in 1998. In 1997 a major privatization program was announced and in 2000, Morgan Stanley Capital International announced that Egypt is graduated into its emerging markets index and electronic trading was introduced. In Nigeria, an Insider Trading Law was introduced in 1979 while in 1991 capital market reforms and a large privatisation program were enacted. In 1995, the Nigerian government allowed foreign investors to invest in the stock market, in 1999 an automated trading system was put in place and in 2000 the government announced a second large privatisation program. In Morocco, restrictions on the participation of foreign investment in local companies were abolished in 1989, and in 1991 the repatriation of foreign investment profits was permitted. In 1993, an Insider Trading Law was enacted, electronic trading was introduced in 1997 and in 1999 the law concerning the privatization of companies was amended to enhance protection from speculators. In 2002 local banks were given the right to invest in international capital markets.

Egyptian stock markets. An analysis of Table 1 indicates that the returns offered were very high over the period being studied while their correlation with developed markets low implying significant diversification potential for international investors.

Insert Table 1 about here

The behaviour of the African stock markets has been examined in a number of studies. Ayadi (1998) found no evidence of the ‘turn of the year’ calendar anomaly in the Nigerian stock market while Mecagni and Sourial (1999) discovered significant inefficiencies in the Egyptian stock market over the period 1994 to 1997. In a more recent study, Smith and Jefferis (2005) also examined market efficiency in the African stock markets during the period 1990 to 2001 and found that the South African stock market was weak form efficient for the whole period while the Egyptian and Moroccan stock market had become weak form efficient from 1999. By contrast, the Nigerian stock market had only become efficient from early 2001. Similar results were reached by Okeahalam and Jefferis (1999) who discovered that the South African stock market was weak form efficient through the period studied. More recently, Jefferis and Smith (2005) examined whether market efficiency changes over the period 1990 to 2001. They confirmed that the South African stock market is weak form efficient throughout the period examined and they also found that the stock markets in Egypt, Morocco and Nigeria are becoming weak form efficient towards the end of this time period. Smith et al. (2002) examined the random walk hypothesis in the eight largest African stock markets and documented supportive evidence only for the Johannesburg stock exchange. Ghysels and Cherkaoui (2003) examined the Moroccan stock market and found that the high level of transaction costs and lack of transparency don’t support the emergence of the stock market. Recently, Lagoarde-Segot and Lucey (2008) assessed the weak form efficiency hypothesis in the Middle

East and North African (MENA) stock markets, including Egypt and Morocco, and found different levels of efficiency among the countries considered; factors such as market depth and corporate governance could explain the different degrees of efficiencies uncovered.

Although most of the studies involving African stock markets focus on the question of market efficiency there is a part of the literature that examined the behaviour of return and volatility. Roux and Gilbertson (1978) examined the return behaviour in the Johannesburg stock exchange and found significant deviations from normality. They also found that the empirical distribution of returns in the Johannesburg stock exchange is more leptokurtic than its New York stock exchange counterpart which implies greater preponderance of extreme returns in the tails of the empirical distribution. Brooks et al. (1997) found that the Johannesburg stock market volatility behaviour was closer to that of developed markets and concluded that it had become more integrated into the international financial system. Smith and Jefferis (2005) reported that the weekly returns in the South African, Egyptian, Moroccan and Nigerian stock markets significantly deviate from normality and that the tails of the empirical distribution is fatter than the normal distribution; these findings imply significantly higher probabilities for large price movements than implied by the normal distribution. Bekaert and Harvey (1997), Claessens et al. (1995) and Harvey (1995) found that volatility in Nigeria tends to be much higher than developed countries and that it is influenced more by local factors. Overall, it appears that it is the presence of large price movements that leads to the non-normality and high volatility of returns in the African stock markets.

3. Data and Methodology

3.1 Data description

Daily prices (in $US) of the S&P/IFC Global indices[4] for the South African, Egyptian, Nigerian and Moroccan stock markets were collected over the period 1996 to 2007. Daily logarithmic returns were then calculated using the formula:

$$R_{i,t} = \ln(P_{i,t} / P_{i,t-1}) \tag{1}$$

where $R_{i,t}$ is the index return for period t, $P_{i,t}$ is the index price at the end of period t, and $P_{i,t-1}$ is the price of the index at the end of the period t-1. From the time series of the daily log-returns, the series of the weekly, monthly and quarterly minima were obtained as the minimum daily returns over non-overlapping successive selection intervals of 5 days (weekly), 20 days (monthly) and 60 days (quarterly) respectively.

Table 2 contains descriptive statistics for the daily returns and for the minima over the various selection intervals. It is noticeable from Table 2 that although the South African stock market offered the lowest daily mean return it also had the highest standard deviation. On the other hand, the Nigerian stock market had a mean daily return which was over two times the daily mean return of its South African counterpart but with significantly lower volatility. This observation can probably be explained by the values of skewness which imply that the South African stock market experienced more negative returns than the Nigerian stock market. It can also be seen that the Moroccan stock market was considerably less volatile compared to the other stock markets; the rather low values of the minimum and maximum daily return in Morocco probably explains the finding.

Insert Table 2 about here

[4] The S&P/IFCG indices are market capitalisation weighted indices constructed to represent the overall market's performance. Bekaert et al. (1997) argued that from the all main emerging markets data providers, the S&P/IFC should be preferred, mainly because its time series are available for longer periods.

Table 3 reveals that the correlations between the African stock markets daily returns were also very low implying significant diversification opportunities. This is not a surprising finding since emerging markets tend to be affected by local and not global or even regional factors (Fifield at al. 2002). The lowest minimum daily return occurred in South Africa (-14.09%) while the highest minimum daily return occurred in Morocco (-4.75%). The values of skewness and kurtosis indicate deviations from normality for all stock markets under investigation; the Jarque-Bera normality test confirms this impression. Similar observations emerge for the weekly, monthly and quarterly minima across all stock markets.

Insert Table 3 about here

3.2 Methodology

If we denote the time series of an index of daily log-returns by the variable $Y_1, Y_2, ..., Y_n$ and set the length of the selection interval to m, we can divide the series into non-overlapping time intervals of length m. The time series of the extreme minima will then be $X_1 = \min(Y_1,\ldots,Y_m)$, $X_2 = \min(Y_{m+1},\ldots,Y_{2m}),\ldots$, $X_{n/m} = \min(Y_{n-m},\ldots,Y_n)$. According to the *extreme value theorem* (Fisher and Tippet, 1928), the limiting distribution of the extremes, which are assumed to be *iid* after being normalised and centered, ought to be the GEV. The GEV is a three parameter distribution whose probability density function (pdf) is given in equation[5] [2].

$$f(x) = \alpha^{-1} e^{-(1-\kappa)y} e^{-e^{-y}}, \text{ where } y = \begin{cases} -\kappa^{-1} \log\left\{1-\kappa(x-\beta)/\alpha\right\}, \kappa \neq 0 \\ (x-\beta)/\alpha, \qquad \kappa = 0 \end{cases} \quad (2)$$

[5] Details about its cumulative distribution function (cdf), quantile function and parameter estimates can be found in the Appendix.

the parameters α, β and κ are measures of scale, location and shape, respectively. The first parameter is analogous to the standard deviation, the second is analogous to the mean and while the third governs the shape of the tail of the distribution; it is probably the most important parameter since larger values correspond to fatter tailed distributions. The Weibull distribution is the special case of the reversed GEV when $\kappa > 0$ and the range of x is $-\infty < x \leq \beta + \alpha/\kappa$. The Gumbel distribution is obtained for $\kappa = 0$ and the range of x is $-\infty < x < \infty$, while when $\kappa < 0$ the Fréchet distribution is obtained and the range of x is $\beta + \alpha/\kappa \leq x < \infty$.

There is, however, strong evidence that when financial returns exhibit heteroscedasticity and serial correlation another distribution can sometimes describe empirical data better than the GEV-the GL distribution (see, for example, Tolikas (2008)). Therefore, the *iid* assumption was relaxed and the GL distribution included in the analysis. The pdf of the GL is given by:

$$f(x) = \alpha^{-1} e^{-(1-\kappa)y} / (1 + e^{-y})^2, \text{ where } y = \begin{cases} -\kappa^{-1} \log\{1 - \kappa(x - \beta)/\alpha\}, \kappa \neq 0 \\ \\ (x - \beta)/\alpha, \qquad\qquad\qquad \kappa = 0 \end{cases} \tag{3}$$

the logistic distribution is the special case of the GL when $\kappa = 0$ and x is in the range $-\infty < x < \infty$, while when $\kappa > 0$, x belongs to $-\infty < x \leq \beta + \alpha/\kappa$ and when $\kappa < 0$, x belongs to $\beta + \alpha/\kappa \leq x < \infty$.

L-moment ratio diagrams can be used to identify the best candidate distribution for the data. L-moments are linear combinations of ordered data which provide a set of summary statistics for probability distributions[6]. Hosking (1990) defined the r^{th} L-moment, λ_r, for any random variable X which has a finite mean as:

[6] The most important feature of the L-moments is that they are more robust to the presence of outliers than conventional moments. This is because the calculations of conventional moments involve powers

$$\lambda_r \equiv r^{-1}\sum_{\kappa=0}^{r-1}(-1)^{\kappa}\binom{r-1}{\kappa}\mathrm{E}X_{(r-\kappa:r)}, \qquad r = 1,2,\cdots \tag{4}$$

where $EX_{(r-\kappa:r)}$ is the expectation of the $(r-\kappa)^{th}$ extreme order statistic. The first two such statistics, λ_1 and λ_2, are measures of location and scale and the two L-moment ratios, $\tau_3 = \lambda_3/\lambda_2$ and $\tau_4 = \lambda_4/\lambda_2$ are measures of skewness and kurtosis respectively. An L-moment diagram contains the curves or points of the theoretical distributions whose ability to fit adequately the empirical data is examined. The identification of the best candidate distributions is achieved by plotting the estimated τ_3 and τ_4 and choosing the distribution whose L-skewness and L-kurtosis theoretical curve is closest to the plotted point.

From the estimation methods available, the Probability Weighted Moments (PWM) method has been found to provide less biased parameter and quantile estimates with lower root mean square errors (Hosking et al., 1985; Landwehr et al., 1979; Hosking and Wallis, 1987; Singh and Ahmad, 2004). PWM involves estimating parameters by equating sample moments to those of the chosen distribution. Hosking et al. (1985) suggested the use of the PWM $M_{1,r,0}$ in order to summarise a distribution[7]:

$$M_{1,r,0} = \beta_r = E\left[X\{F(X)\}^r\right], \qquad r = 0,1,\cdots \tag{5}$$

where $E[X(\cdot)]$ is the expectation of the quantile function of X and r is an integer number.

Once the parameters have been estimated it is important to assess the goodness of fit to the data. Anderson and Darling (1954) defined a goodness of fit test by:

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which give greater weight to outliers that can lead to considerable bias and variance in the parameter estimates.

[7] This is because the implied relationship between parameters, quantiles and moments is linear since only the first power of X appears in the expression of $M_{1,r,0}$.

$$A_n^2 = -n - (1/n)\sum_{i=1}^{n}\left[(2i-1)\log z_i + (2n+1-2i)\log(1-z_i)\right] \qquad (6)$$

where, $z_i = F(x_i)$, $i = 1, \cdots, n$ is the empirical distribution function of a variable X of size n. Stephens (1976) and Choulakian and Stephens (2001) have reported that the AD test is the most powerful among a wide set of available tests for small samples.

4. Empirical analysis and results

The values of the L-skewness (τ_3) and L-kurtosis (τ_4) were estimated for the series of the weekly, monthly and quarterly minima for the South African, Egyptian, Nigerian and Moroccan stock markets and were plotted on an L-moment ratio diagram. Figure 1 shows the relationship between sample estimates of the τ_3 and τ_4 calculated from the weekly, monthly and quarterly[8] minima of all African stock markets under investigation. Figure 1 reveals that the plotted points mainly congregate in the region between the theoretical curves of the GEV and GL distributions; it can also been seen that any other distribution (e.g. Generalised Pareto and Normal) can be eliminated from further consideration since their curves or points are far from the plotted values.

Insert Figure 1 about here

The GEV and GL distributions were then fitted to the weekly, monthly and quarterly minima by PWM. The parameter estimates and the *p*-values of the AD goodness of fit test were estimated and are reported in Table 4.

Insert Table 4 about here

[8] The examination of the L- moment ratio diagrams for the monthly and quarterly minima led to similar inferences. However, in the interest of brevity, these diagrams are not included in the paper.

An analysis of Table 4 reveals that the location parameter increases[9] for both the GEV and GL distributions, in absolute terms, as extremes are collected over longer intervals. For example, when the GL distribution is fitted to the weekly and quarterly minima of daily returns for the South African, Egyptian, Nigerian and Moroccan stock markets, the location parameter increases, in absolute terms, from -0.013 to -0.035, from -0.010 to -0.033, from -0.007 to -0.025 and from -0.006 to -0.020, respectively. This finding is expected as extremes selected over longer periods are automatically larger. The results also suggest that the location parameter values seem to be larger for the South African and the Egyptian stock markets than for their Nigerian and the Moroccan counterparts; for example, in the case of monthly minima, the location parameter of the GL distribution takes the value of -0.024 and -0.022 for the South African and Egyptian stock markets respectively, and -0.016 and -0.013 for the Nigerian and Moroccan stock markets respectively. This implies that extremes tend to be of a larger size in the former rather than in the latter stock market groupings. The scale parameter is related to the volatility (spread) of the distribution. Unsurprisingly, the scale parameter values for the South African and Egyptian stock markets appear to be larger than the scale parameter values for the Nigerian and Moroccan markets, irrespective of the selection interval. For example, in the case of monthly minima, the scale parameter of the GEV distribution takes the value of 0.010 and 0.011 for the South African and Egyptian stock markets respectively, and 0.007 and 0.005 for the Nigerian and Moroccan stock markets respectively. This implies that the extremes of the daily returns in the former two stock markets may be more volatile than the extremes in the latter two stock markets. A visual inspection of Table 4 indicates that in all stock markets the scale parameter tends to grow as the length of

[9] The GEV distribution is fitted to the reverse minima because although it is not symmetric around its location, results that hold for a random variable X_n generated by the GEV can be extended for the reverse variable $-X_n$. This affects both the location and shape parameters sign.

the selection interval increases, suggesting that over longer periods the chance of observing an extreme price movement rises.

It is the shape parameter whose value is dominant in determining the tail behaviour of the extremes, with absolute larger values indicating a fatter tail. An examination of the shape parameter values for the GEV and GL distributions for all stock markets reveals a number of interesting findings. First the shape value for the South African stock market tends to increase, in absolute terms, as extremes are collected over intervals of increasing length. For example, the shape parameter value for the GEV distribution takes the value of -0.149 for the weekly extremes and -0.294 for the quarterly extremes. This finding implies that the distribution of extremes becomes fatter tailed as extremes are collected over longer time periods. Although the probabilities of extremes occurring depend on the three parameters of the assumed distribution, this finding implies that the probability of an extreme daily return occurring would tend to be higher over a quarterly interval than in a week. However, in the case of the Egyptian stock market it appears that the shape parameter value tends to decrease, in absolute terms, as the length of the selection interval increases, which indicates that the distribution of extremes becomes less fat tailed. The latter result implies that the probability of extremes occurring is lower in quarterly than in weekly time horizons. However, it should also been said that the values of the location parameter indicate that the extremes occurring in a quarter would tend to be much larger compared to the extremes occurring in a week. For the Nigerian and Moroccan stock markets, however, the shape parameter for both the GEV and GL distributions increases as we go from weekly to monthly minima and then to decrease as we go from monthly to quarterly minima.

A comparison of the estimated parameters of the fitted GEV and GL distributions reveals that the shape parameter values tended to be rather unstable while the scale parameter values were more predictable. However, there is less variation among the parameters for the GL distribution. An examination of Table 4 reveals that the GEV provides an adequate fit in the case of the South African stock market for all selection intervals, in the case of the Egyptian stock market for all but weekly extremes and in the cases of the Nigerian and Moroccan stock markets only for the monthly minima. For example, the *p*-value of the AD goodness of fit test takes values from 0.157 to 0.503 for the South African stock market minima, from 0.000 to 0.456 for the Egyptian stock market minima, from 0.001 to 0.071 for the Nigerian stock market minima, and from 0.001 to 0.174 for the Moroccan stock market minima. The GL distribution, on the other hand, provides an adequate fit in the case of the South African stock market for all selection intervals, in the case of the Egyptian stock market for all but the weekly extremes, in the case of the Nigerian stock market only for the monthly extremes and in the case of the Moroccan stock market for all but the quarterly extremes. For example, the *p*-value of the AD goodness of fit test takes values from 0.160 to 0.484 for the South African stock market minima, from 0.001 to 0.395 for the Egyptian stock market minima, from 0.024 to 0.083 for the Nigerian stock market minima, and from 0.099 to 0.233 for the Moroccan stock market minima.

Overall, although the GEV cannot be ruled out, it is the GL that provides a better fit in most of the cases[10]. This finding is similar to the results of Gettinby et al. (2006) and Tolikas (2008) for developed markets. In addition, the size and behaviour

[10] The dynamics of the extremes behaviour was also investigated by splitting the data into sub-periods and by using moving windows. The empirical results do not appear to follow a particular pattern over time. It seems that the underlying distribution of the extreme daily returns is independent of the stochastic process that drives the daily returns.

of the estimated parameters for both the GEV and GL appear to be in line with the findings of other researcher for both developed (e.g. Longin, 1996; Gettinby, 2006; Tolikas; 2008) and developing markets (Jondeau and Rockinger, 2003; Pownall and Koedijk, 1999). Figures 2 and 3 show the lower tail of the daily returns of the South African, Egyptian, Nigerian and Moroccan stock markets from 1996 to 2007; the cumulative density function (CDF) of the GL, GEV and the normal were also plotted. It can be clearly seen that in all four African stock markets under investigation, only the GL is as heavy tailed as the data, whereas the GEV lies below the data and the Normal is even further below the actual observations.

Insert Figure 2 about here

Insert Figure 2 about here

5. Implications for Financial Risk Management

The EVT methods and the empirical results of this paper can potentially have important implications for financial risk assessment. In order to illustrate the importance of accurate modelling of the lower tail of the returns' distribution the following exercise was conducted. The probabilities of obtaining a daily return within the intervals [μ-1σ, μ-2σ], [μ-2σ, μ-3σ], [μ-3σ, μ-4σ], [μ-4σ, μ-5σ] and [μ-5σ, μ-6σ], where μ and σ are the mean and standard deviation of the daily returns over the period examined, were estimated according to the normal, GEV and GL distributions. This analysis could be of particular interest to international investors who are interested in diversifying their portfolios by investing in African stock markets and are concerned with the probabilities of suffering a big loss on a single day.

Insert Table 5 about here

The results, contained in Table 5, indicate that the assumption that returns follow a normal distribution can lead to substantial underestimation of the extreme risk involved in the four African stock markets under examination. For example, in all stock markets the large negative returns located between the intervals [μ-4σ, μ-5σ] and [μ-5σ, μ-6σ] have almost zero probability to occur. However, the empirical probability (frequency) indicates that daily returns of this size do occur 0.46%, 0.23%, 0.32% and 0.39% of the times for South Africa, Egypt, Nigeria and Morocco respectively. These extremes can have potentially catastrophic results if we consider that they would tend to be of large size. The results of this table indicate that the normal distribution overestimates the risk for the returns lying in the intervals [μ-1σ, μ-2σ] and [μ-2σ, μ-3σ]. From Table 5, it seems that both the GEV and GL distributions assign much higher probabilities than the normal distribution to the really ruinous extreme returns in all stock markets. For example, in the case of the South African stock market, the percentage empirical frequency of obtaining a daily return within the interval [μ-4σ, μ-5σ] was 0.23%. The GEV assigns a probability of 0.06% but a much more accurate probability was given by the GL (0.16%). Similar results emerge for the Egyptian, Nigerian and Moroccan stock markets. Indeed, it is noticeable that the GL distribution seems to be more accurate than the GEV, and sometimes the normal, even as we move towards the central part of the distribution. It becomes clear, therefore, that the choice of an appropriate distribution for the extremes can have important implications for risk assessments.

6. Summary and Conclusion

In this paper the empirical distribution of the extreme daily share returns in the South African, Egyptian, Nigerian and Moroccan stock markets over the period 1996 to 2007 was investigated. It was found that the popular GEV distribution is not the best model for the extreme minima in all but the Egyptian stock market. Instead, a fatter tailed distribution, the GL, provided a better fit to the empirical data. Although the GEV is a better fit model than the normal for the lower tail of the South African, Egyptian, Nigerian and Moroccan returns, it seems that it may still underestimate extreme risk.

The main implication of this finding is that the GEV and normal distributions would tend to underestimate the probabilities of large price movements. This can be of interest to both local and international investors who are concerned with the likelihood of losing a big part of the value of their portfolios in a short time period. It can also have implications for international and local financial regulators who require that investment banks in African stock markets keep aside enough capital to cover any losses that might arise in the market place. The determination of these capital requirements is based on inputs provided by models (i.e. Value-at-Risk) which are based on distributional assumptions. Assuming, therefore, a normal (or even a GEV) distribution could lead to underestimation of adequate capital requirements, thus exposing the financial institution to extreme risk that could endanger financial stability.

Appendix

The GEV and GL are three parameter distributions which have the following CDFs, quantile functions ($X(F)$) and parameter estimates. The parameters α and β are called scale and location respectively while the parameter κ is called the shape parameter and it determines the type of the distribution.

Generalised Extreme Value (GEV)	**Generalised Logistic (GL)**
Cumulative Distribution Function (CDF)	
$F(x) = e^{-e^{-y}}$, where $y = \begin{cases} -\kappa^{-1}\log\{1-\kappa(x-\beta)/\alpha\}, & \kappa \neq 0 \\ (x-\beta)/\alpha, & \kappa = 0 \end{cases}$	$F(x) = 1/(1+e^{-y})$, where $y = \begin{cases} -\kappa^{-1}\log\{1-\kappa(x-\beta)/\alpha\}, & \kappa \neq 0 \\ (x-\beta)/\alpha, & \kappa = 0 \end{cases}$
Quantile function	
$X(F) = \begin{cases} \beta + \alpha\{1-(-\log F)^{\kappa}\}/\kappa, & \kappa \neq 0 \\ \beta - \alpha\log(-\log F), & \kappa = 0 \end{cases}$	$X(F) = \begin{cases} \beta + \alpha[1-\{(1-F)/F\}^{\kappa}]/\kappa, & \kappa \neq 0 \\ \beta - \alpha\log\{(1-F)/F\}, & \kappa = 0 \end{cases}$
Parameter estimates	
$\kappa = 7.8590c + 2.9554c^2$ where $c = \frac{(2\beta_1 - \beta_0)}{(3\beta_2 - \beta_0)} - \frac{\ln 2}{\ln 3}$	$\kappa = -\tau_3$
$\alpha = \frac{\lambda_2 \kappa}{(1-2^{-\kappa})\Gamma(1+\kappa)}$	$\alpha = \frac{\lambda_2}{\Gamma(1-\kappa)\Gamma(1+\kappa)}$
$\beta = \lambda_1 - \frac{\alpha}{\kappa}\{1-\Gamma(1+\kappa)\}$	$\beta = \lambda_1 - \frac{\alpha}{\kappa}\{1-\Gamma(1-\kappa)\Gamma(1+\kappa)\}$

Table 1

Summary information for the South African, Egyptian, Nigerian and Moroccan stock markets from 1996 to 2006

	1996	1997	1998	1999	2000	2001	2002	2003	2004	2005	2006
Market capitalisation ($US ml)											
South Africa	241,571	232,069	170,252	262,478	204,952	139,750	184,622	267,745	455,536	565,408	715,025
Egypt	14,173	20,830	24,381	32,838	28,741	24,335	26,094	27,073	38,516	79,672	93,477
Nigeria	3,560	3,646	2,887	2,940	4,237	5,404	5,740	9,494	14,464	19,356	32,819
Morocco	8,705	12,177	15,676	13,695	10,899	9,087	8,591	13,152	25,064	27,220	49,360
Market capitalisation/GDP (%)											
South Africa	1.69	1.57	1.28	2.02	1.63	1.22	1.67	1.61	2.12	2.36	-
Egypt	0.21	0.28	0.29	0.37	0.29	0.25	0.30	0.33	0.49	0.89	-
Nigeria	0.10	0.09	0.07	0.08	0.10	0.11	0.12	0.16	0.20	0.20	-
Morocco	0.24	0.36	0.44	0.39	0.33	0.27	0.24	0.30	0.50	0.53	-
Turnover ratio % (liquidity)											
South Africa	10.9	18.3	30.4	34.1	33.9	37.4	49.6	44.8	47.4	41.6	49.2
Egypt	22.2	33.5	22.3	31.6	34.7	14.2	10.2	13.7	17.3	42.4	52.4
Nigeria	2.6	3.9	5.2	5.1	7.3	10.2	8.4	11.0	13.7	11.5	13.5
Morocco	5.9	10.2	10.1	17.6	9.2	10.0	6.7	6.5	9.1	16.4	35.0
Number of listed companies											
South Africa	626	642	668	668	616	542	450	426	403	388	401
Egypt	649	654	861	1,033	1,076	1,110	1,148	967	792	744	603
Nigeria	183	182	186	194	195	194	195	200	207	214	202
Morocco	47	49	53	55	53	55	55	53	52	56	65
Annual return (%)											
South Africa	6.9	-6.8	-12.4	57.3	-2.5	25.4	-11.2	12.0	21.9	43.0	37.7
Egypt	41.1	16.3	-25.4	43.9	-37.6	-37.9	3.5	152.2	110.9	127.4	11.5
Nigeria	37.3	-7.9	-11.9	-7.2	54.0	35.2	10.7	65.8	18.5	1.0	37.8
Morocco	33.6	58.1	24.2	-5.2	-19.5	-13.1	-14.9	27.6	13.9	18.8	78.8

This table contains information for the South African, Egyptian, Nigerian and Moroccan stock markets from 1996 to 2007 in terms of market capitalisation ($US ml), ratio of market capitalisation to GDP (%), turnover ratio (%), number of listed companies and annual return.

Table 2

Descriptive statistics for extremes of daily returns and minima over various selection intervals for the period 1996 to 2007 for the South African, Egyptian, Nigerian and Moroccan stock markets

Daily Returns	*N*	*Mean* (%)	*S.D* (%)	*Min* (%)	*Max* (%)	*Skew* (S.E)	*Kurt* (S.E)	*J-B* (p-value)
South Africa	3053	0.03	1.59	-14.09	8.16	-0.620	5.317	878.78
						(3.111)	(2.124)	(0.000)
Egypt	3053	0.06	1.44	-11.11	8.96	-0.137	6.512	1578.31
						(6.617)	(1.920)	(0.000)
Nigeria	3053	0.08	1.13	-10.44	10.28	-0.031	8.277	3543.42
						(13.876)	(1.703)	(0.000)
Morocco	3053	0.06	0.88	-4.75	4.93	-0.021	4.206	185.28
						(16.826)	(2.389)	(0.000)
Selection Interval								
Weekly Minima								
South Africa	611	-1.62	1.52	-14.09	1.35	-2.432	11.011	2236.09
						(1.571)	(1.476)	(0.000)
Egypt	611	-1.37	1.43	-11.11	0.68	-2.228)	8.037	1151.11
						(1.641	(1.728)	(0.000)
Nigeria	611	-0.97	1.07	-10.44	1.12	-2.558	13.035	3230.04
						(1.531)	(1.357)	(0.000)
Morocco	611	-0.80	0.78	-4.75	0.82	-1.889	5.640	540.92
						(1.782)	(2.063)	(0.000)
Monthly Minima								
South Africa	153	-2.88	1.93	-14.09	-0.42	-2.387	8.254	321.31
						(1.585)	(1.705)	(0.000)
Egypt	153	-2.60	1.79	-11.11	0.00	-1.897	5.430	129.43
						(1.778)	(2.102)	(0.000)
Nigeria	153	-1.92	1.39	-10.44	-0.07	-2.455	9.634	434.25
						(1.563)	(1.578)	(0.000)
Morocco	153	-1.49	0.92	-4.75	-0.19	-1.625	2.629	68.23
						(1.921)	(3.021)	(0.000)
Quarterly Minima								
South Africa	51	-4.17	2.38	-14.09	-1.71	-2.054	5.201	46.15
						(1.709)	(2.148)	(0.000)
Egypt	51	-3.72	1.97	-11.11	-1.07	-1.495	3.315	19.20
						(2.003)	(2.691)	(0.000)
Nigeria	51	-2.91	1.78	-10.44	-0.94	-1.847	5.151	38.83
						(1.802)	(2.159)	(0.000)
Morocco	51	-2.20	1.11	-4.75	-0.71	-0.868	-0.300	29.54
						(2.629)	(8.948)	(0.000)

This table shows the descriptive statistics for the daily returns as well as the minima over the different selection intervals: weekly, monthly and quarterly. These are defined as the minimum daily returns over non overlapping periods of equal length; 5, 20 and 60 trading days for the weekly, monthly and quarterly respectively. The number of observations (*N*), the minimum (*Min*), the maximum (*Max*), the mean, the standard deviation (*S.D*) and the coefficients of skewness (*Skew*) and kurtosis (*Kurt*) together with their standard errors (*S.E*) (in brackets) are reported. *J-B* denotes the test statistic for the Jarque-Bera normality test, which has a Chi-squared distribution with two degrees of freedom.

Table 3

Correlation values between African and developed stock markets

Correlation	S&P500	FTSE100	NIKKEI225	South Africa	Egypt	Nigeria	Morocco
South Africa	0.35	0.50	0.57	1			
Egypt	0.09	0.21	0.20	0.09	1		
Nigeria	0.09	0.15	0.11	-0.01	0.02	1	
Morocco	0.32	0.39	0.27	0.07	0.07	0.04	1

This table contains the correlation values between the South African, Egyptian, Nigerian and Moroccan stock markets as well as their correlation with developed stock markets. The correlation values between the African and developed stock markets have been calculated using 60 months of data of the S&P/IFC Global indices from 2001 to 2006, while the correlation between African stock markets have been calculated using daily data from 1996 to 2007. Source: S&P Global Stock Markets Factbook (1996 to 2007).

Table 4

Parameter estimates and goodness of fit tests for the GEV and GL distributions, for the minima of daily returns for the South African, Egyptian, Nigerian and Moroccan stock markets from 1996 to 2007

	GEV distribution					GL distribution				
	Location	*Scale*	*Shape*	*AD*	*p-value*	*Location*	*Scale*	*Shape*	*AD*	*p-value*
South Africa										
1 week (T=5, N=611)	0.009	0.009	-0.149	0.314	0.286	-0.013	0.007	0.269	0.297	0.484
1 month (T=20, N=153)	0.020	0.010	-0.251	0.234	0.503	-0.024	0.008	0.342	0.335	0.376
1 quarter (T=60, N=51)	0.030	0.012	-0.294	0.365	0.157	-0.035	0.009	0.373	0.464	0.160
Egypt										
1 week (T=5, N=611)	0.007	0.008	-0.228	2.229	0.000	-0.010	0.006	0.325	3.131	0.001
1 month (T=20, N=153)	0.018	0.011	-0.163	0.466	0.072	-0.022	0.008	0.279	0.721	0.050
1 quarter (T=60, N=51)	0.028	0.013	-0.087	0.237	0.456	-0.033	0.009	0.227	0.319	0.395
Nigeria										
1 week (T=5, N=611)	0.005	0.006	-0.150	1.408	0.001	-0.007	0.005	0.270	1.068	0.024
1 month (T=20, N=153)	0.013	0.007	-0.255	0.468	0.071	-0.016	0.005	0.345	0.603	0.083
1 quarter (T=60, N=51)	0.021	0.011	-0.172	0.500	0.045	-0.025	0.008	0.286	0.698	0.042
Morocco										
1 week (T=5, N=611)	0.004	0.005	-0.108	1.295	0.001	-0.006	0.004	0.241	0.424	0.233
1 month (T=20, N=153)	0.010	0.005	-0.210	0.366	0.174	-0.013	0.004	0.313	0.569	0.099
1 quarter (T=60, N=51)	0.017	0.008	-0.092	0.617	0.015	-0.020	0.006	0.231	0.856	0.021

This table shows the comparison of parameter estimates and goodness of fit for the GEV and GL distributions fitted by PWM to the extremes of daily minima over various selection intervals over the 11 year period. N is the number of extreme observations, T is the length of the extremes selection interval, *AD* denotes the Anderson Darling statistic and *p*-value denotes the probability of such a fit being obtained in a random sample from a GEV or GL distribution. The GEV distribution is fitted to the reverse minima because although it is not symmetric around its location, results that hold for a random variable X_n generated by the GEV can be extended for the reverse variable $-X_n$. This affects both the location and shape parameters sign.

Table 5

Probability (%) of obtaining a daily return within specific intervals.

Interval (%)	*[μ-1σ, μ-2σ]*	*[μ-2σ, μ-3σ]*	*[μ-3σ, μ-4σ]*	*[μ-4σ, μ-5σ]*	*[μ-5σ, μ-6σ]*
South Africa	[-1.56, -3.16]	[-3.16, -4.75]	[-4.75, -6.35]	[-6.35, -7.94]	[-7.94, -9.53]
Empirical interval	[-1.56, -3.16]	[-3.16, -4.77]	[-4.77, -6.32]	[-6.32, -7.83]	[-7.83, -9.35]
Empirical	9.20	2.00	0.39	0.23	0.13
Normal	13.66	2.13	0.13	0.00	0.00
GL	7.64	1.55	0.42	0.16	0.07
GEV	1.38	0.41	0.14	0.06	0.03
Egypt	[-1.38, -2.82]	[-2.82, -4.25]	[-4.25, -5.69]	[-5.69, -7.13]	[-7.13, -8.56]
Empirical interval	[-1.38, -2.79]	[-2.79, -4.25]	[-4.25, -5.71]	[-5.71, -6.73]	[-6.73, -9.06]
Empirical	6.22	2.00	0.79	0.20	0.03
Normal	13.52	2.23	0.13	0.00	0.00
GL	6.31	1.44	0.45	0.14	0.14
GEV	1.58	0.53	0.20	0.07	0.07
Nigeria	[-1.05, -2.18]	[-2.18, -3.31]	[-3.31, -4.44]	[-4.44, -5.57]	[-5.57, -6.69]
Empirical interval	[-1.05, -2.19]	[-2.19, -3.36]	[-3.36, -4.48]	[-4.48, -6.00]	[-6.00, -6.69]
Empirical	7.34	1.74	0.56	0.29	0.03
Normal	13.51	2.05	0.16	0.00	0.00
GL	6.33	1.24	0.43	0.16	0.03
GEV	1.76	0.47	0.19	0.07	0.01
Morocco	[-0.82, -1.69]	[-1.69, -2.57]	[-2.57, -3.45]	[-3.45, -4.33]	[-4.33, -5.21]
Empirical interval	[-0.82, -1.70]	[-1.70, -2.56]	[-2.56, -3.43]	[-3.43, -4.35]	[-4.35, -4.75]
Empirical	8.97	1.64	0.43	0.26	0.13
Normal	13.59	2.07	0.14	0.00	0.00
GL	7.29	1.38	0.38	0.14	0.03
GEV	1.60	0.41	0.13	0.05	0.01

This table includes the probabilities of obtaining a daily return contained within specific intervals under the corresponding distribution. It also includes the empirical probability (frequency). The bounds of these intervals are defined as numbers of daily standard deviations away from the daily mean. The row named *Empirical interval* contains the best approximation interval (based on the empirical returns) to the theoretical interval. For each period μ denotes the overall daily mean and σ denotes the overall daily standard deviation.

Figure 1

L-moment ratio diagram together with the L-skewness and L-kurtosis plots of the weekly, monthly and quarterly minima of daily log-returns for the South African, Egyptian, Nigerian and Moroccan stock markets from 1996 to 2007

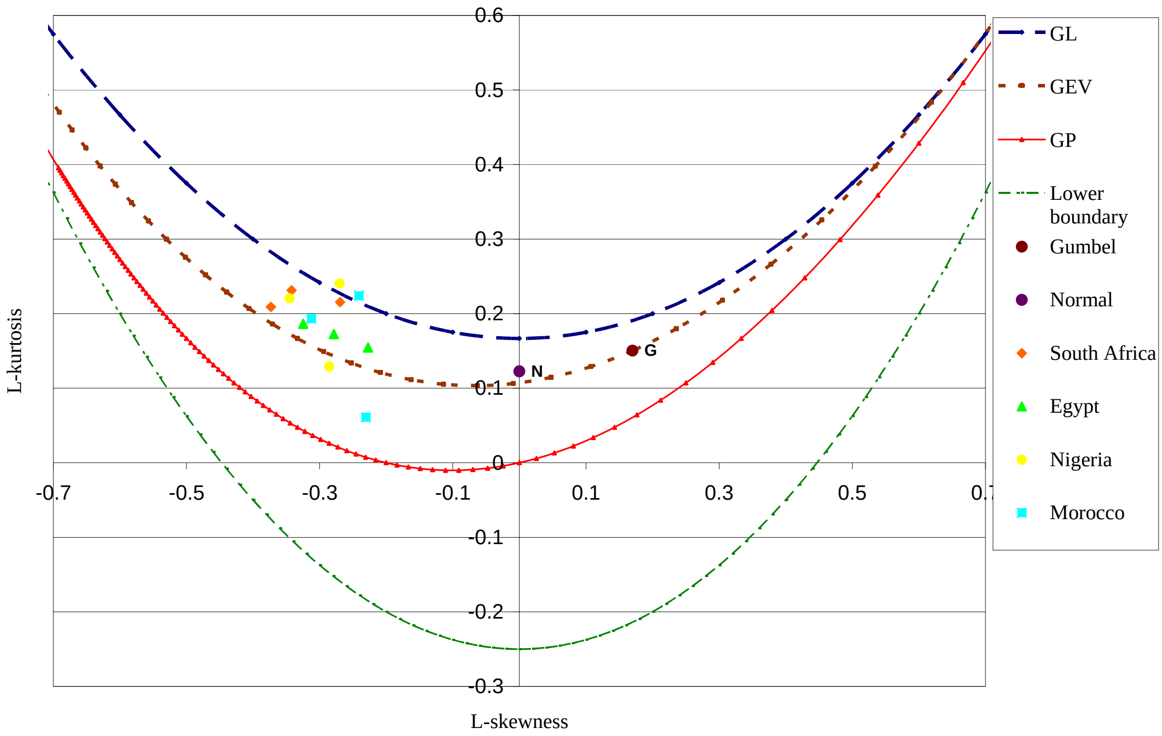
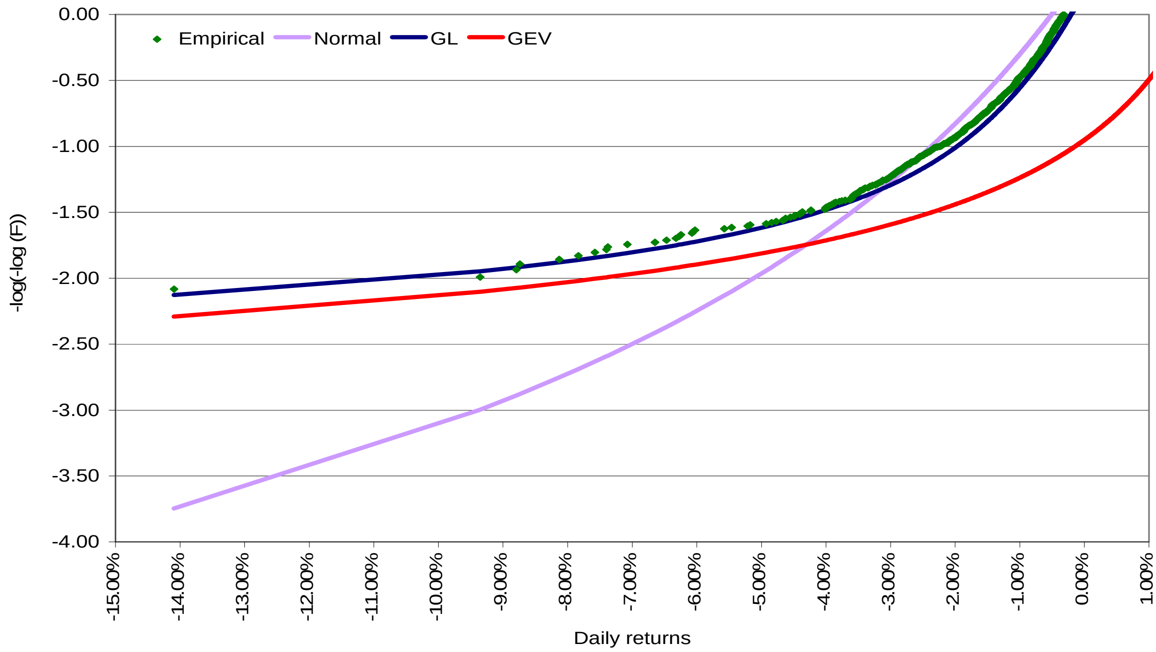


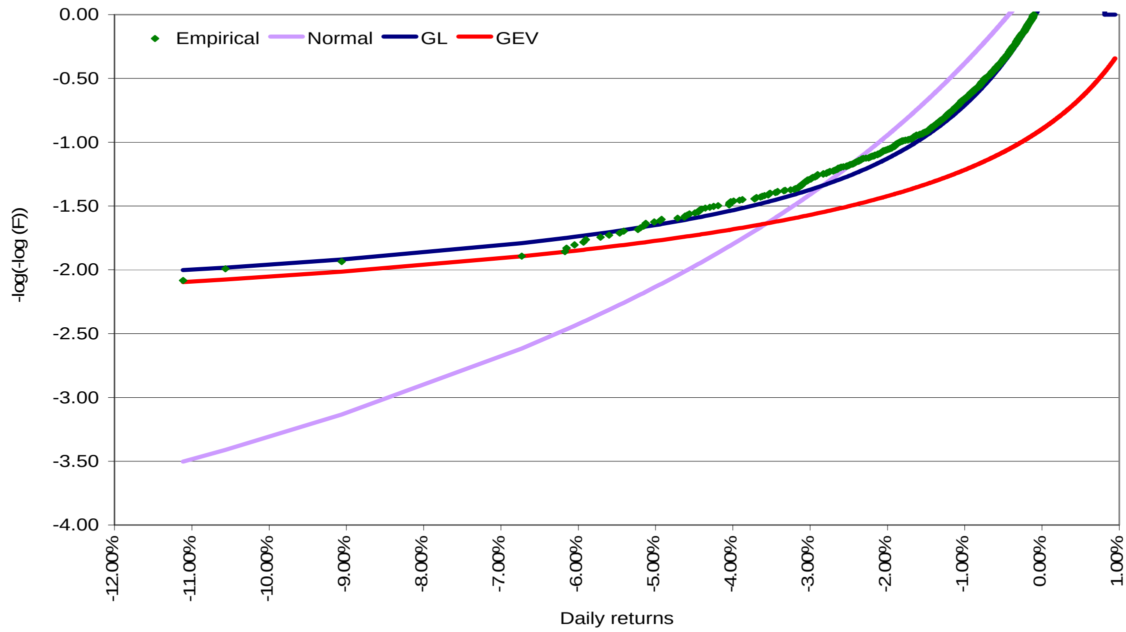
Figure 1 shows the L-skewness and L-kurtosis for the various distributions for weekly minima. The distributions plotted are: GL= Generalised Logistic, GEV= Generalised Extreme Value, GP= Generalised Pareto, Lower boundary= lower bound for all distributions, G= Gumbel and N= Normal.

Figure 2

South Africa: GL vs GEV vs Normal



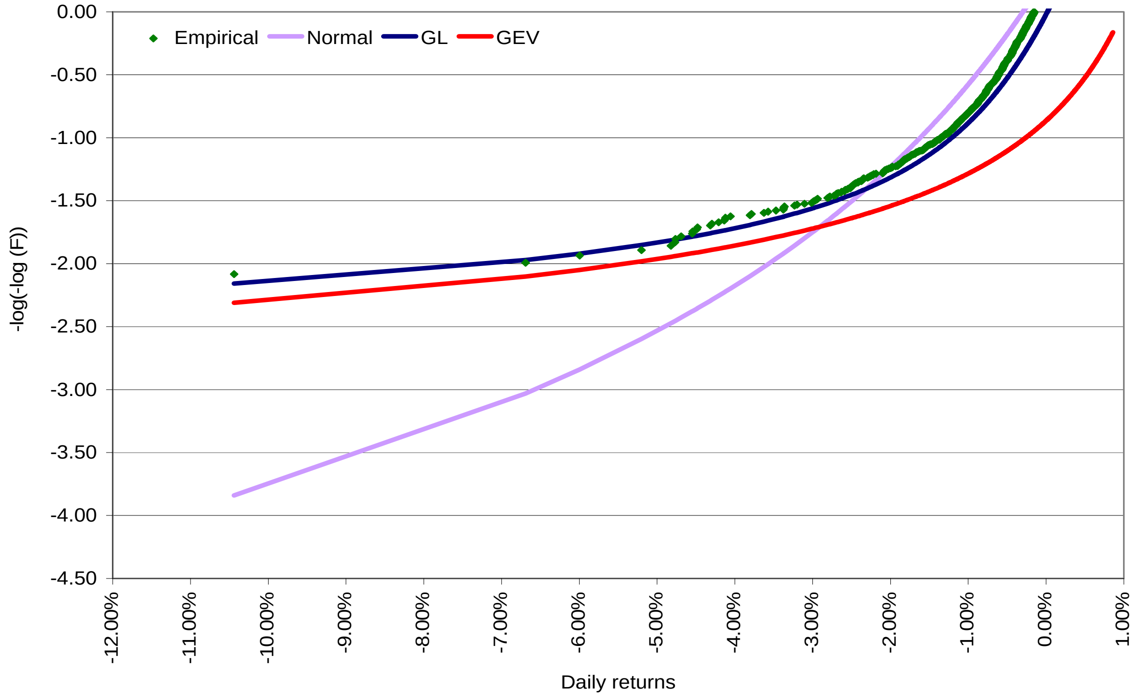
Egypt: GL vs GEV vs Normal



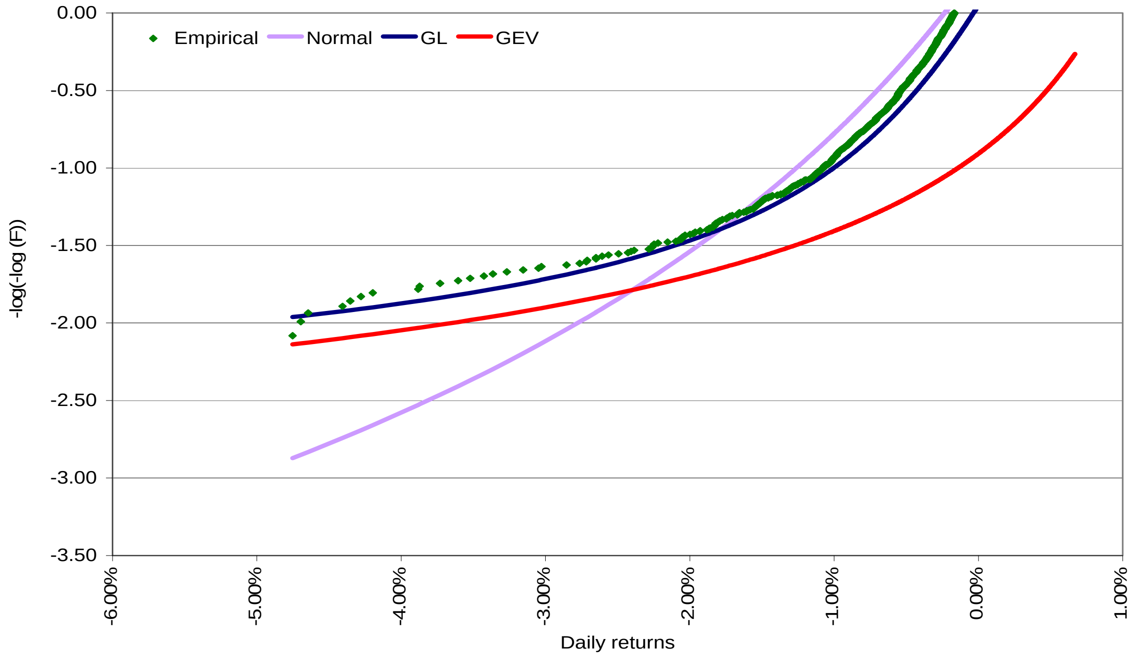
This figure shows the left tail of the daily returns of the South African and Egyptian stock markets from 1996 to 2007. The GL and GEV distributions are plotted using the parameter estimates derived from weekly minima of daily logarithmic returns while the Normal is plotted using the parameter estimates derived using the daily returns.

Figure 3

Nigeria: GL vs GEV vs Normal



Morocco: GL vs GEV vs Normal



This figure shows the left tail of the daily returns of the Nigerian and Moroccan stock markets from 1996 to 2007. The GL and GEV distributions are plotted using the parameter estimates derived from weekly minima of daily logarithmic returns while the Normal is plotted using the parameter estimates derived using the daily returns.

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