Topics in Middle Eastern and African Economies
Vol. 8, September 2006

Extreme Observations in the MENA Stock Markets and Their Implication for VaR measures

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Presented to: MEEA Held with the Allied Social Science Association Annual Meeting
Boston, January 6-8, 2006
Preliminary Version: Please do not quote

Abstract

The standard "delta-normal" Value at Risk methodology requires that the underlying returns generating distribution for the security in question is normally distributed, with moments which can be estimated using historical data and are time-invariant. However, the stylized fact that returns are fat-tailed is likely to lead to under-prediction of both the size of extreme market movements and the frequency with which they occur. In this paper, we use the extreme value theory to analyze four emerging financial markets belonging to the MENA region (Egypt, Jordan, Morocco, and Turkey). We focus on the tails of the unconditional distribution of returns in each market and provide estimates of their *tail index* behavior. In the process, we find that the returns have significantly fatter tails than the normal distribution and therefore introduce the extreme value theory. We then estimate the maximum daily loss by computing the Value-at-Risk (VaR) in each market and explore the implications for portfolio diversification and risk management. Generally, we find that the VaR estimates based on the *tail-index* are higher than those based on a normal distribution for all markets, and therefore a proper risk assessment should not neglect the tail behavior in these markets, since that may lead to an improper evaluation of market risk. Our results should be useful to investors, bankers, and fund managers, whose success depends on the ability to forecast stock price movements in these markets and therefore build their portfolios based on these forecasts.

Keywords: Extreme Value Theory; MENA Stock Markets; Hill Estimator; VaR

JEL classification: C14/ C15/G15

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1. Introduction

The well documented high average stock returns and their low correlations with industrial markets seem to make emerging equity markets an attractive choice for diversifying portfolios. De santis (1993) finds that adding assets from emerging markets to a benchmark portfolio consisting of US assets creates portfolios with a considerable improved reward-to-risk performance. Harvey (1995a) finds that adding equity investments in emerging markets to a portfolio of industrial equity markets significantly shifts the mean-variance efficient frontier to the left. Harvey (1995a, b) and Claessens *et al.* (1995) document that emerging markets returns significantly depart from normality. This departure from normality is greatly influenced by the behavior of extreme returns. These observed extreme returns produce a fatter tail empirical distribution for emerging markets stock returns than for the industrial markets.

Fat tails for stock returns in industrial markets have been extensively studied. Mandelbrot (1963) and Fama (1965) point out that the distribution of stock returns has fat tails relative to the normal distribution. Mandelbrot (1963) proposes a non-normal stable distribution for stock returns, in which case the variance of the distribution does not exist. Blattberg and Gonedes (1974) and, later, Bollerslev (1987), in an ARCH context, propose the Student-t distribution for stock returns, which has the appeal of a finite variance with fat tails. Jansen and de Vries (1991) and Loretan and Phillips (1994) use extreme value theory to analyze stock return in the US. Their results indicates the existence of second moments and possibly third and fourth moments, but not much more than the fourth moment.

In financial markets, extreme price movements may correspond to market correction during ordinary periods, to stock market crashes or to foreign exchange crises during extraordinary periods. Recently, emerging markets have experienced several extreme market events. Examples, include the Mexican devaluation at the end of 1994, the Brady bond crisis at the end of 1995, the Asian series of devaluation during 1997 and the Russian crisis at the end of 1998, among others. The common lesson from these financial disasters is that billions of dollars can be lost because of poor supervision and management of financial risks. The Value-at-Risk was developed in response to these financial disasters. The VaR summarizes the worst loss over a target horizon with a given level of confidence, and summarizes the overall market risk faced by an institution[1]. In the con-

[1] See Dowd (1998) and Jorion (1997) for more details on the VaR methodology.

text of VaR, precise prediction of the probability of an extreme movement and understanding the influence of extreme market events is of great importance for risk managers. Since all risk measurement methodologies used to estimate the Value-at-Risk (VaR) of a portfolio assume that the market behavior is stable, extreme market events demand a special approach from risk managers. Extreme movements are related to the tails of the distribution of the underlying data generating process. One approach that can be used to estimate the VaR focuses on modelling the tail of the distribution based on extreme value theory. The link between the extreme value theory and risk management is that EVT methods fit extreme quantiles better than the conventional approaches for heavy-tailed data. Also, the EVT allows for a separate treatment of the tails of a distribution which allows for asymmetry, considering the fact that most financial return series are asymmetric (see Longin (2000), Danielson and De Vries (1997), Diebold et al. (1999), and McNeil (1998)). Even though extreme value theory has previously found many applications in fields of climatology and hydrology, there have been a number of extreme value studies in the finance literature.. Examples, include (Reiss and Thomas (1997), Leadbetter *et al.* (1993), Embrechts *et al.* (1997) and other financial applications like (Longin (1996), Longin (2000), Longin and Solnik (1998), Danielson and De Vries (1997), Danielson and De Vries (1998), Diebold *et al.* (1999), McNeil (1998) and McNeil and Frey (1998), among other studies. For example, McNeil (1998) study the estimation of the tails of loss severity distribution and the estimation of the quantile risk measures for financial time series using EVT. McNeil and Frey (1998) study the estimation of tail-related risk measures for heteroskedastic financial time series and Embrechts et al. (1997) is a comprehensive source of the extreme value theory to the finance and insurance literature.

Despite the extensive research on the behavior of stock prices in the well-developed financial markets, less is known about it in other markets, specifically in the emerging markets of the Middle East and North African (MENA) region. Research on these markets has focused on the issue of efficiency as well as on their integration with international markets. Butler and Malaikah (1992) examine individual stock returns in both the Kuwaiti and Saudi Arabian markets over the second half of the 1980s and conclude with market inefficiency in both markets. Darrat and Hakim (1997) examine price linkages among three Arab stock markets (Amman, Cairo and Casablanca) and their integration with international markets, and find that theses markets are integrated within the region but not at the international level. Darrat and Pennathur (2002) studied economic and financial integration among the countries in the Arab Maghreb region (Algerian, Morocco, and Tunisia) and found that they share a robust relation bringing their financial and economic policies[2]. Abraham *et al.* (2002) examine the random walk properties of three Gulf stock markets - Kuwait, Saudi Arabia, and Bahrain - after correcting for infrequent trading. They cannot reject the random walk hypothesis for the Saudi and Bahrain markets, however, the Kuwaiti market fails to follow a random walk even after the correction[3]. In general, the MENA region is considered a part of the emerging markets and these markets are typically much smaller, less liquid, and more volatile than well-known world financial markets (Domowitz, Glen, and Madhavan (1998)). There is also more evidence that emerging markets may be less informationally efficient[4], and their industrial organization is often quite different from that in developed economies. Further, the industrial organization found in emerging economies is often quite different from that in developed economies. All of these conditions and others may contribute to a different behavior in emerging stock markets.

The purpose of this work is to use the extreme value theory to analyze four emerging financial markets belonging to the Middle East and North African region (Egypt, Jordan, Morocco, and Turkey). This article extends previous studies by providing a more extensive and systematic study of stock market dynamics in several aspects. First, we provide an extensive analysis of the financial and economic characteristics of these markets. Second, we apply the extreme value theory for each market. Third, we estimate the maximum daily loss in each market by computing the Value-at-Risk. The paper is organized as follows. Section 2 provides an overview of the economic and financial characteristics to the markets. Section 3 presents the data and its properties. Section 4 presents the extreme value theory. Section 5 provides the estimation results with the value-at-risk analysis. Section 6 contains a summary of our findings and concluding remarks.

2. Financial and economic background to the markets

Over the last decade, the empirical finance literature has been concerned with the financial dynamics of the world major stock markets. Recently, there has been a shift in attention to the "emerging markets" of developing countries (Bekaert and Harvey (1997), DeSantis and Imrohoroglu (1997). An emerging market is defined according to the following conditions: 1) has securities that trade in a public

[2] For more studies on the emerging markets in the Mediterranean, see Harvey (1995), Bekaert and Harvey (1995,1997), Errunza (1994) and Choudhry (1996). For an overview of the state of equity markets in some Middle Eastern countries, see El Erian and Kumar (1995).

[3] Two other studies examined the efficiency of the Kuwaiti stock market: Al-Loughani (1995) and Al-Loughani and Moosa (1997).

[4] This could be due to several factors such as poor-quality (low precision) information, high trading costs, and/or less competition due to international investment barriers.

market; 2) is not a developed market (as defined by countries covered within the Morgan Stanley Capital International Indices or Financial Times Indices); 3) is of interest to global institutional investors; and 4) has a reliable source of data. The new focus stems from the fact that these markets present portfolio and fund managers a new possibility to enhance and optimize their portfolios. For example, Bekaert and Harvey (1997) found that stock market returns in emerging markets were high and predictable but lacked strong correlation with major markets. As emerging markets mature, they are likely to become increasingly more important. The MENA (Middle East and North Africa) region is part of these markets and offer those opportunities to investors. The importance of this region is that all MENA equity markets are open to foreign investor participation and also allow repartriation of dividends and capital. Apart from Jordan where foreign investors are restricted to certain sectors but allowed to own 99% of the tourism share capital, the three others markets (Egypt, Morocco, and Turkey) have no restrictions on foreign investors[5]. Despite their openness, these markets remain somewhat unsophisticated and MENA's combined market capitalization remains small – both in comparison to other regions, and in proportion to its overall GDP.

The underdevelopment of the region's stock markets is the result of several factors, not least of which is the fact that MENA still attracts a small proportion of the world's foreign direct investment (FDI). According to figures obtained from the Institute of International Finance, the Middle East and African attracted just US$10bn of foreign direct investment in 2001, compared with US$50.4bn for Latin American and almost US$70bn for Asia. The Middle East and African share represents just 6.7% of total equity investment inflows to emerging markets. A further drain on investor's confidence is the memory of recent stock market crashes that took place at the end of the last decade. For example, investors in Egypt were burned by their own stockmarket crash of 1997-1998, precipitated by the East Asian financial crisis and the subsequent emerging markets financial crisis. Nevertheless, as these countries launch their privatization programs with the government sell-offs, foreign investors will be more encouraged putting their money into MENA countries. The resultant link between privatization and stock market vitality is clear. Egypt is a case in point, where the development of the market has closely tracked the progress of the country's privatization program (faltering when share issues were under-subscribed, and rising strongly when the privatization program picked up pace in 1996).

The comparative underdevelopment of MENA stock markets has focused the

[5] For issues related to market efficiency and organizational structure, look at Claessens *et al.* (1995) and Karemera *et al.* (1999) for Jordan and Turkey; Ghysels & Cherkaoui (2003) for Morocco, and Appiah-Kusi & Menyah (2003) for Egypt and Morocco.

minds of many MENA governments in addressing them and several stock markets are working to upgrade their trading infrastructure and systems. For example, Egypt revitalized its capital market laws and a computer-based screen trading system has been adopted, and the market has one 4-hours trading session which is a continuous order-driven market. A circuit breaker has been implemented since 1997 to dampen the increasing volatility in the market. Between 1996 and 2000, the market went through volatile and sluggish periods, due to speed up of the privatization program. In early 2000, the market peaked recording new highs, but the outstanding performance did not continue and the market sloped downwards to record new lows due to deterioration in monetary indicators and tension in the foreign exchange market. By the end of 2000, exchange-rate volatility plunged the Cairo bourse and in the beginning of 2001, the Central Bank returned to a managed-peg system, with the exchange rate fixed much below the prevailing market level. This, and three subsequent devaluations, led to a rush to buy US dollars, an increase in black-market activities, and fears of a liquidity crunch. The exchange instability forced the central bank to devalue the pound, reaching 7.8% devaluation by December, the biggest drop in 10 years.

In Jordan, the Securities Law, No. 23 introduced in 1997, involved institutional changes in the capital market, use of electronic trading, and elimination of obstacles to investment. During 1999, the Amman Stock Exchange (ASE) was established and considered one of the largest in the region with the government selling stakes in different Industries. However, the positive signs, such as reorganization of more than $800 million in Paris Club debt, and IMF approval of a $220 million loan packaged, failed to boost market activity. By 2000, the ASE began implementing new directives to secure settlement of trades and provide assurance to dealers of timely settlements. By 2001, S&P revised its outlook on Jordan's long-term foreign currency rating to positive from stable and the ASE's performance was the strongest in the Middle East. The reforms in Morocco started earlier, and under law 1-93-211, the Casablanca Stock Exchange (CSE) was privatized. In 1995, a professional association of the market makers was created and a document called Protocole de Place organizes the procedures, payment delivery and compensation for the CSE. As a result, the CSE was included in the IFC Emerging Market data base in 1996 together with stock exchanges from two other countries, Egypt and Russia[6]. By 2000, Morocco concluded a free trade zone agreement with the European Union, and in 2001, Morocco was announced to be included in the MSCI Emerging Markets Index Series. Then the govern-

[6] The IFC attributed a weight of 0.4% to the Morrocan index in the computation of the global emerging market index. This weight exceeds that of Egypt (0.1%) and some of the previously incorporated emerging markets such as Jordan (0.2%).

ment implemented some measures (i.e., individual investors were exempted from the 10% profit tax) to boost stock market activity, but, the Casablanca Exchange General Index had drifted down to five-year lows.

In Turkey, between 1997 and 1998, the government targeted $5 billion in privatization programs in order to balance the budget and implemented a "shock program" to rein in inflation and eased tax legislation by lowering the stock holding period from one year to three months to be exempt from capital gain taxes. In 1999, a banking law was passed and the government measures won the support of the IMF for fighting inflation and financial reforms. However, by 2000, a banking crisis was triggered by anxiety over bank liquidity problems and rumors of takeovers with the lira depreciating to its lowest level. The daily average overnight rate of interest was pushed to more than 1,000%, but then the crisis was contained with an IMF package and new capital markets and banking laws were initiated.. In 2001, weak banks were sold and the central bank let the lira to float. Share prices plunged and the Central Bank warned about the liquidity needs after the September attack. By the end of 2001, rates were lowered to 59% and Turkey agreed to strengthen its banking system and accelerate privatization.

These market developments are reflected in the performance of their stock markets. Table 1 presents some market characteristics for the period 1997-2002. We can see that these countries showed a noticeable growth in market capitalization, the value of traded shares, turnover ratio and the number of listed companies. This growth is associated with the massive privatization plans introduced in the region; the sale of government assets to private firms; and the considerable efforts devoted towards enhancing the efficiency, depth, and liquidity of MENA stock markets. Generally, these markets have gone through different changes in the last few years, and as these countries liberalize their financial markets, the dynamics of asset returns in their equity markets are likely to be affected. This would raise the question of whether their returns or volatility will behave differently from those in developed markets.

3. Data and its properties

We specifically study four emerging markets, namely, Egypt, Jordan and Morocco. While not geographically located in MENA, the study will also include Instabull's stock market of Turkey. The sample data are daily returns of stock market indexes and they cover the sample period from April 1, 1997 to April 26, 2002. The data consists of daily closing index values for the Egyptian Stock Exchange index (CCSI), Jordan, Morocco, and Turkey (ISE National 100). The data was acquired from Morgan Stanley database on emerging markets. We analyze the continuously compounded rate of return, $r_t = log(S_t/S_{t-1})$, where S_t denotes the stock index in day t. Such transformation implements an effective detrending of the series.

Table 2 summarizes the statistical properties of the returns: we show the first four moments, the autocorrelation coefficient at lag one and the Ljung and Box test statistic for autocorrelation in returns and squared returns. All series exhibit a negative mean returns and high variability as indicated by the standard deviation. Egypt is the most volatility market within the MENA region. Considering the autocorrelation of returns, at lag one the Morocco market has the highest coefficient at 0.123 and is significant at the 5% level. In the table, we further observe two stylized facts for return series which has universal validity, as documented in the survey by Pagan (1996). The first stylized fact is nonnormality of the unconditional distribution of returns in the form of leptokurtosis. This phenomena has been termed fat tails. The second stylized fact is that the volatility of returns is time-varying. This dependence is indicated by the significant Ljung-Box $Q(20)$ test statistics showing strong autocorrelation in squared returns. Table 2 focuses also on the extreme observations in our sample. For our purposes, extreme observations are defined as observations, which are outside of two standard deviations. Further, we show the number of single extreme observations, where a single extreme observation is defined as an extreme observation not followed or preceded by another extreme observation in five days. Surprisingly, Turkey shows the highest number of extreme observations, on the plus and minus sides, an indication of the "financial earthquakes" experienced by this market during our sample period. Further, we test the series for stationarity. Table 3 includes the implementation of KPSS tests proposed by Kwiatkowski *et al.* (1992) for the null hypothesis of $I(0)$. We consider two tests, denoted by Const and Trend based on a regression on a constant, and on a constant and time trend, respectively. As the table shows, the null hypothesis is strongly rejected for the level series, while it is accepted for return series at the levels of significance.

Further, we provide some explanatory data analysis to uncover the underlying structures in the markets and analyze the extreme values in the data sets. We provide some probability and quantile plots of the four markets. The theoretical basis that underlies probability plots is a quantile transformation, which implies that for a continuous distribution function F, the random variable $U_i = F(X_i)$, for $i = 1, ..., T$, are *iid* uniform on (0,1). Moreover, defining the ordered sample $X_{T,Tn} \leq ..... \leq X_{1,T}$, $(F(X_{k,T}))_{k=1,...,T} = (U_{k,T})_{k=1,....,T}$. From this it follows that: $EF(X_{k,T}) = \frac{T-k+1}{T+1}$, $k = 1, ..., T$. Also note that $F_T(X_{k,T}) = (T-k+1)/T$, where F_T stands for the empirical distribution function of F. The graph $\{F(X_{k,T}) = \frac{T-k+1}{T+1} : k = 1, ..., T\}$ is called the *probability*

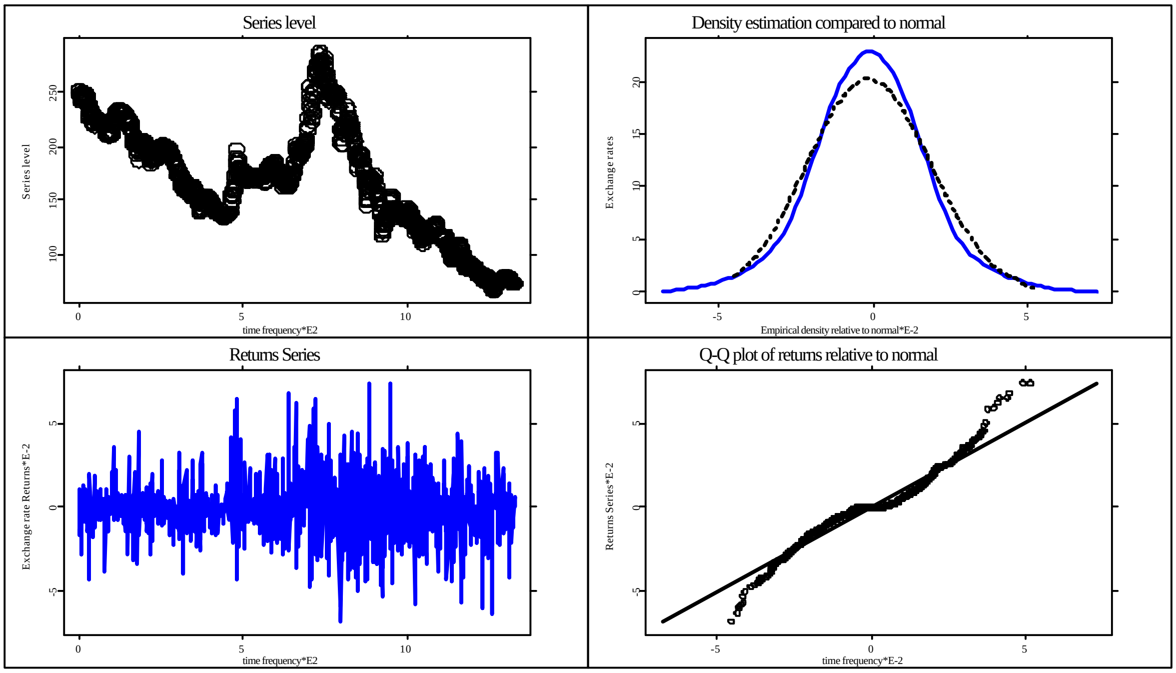

Figure 3.1: Egyptian stock market level, daily returns, and daily empirical and QQ-plot against the normal distribution.

plot, PP Plot. More common however is to plot the graph $\{(X_{k,T}, F^{-1}(\frac{T-k+1}{T+1})) : k = 1, ..., T\}$ typically referred to as the *quantile plot*, QQ-Plot, where F^{-1} denotes the quantile function of the distribution function F. In Figures 3.1 to 3.4 we provide these plots. The distributions exhibit in comparison to a normal distribution function fatter tails and sharper peaks. The leptokurtic behavior is clearly demonstrated in the QQ-plots for all series. The plotted points deviate significantly from the straight line. The extreme points have more variability than points toward the center, and the typical "S" shape of the curve implies that one distribution has longer tails than the other.

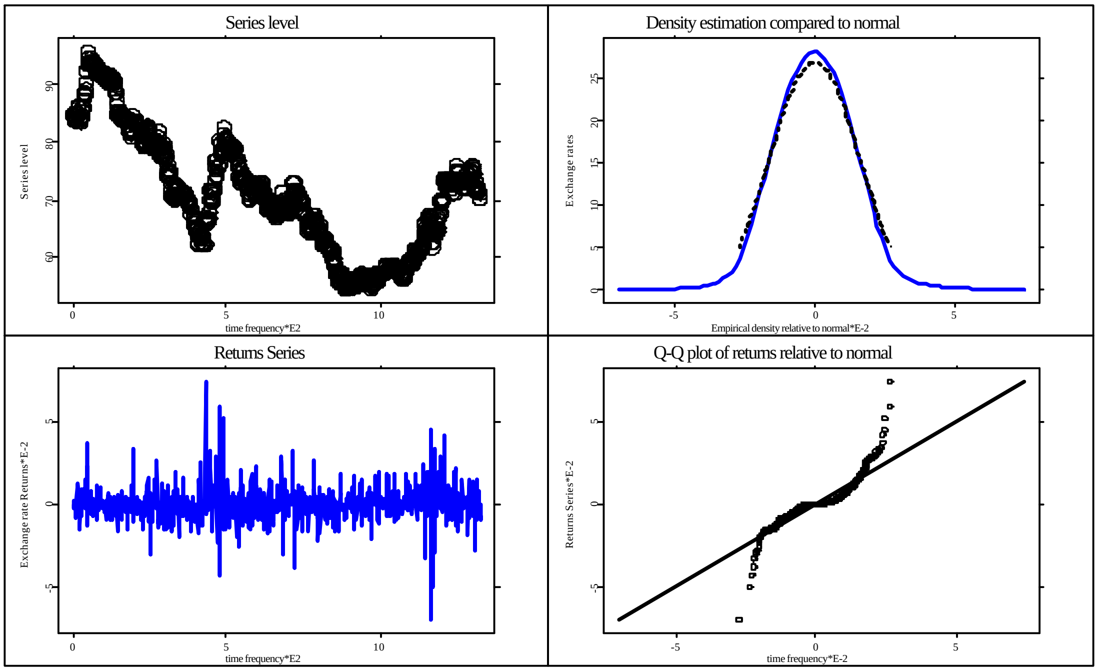

Figure 3.2: Jordanian stock market level, daily returns, and empirical and QQ-plot against the normal distribution.

4. Extreme value theory

There is considerable evidence that large positive and negative daily returns occur more frequently for financial data than one would expect with the normal distribution. This evidence implies that extreme return - the tails of the density function - have higher probabilities than with the normal distribution. When extreme returns have higher probabilities than with the normal distribution, in this case the distribution has fat tails. Fat tails for stock returns in industrial markets have been extensively studied. Mandelbrot (1963) and Fama (1965) point out that the distribution of stock returns has fat tails relative to the normal distribution. Mandelbrot (1963) proposes a non-normal stable distribution for stock returns, in which case the variance of the distribution does not exist. Jansen and de Vries (1991) and Loretan and Phillips (1994) use extreme value theory to analyze stock return in the US. Their results indicate the existence of second

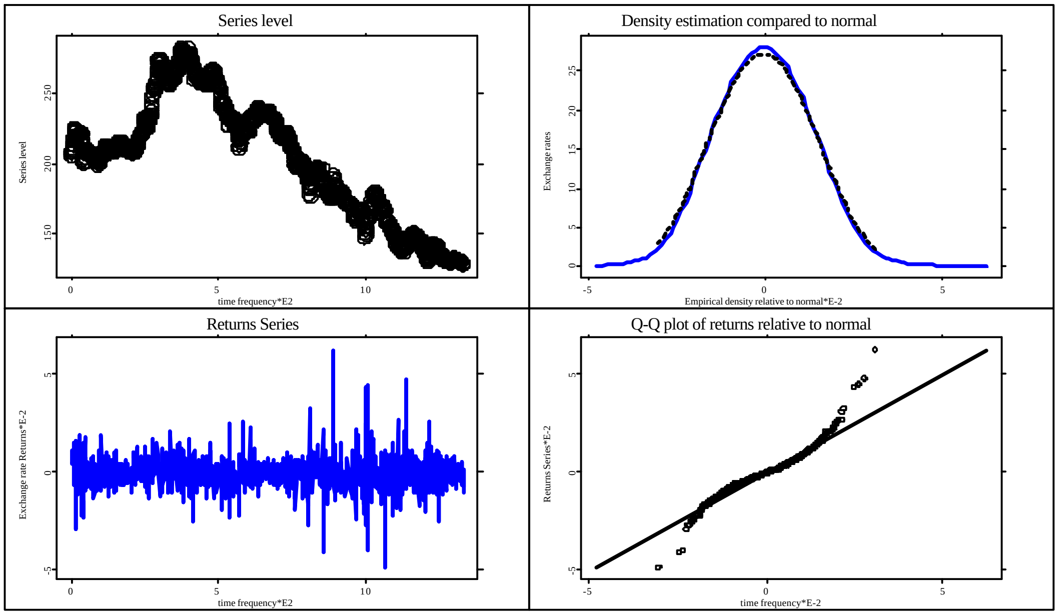

Figure 3.3: Morocco stock market level, daily returns, and daily empirical and QQ-plot against the normal distribution.

moments and possibly third and fourth moments, but not much more than the fourth moment.

4.1. Asymptotic behavior of distribution

Extreme value theory gives some interesting results about the statistical distribution of extreme returns. In particular, the limiting distribution of extreme returns observed over a long time period is largely independent of the distribution of returns itself. Consider a stationary sequence of X_1, X_2, ...X_T of iid random variables with distribution function $F(.)$. We want to find the probability that M_T, the maximum of the first T random variables, is below a certain value x (M_T could be multiplied by -1 if one is interested in the minimum). We denote this probability by $P(M_T < x) = F_T(.)$. The distribution function $F^T(.)$, when suitably normalized and for large T, converges to a limiting distribution $G(x)$, where $G(x)$ is one of three asymptotic disruptions (see Leadbetter et al. (1983)). Leadbetter et al. (1983) and Embrechts et al. (1997) document a family of distri-

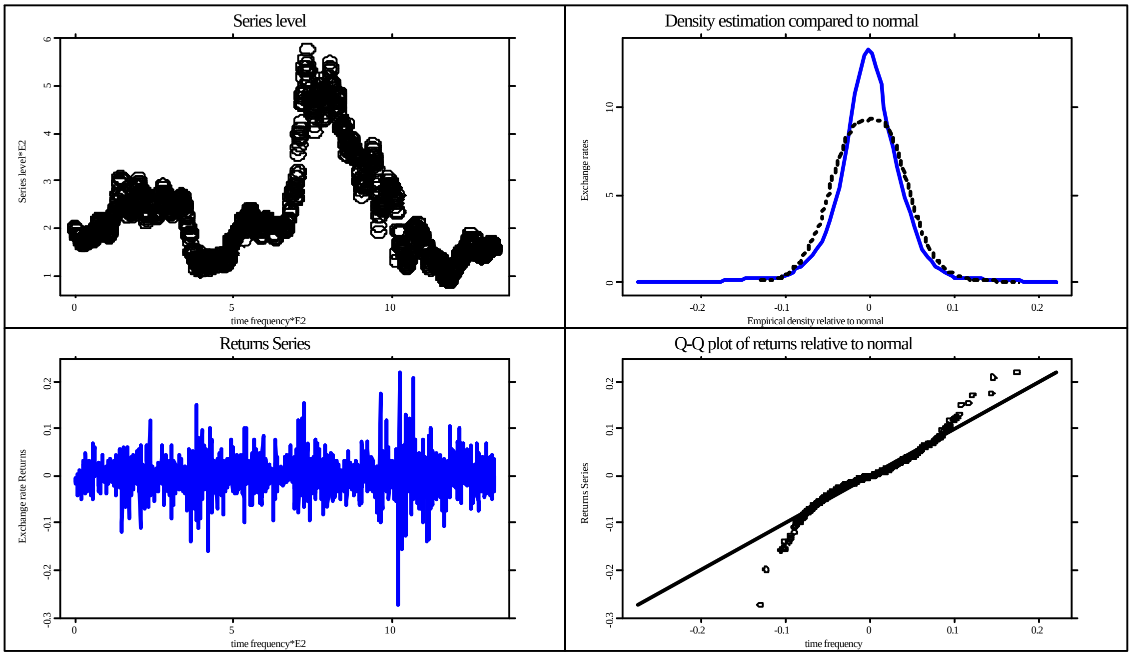

Figure 3.4: Turkish stock market level, daily returns and daily empirical and QQ-plot against the normal distribution.

butions that are separated into three distinguishing types, the assumption is that a sequence of values display asymptotic behavior belonging either to a Gumbell, Frechet or Weibull distribution. In that the fitting of a sequence of price changes is not exact in nature, but rather involves weak converge. For this reason, a non-parametric tail statistic should be applied (Danielson and Vries, 1997), and the Hill index is found to have the optimal estimation properties (Kearns and Pagan, 1997), and is therefore utilized in this study.

The Fisher-Tippett theorem is used to examine asymptotic behavior of the distribution. From this theorem, there are three types of limit laws and these incorporate the extreme value distributions, namely the Gumbell, Frechet and Weibull distributions. The Fisher-Tippet theorem indicates that the maxima at the limit converges in distribution to G after normalizing and centering. Formally this is expressed as:

$$c_T^{-1}(M_T - d_T)d \rightarrow G \text{ for } c_T > 0, -\infty < d_T < \infty \tag{1}$$

where d represents convergence in distribution, c_T is a normalizing constant and d_T is a centering constant that is determined as a particular quantile or related measure. These extreme value distributions can be divided into three separate types depending on the value of their shape parameter, α. The classification of a Weibull distribution ($\alpha < 0$) includes the uniform example where the tail is bounded having a finite right end point and is a short tailed distribution. The second classification of densities include the normal and gamma distributions and these belong to the Gumbell distribution, having a characteristic of tails decaying exponentially. Of primary concern to the analysis of fat-tailed distributions is the Frechet classification, and examples of this type generate are the Cauchy, student-t, ordinary frechet, and the pareto distributions. This important classification of distributions for extreme price movements has tail values that decay by a power function.

Since returns on financial assets are fat tailed (i.e., Longin (2000), Danielson and de Vries (1997), Pagan (1997) among others) Koedijk *et al.* (1990) and others consider the limiting distribution of $G(x)$ which characterized by a lack of some higher moments:

$$G(x) = \begin{cases} 0, \text{ if } x \leq 0 \\ \exp(-x)^{-1/\xi} = \exp(-x)^{-\alpha}, \text{ if } x > 0, \end{cases} \tag{2}$$

Equation (2) is the Jenkinson-Von Mises representation of the generalized extreme value distribution. This representation for the Frechet extreme value distribution focuses on a single parameter γ where $\xi = 1/\alpha > 0$ and α is the tail index. Leadbetter *et al.* (1983) show that when the dependence among the X_i's is not too strong, this limiting distribution is valid. The Student t with finite degrees of freedom, the stable distribution, and the stationary distribution of the ARCH process are in the domain of attraction of the limit law $G(x)$. The tail index α can be estimated and indicates the number of moments that exist.

Theorem 4.1. *Fisher-Tipped: Suppose $(X_1, \ldots.., X_T)$ are iid random variables with distribution function F. If there exist constants $a_T > 0$ and $b_T \in R$ so that*

$$\frac{M_T - b_T}{a_T} \rightarrow Y, T \rightarrow \infty \tag{3}$$

$\mathrm{M}_T = X_{1,T} = \max(X_1, \ldots..X_T)$ and Y is a non-degenerate random variable with distribution function G then G is equal to one of the following types of distributions:

$$I - Gumbel : \Lambda(x) = \exp\{-e^{-x}\},\ x \in R \tag{4}$$

$$II - Frechet : \Phi_\alpha(x) = \begin{cases} 0,\ x \leq 0 \\ \exp\{-x^{-\alpha}\},\ x > 0 \end{cases} \alpha > 0 \tag{5}$$

$$III - Weibull : \Psi_\alpha(x) = \begin{cases} \exp\{-(-x^{-\alpha})\},\ x \leq 0 \\ 1,\ x > 0 \end{cases} \alpha > 0 \tag{6}$$

Collectively, the three classes of distributions are referred to as the extreme value distributions, with Types I, II, and III widely known as the Gumbel, Fréchet and Weibull types, respectively. For the Fréchet type, the extreme value distributions are heavy tailed functions whose tails decay powerlike. In contrast, the Gumbel and the Weibull functions are light tailed[7]. The distribution functions of the Fréchet, Weibull and Gumbel types are called the *generalized extreme value distributions*. In many cases and by taking the reparameterization $\xi = 1/\alpha$ due to von Mises (1936) and Jenkinson (1955), it is inconvenient to work with the three distinct classes of limiting distributions, so it is usual to adopt a parameterization which encompasses all three types in the following format::

$$H_{\xi;\mu,\beta}(x) = \exp\{-(1 + \xi\frac{x-\mu}{\sigma})^{1/\xi}\} \tag{7}$$

where $\xi = 1/\alpha$is the shape parameter and α is the tail index and the distribution defined on $\{x : 1 + \xi\frac{x-\mu}{\sigma} > 0\}$. The type II and III classes of extreme value distributions correspond respectively to the cases $\xi > 0$ and $\xi < 0$ in this parameterization, while the type I class arise in the limit $\xi \to 0$. The parameter ξ referred to as the *shape* parameter, while μ and σ are *location* and *scale* parameters, respectively. The standard case $\mu = 0$. $\sigma = 1$ will be denoted by $H_\xi = H_{\xi;0,1}$.

The estimation of extreme quantiles x_p make the importance of the shape parameter ξ quite evident. Inverting equation(....it is the equation of H function .....) yields

$$x_p = \mu - \frac{\sigma}{\xi}[1 - \{-\log(1-p)\}^{-\xi}], \tag{8}$$

[7] Put in a different way, the tails of the distributions can be classified into three categories: (i) Thin-tailed for which all moments are finite and whose cumulative distribution function declines exponentially in the tails; (ii) Fat-tailed whose cumulative distribution function declines with a power in the tails; and (iii) Thin-tailed distributions with finite tails. The use of only one parameter, the tail index α can distinguish these categories, with $\alpha=\infty$ for distributions of category (i), $\alpha > 0$ for category (ii), and $\alpha < 0$ for category (iii).

where $H(x_p) = 1 - p$. In extreme value terminology, x_p is the return level associated with the return period 1/p, and it is common to extrapolate the above relationship to obtain estimates of return levels considerably beyond the range of the data to which the model has been fitted.

4.2. The Tail Estimation

Due to the semi-parametric specification of being in the maximum domain of attraction of the fat-tailed Frechet distribution, it is appropriate to apply non-parametric measures of our tail estimates. For example, from an analysis of different extremal statistics, Danielsson and de Vries (1997) note that non-parametric measures offer an advantage over their parametric counterparts in that under non-Gaussian conditions one obtains better bias and mean squared error properties. The non-parametric Hill index (1975) determines the tail estimates of the stock index returns. We first obtain the order statistics $X_{(T)}$, $X_{(T-1)}$, ...$X_{(1)}$ from our sample, where $X_{(T)} > X_{(T-1)} >$, ...$> X_{(1)}$. Then, the Hill estimator is given by:

$$\widehat{\xi} = \frac{1}{m} \sum_{i=1}^{i=m} \ln(X_{T-1-i} - X_{T-m}) \tag{10}$$

where m is the number of upper order statistics included, T is the sample size, and $\alpha = 1/\xi$ is the tail index. Whereas the concept of the Hill estimator are straightforward, the choice of m is not. On the one hand, the approximation of the tails by the Pareto distribution improves as one moves further out into the tails. On the other hand, this leads to a reduction in the number of data points available, which drives up the variance. No general solution for this trade-off exits and many competing methods are available. An often heuristical method is the Hill plot. The Hill estimates are plotted for all possible values of m and an optimal m is selected by eye-ball search for a range that is robust with respect to m[8]. The Hill estimator can be applied to either tail of a distribution by calculating order statistics from the opposite tail and multiplying the data by -1. We can also combine the tail observations (by taking absolute values) to estimate a common α. The Hill estimator is proven to be consistent estimator of ξ for fat-tailed distributions in Mason (1982), also Deheuvels et al. (1988) investigates the conditions for the strong consistency of the Hill's estimator. Further, Goldie and Smith (1987) show that $(1/\widehat{\alpha} - 1/\alpha)m^{1/2}$ is asymptotically normal $N(0, \xi^2)$ if m increases suitably as T tends to infinity[9].

[8] See Reiss and Thomas (2001).

[9] Tail estimates using extreme value theory have been estimated for exchange rates by Hols

We apply the extreme value theory the daily MENA equity market returns. The returns are measured in percentages, and the sample size is 1324. Tables 4 and 5 summarize some estimation results of the tail index parameter α via the Hill estimator. We report estimates of the tail index of the returns' distribution for the upper and lower tails. We also report for each estimate the number of order statistics used to estimate the tail index, m. We consider four choices of m . The tables also report the corresponding bootstrap confidence interval based on 100 simulations and for 5% significance level. Comparing the results between Tables 4 and 5, we notice that the results are stable over the range of m. The results also indicate that the right tail and the left tail of the stock return distributions have different moments, implying that the risk and reward in these countries are not equally likely in these countries. The upper tail estimates for Egypt, Jordan and Morocco tend to be fatter (smaller) than the lower tail. However, for Turkey the lower tail tend to be fatter than the upper tail[10]. Therefore, positive returns are more likely in Egypt, Jordan, and Morocco than similar losses in these countries, but negative returns are more likely in the case of Turkey than similar gains.

We also report on the point predictions at the tails by looking at the expected extreme returns. A portfolio manager or a financial institution might be interested, not only in expected return in a given market, but also expected extreme returns. This is possible by estimating a tail percentile through an extreme value distribution model. For example, we obtained 0.9992 percentile values (one day in a five years, since there are approximately 250 trading days in each year) for left and right tails. The significance level is calculated as $\alpha = 1-(5{*}250)^{-1} = 99,92\%$. For a period of 50 years, the significance level can be calculated in the same way and then $\alpha = 99,992\%$[11]. These significance levels are very high and the use of extreme value theory render the calculations of percentiles more applicable. If we take m to be the size of the blocks, then we get $\alpha_{GEV} = 1 - n/\widetilde{t}$, where $\widetilde{t}$ here represents the specified period for which we are finding the expected extreme returns. For example, for $\widetilde{t} = 5$ years, we get the significance level of 98,24%, given the blocks is 22 trading days. The results are reported in Table 6. The estimated highest negative returns are those occurring in Turkey. Comparing Turkey with the other three countries, we find Jordan and Morocco having the lowest expected extreme returns over the specified time period. The results obtained in Table 6,

and de Vries (1991) and Koedijk *et al.* (1990), and for stock returns by Jansen and de Vries (1991) and JKV.

[10] Given that the MENA equity markets have been experiencing substantial deregulation and liberalization during the past ten years, it would be interesting to test for structural stability of the tail index estimates. However, this is not the objective of our paper, but results obtained by Bekaert and Harvey (1995, 1997) might lead us to investigate this issue for the MENA region.

[11] α here is the not the same as the estimated tail index.

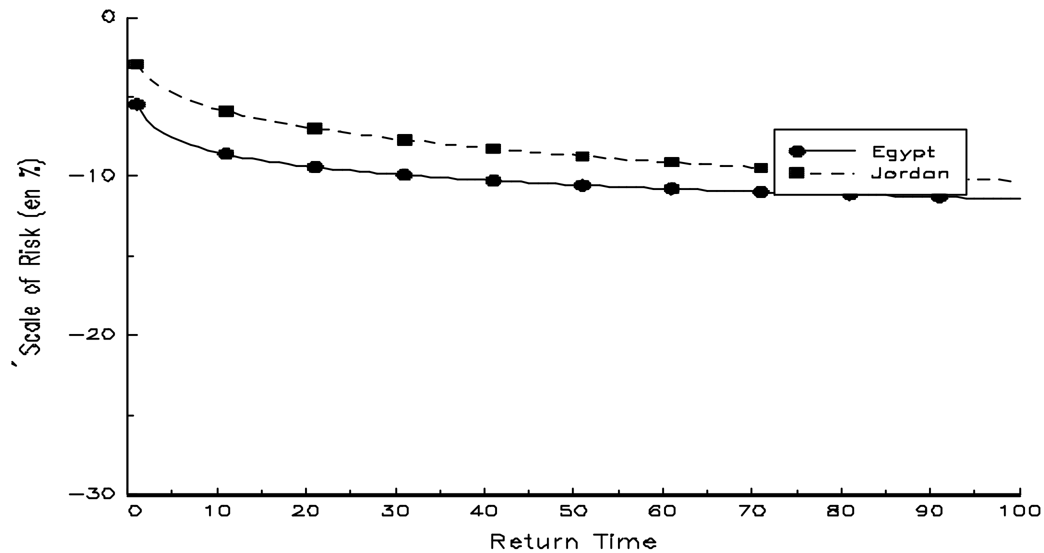

Figure 4.1: Scale of Risk and return time for Egypt and Jordan

when compared to those obtained in Table 2, imply that Turkey dominates other countries in the number of positive and negative returns and also in the number of occurrence of those numbers. Table 2 included the lowest and highest returns for Turkey in our sample, and according to Table 6, a low return of -29.1% will only be expected in 50 years according to the extreme value theory. Remember -29.1% is greater than the -27.1% that we found in Table 2.

We also graph the return time for the specified returns in years only for the long position (left tail) for the four countries (Fig 4.1, 4.2). Turkey shows the fastest return time to very extreme values compared to other MENA equity markets.. Again that explains the results obtained in Table 2.

4.3. Value at Risk (incomplete)

The Value-at-Risk is the maximum potential increase in a value of a portfolio given the specifications of normal market conditions, time horizon and a level of statistical confidence. The VaRs popularity comes from the aggregation of several components of risk into a single number. The methods used for VaR can be grouped under the parametric and nonparametric approaches. Here, we use the extreme value theory which is a parametric approach. Using the extreme value

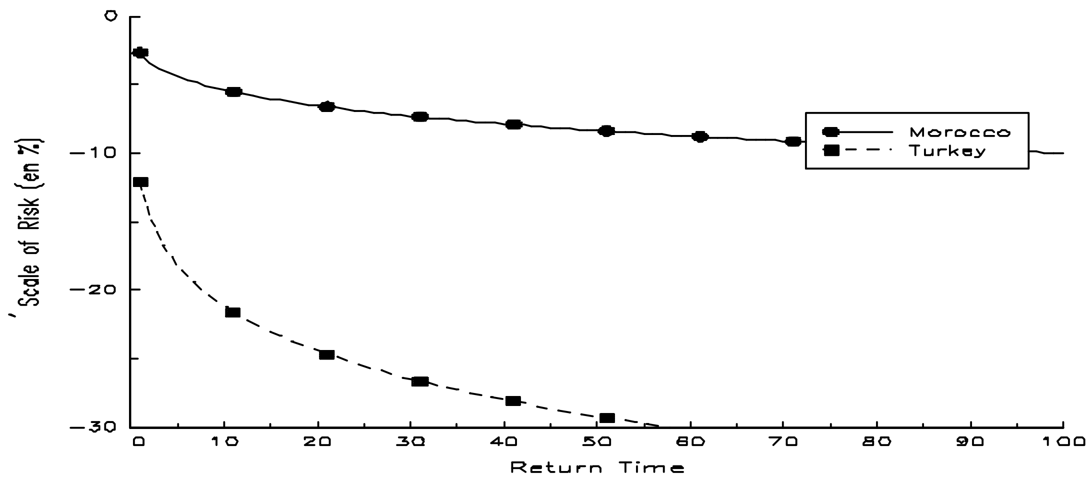

Figure 4.2: Scale of Risk and return time for Morocco and Turkey

theory to estimate Value at Risk can be conveniently thought as a complement to the Central Limit Theory: while the latter deals with fluctuations of cumulative sums, the former deals with fluctuations of sample maxima. In this view, one treats VaR as a measure of loss associated with a rare (or extraordinary) event under normal market conditions. The advantages of the EVT is that it focuses on the tails of the sample distribution when only the tails are important for practical purposes.

The VaR is a quantile of the loss distribution which must be estimated from the data. To define VaR under probabilistic framework, suppose that at the time index t, we are interested in the risk of a financial position for the next l periods. Let V_0 and V_T be the market values of a single speculative asset at the times $t = 0$ and $t = T$. Usually the time horizon is a day or a month.

Losses and profits within the given period T-days will be expressed by the loss (profi/loss) variable

$$L_T = -(V_T - V_0) \tag{11}$$

Notice that losses are measured as positive values. Conversely, there is a profit if L_T is negative.. Under this convention, we may say that a loss is, for example, smaller than the 99% VaR with a probability of 99%. The T-day loss L_T will be expressed by means of $T-$day returns $R_{(T)} = \sum_{t \leq T}(-R_t)$ taken with changed sign. The total market value V_t of an asset at time t can be expressed as $V_t = hS_t$, where h is the number of shares held in the given period, and S_t is the price at time t. It is apparent to define that the price S_T at time T can be regained from the daily returns $r_{1,}......, r_T$ and the initial price S_0 by:

$$S_T = S_0 \exp(\sum_{t \leq T} r_t) \tag{12}$$

Conversely, the T-day log-return $\log S_T - \log S_0$ of the period 0 to T is the sum of the daily log-returns.

From the above equation, where prices are represented by means of the daily log-returns, we conclude that the loss at time T is:

$$L_T = V_0(1 - \exp(-R_{(T)}) \approx V_0 R_{(T)} \tag{13}$$

The Value at Risk parameter VaR (T, q) is the q-quantile of the loss distribution. The VaR at the probability distribution q satisfies the equation: $P\{L_T \leq VaR(T, q)\} = q$,where L_T is the loss variable given above. We also speak of a VaR at the 99% or 95% level, if $q = 0.99$ or $q = 0.95$. Thus, for example, the loss is smaller than the VaR at the 99% level with probability of 99%.

Let F_T denote the density function (df) of the T-day log-return $R_{(T)} = \sum_{t \leq T}(-R_t)$. Thus, $F_T(x) = P\{R_{(T)} \leq x\}$
and applying the equation for L_T we see that the VaR can be written as:

$$VaR(T, q) = V_0(1 - \exp(-F_T^{-1}(q)) \approx V_0 F_T^{-1}(q) \tag{14}$$

where V_0 is the market value at time $t = 0$.

The variance-covariance method is the simplest approach among the various methods used to estimate the VaR. Despite its use, this method has some drawbacks at high quantiles of a fat-tailed empirical distribution. The quantile estimates of the variance-covariance method for the right tail (left tail) are biased downwards (upwards) for high quantiles of a fat-tailed empirical distribution. Therefore, the risk is underestimated with this approach. Another problem with the variance-covariance approach is that is it is not applicable for asymmetric distributions.

A second method that is used for estimating the VaR is the historical simulation. This method estimates the quantiles of an underlying distribution from the realization of the distribution. However, the problem with this approach is that the empirical distribution function is not one-to-one but constant between realizations. That is, we may not have observations corresponding to certain quantiles of the underlying distribution. Second, it is possible, using this method, that the high quantile estimates are not reliable since they are calculated from only a few observations. Furthermore, it is not possible to obtain any quantile estimates above the highest observed quantile.

Due to the problems in both variance-covariance method and that of a historical simulation, we use the extreme value theory to estimate the VaR. After estimating the shape and scale parameters ξ and σ, the EVT can be utilized to obtain the VaR estimate. For a given probability $\alpha > F(u)$, an estimate of the VaR may be calculated by inverting the tail estimate obtained from the EVT, and results in the following estimate:

$$VaR(T,q) = u + \widehat{\sigma}/\widehat{\xi}[(\frac{T}{T_u}q)^{-\widehat{\xi}} - 1] \tag{15}$$

where u is a threshold, $\widehat{\sigma}$ is the estimated scale parameter, $\widehat{\xi}$ is the estimated shape parameter, T is the sample size, T_u is the number of exceedances and $q = 1 - \alpha$. For example, suppose we obtain according to daily stock returns, the threshold is 6%, and estimated parameters are $\widehat{\sigma} = 0.05, \widehat{\xi} = 0.5, T = 1000$ and $T_u = 50$. The VaR at 1% is 0.184, or that means that the stock return will not exceed 18.4% in one day 99 percent of the time[12].

Table 7 provides the VaR estimates in the MENA equity markets based on Gaussian distribution (variance-covariance method), historical simulation and extreme value distribution. Jordan and Morocco show the lowest values of their Value-at-Risk over one day for all significance levels. Egypt comes third in its market risk measures, while Turkey shows again the most at loss at all levels. Comparing the three methods, we observe that the Gaussian and Historical simulation methods underestimates the level of market risk in all markets., and all markets according to the extreme value theory have the highest Value-at-Risk.

5. Conclusion

Methods that are used to measure VaR (i.e., Gaussian and Historical simulation) present to us two problems. First, most VaR use the normal approximation, which underestimates the risk of the high quantiles because of the fail tail phenomenon. And second, VaR methods use all the data of the time series for the estimation. However, because most of the observations are central, the estimated distribution tends to fit central observations, while falling short on fitting extreme observations because of their scarcity.. These extreme observations are found to be of greater interest for investors and risk managers. In this paper, we employ the Extreme

[12] See Embrechts *et al.* (1997) and McNeil (1998).

Value Theory (EVT) to measure the Value-at-Risk (VaR) in the MENA equity markets. The EVT techniques make it possible to concentrate on the behavior of extreme observations in these markets. For all markets, it is shown that returns distributions are fait-tailed, and the return generating process lay in the domain of attraction of a Fréchet distribution. We show that the Hill estimates of the tail indices are of roughly similar magnitude across all markets. We then estimate the market risk in each market by measuring the average time before a given extreme value occurs, and estimating the Value-at-Risk in each market. We find that all markets show some market risk, with Turkey being the most riskier according to our measure of "return time" and the amount at loss. Overall, the VaR estimates based on the *tail-index* are higher than those based on a normal distribution for all markets, and therefore a proper risk assessment should not neglect the tail behavior in these markets, since that may lead to an improper evaluation of market risk. Our results should be useful to investors, bankers, and fund managers, whose success depends on the ability to forecast stock price movements in these markets.

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Table 1: Characteristics of MENA stock markets

	Market capitalization		Number of listed companies		Value Traded	
Year	1997	2002	1997	2002	1997	2002
Egypt	20,875.70	26,338.69	650	1150	6,017.91	6,443.71
Jordan	5,456.15	7,087.03	139	158	501.83	1,334.67
Morocco	12,248.77	8,564.24	49	55	1,067.11	1,440.46
Turkey	61,348	33,773	244	264	58,104	70,756
	Shares traded			Turnover ratio (%)		
	1997	2002		1997	2002	
Egypt	274.76	832.86		28.83	24.46	
Jordan	191.10	455.72		9.20	18.83	
Morocco	9.77	22.44		8.71	16.82	
Turkey	17.00	28.064		94.7	209.50	

Source: Arab Monetary Fund, and Istanbul Stock Exchange. Market capitalization and value traded are in $Million. Shares traded in million shares and the turnover rate is in percentage. Stock market capitalization represents the year-end total market values of listed domestic companies; Number of listed companies represents the year-end totals, excluding listed investment funds where possible; Value traded represents the year-end total value traded of listed domestic company shares; and Turnover ratio is calculated by dividing the value of total shares traded by market capitalization for the year.

Table 2: Summary Statistics of daily returns

	Egypt	Jordan	Morocco	Turkey
Mean	-0.092	-0.013	-0.036	-0.0002
S.D.	1.588	0.854	0.798	0.038
Skewness	0.202	0.663	0.568	-0.074
Kurtosis	5.864	17.029	10.537	8.465
J.B.	461.06 (0.000)	10938 (0.000)	3200.6 (0.000)	1646.5 (0.000)
ρ_1	0.036	0.054	0.123	0.058
ρ_2	0.066	-0.022	0.067	0.010
ρ_3	0.063	0.010	0.050	-0.007
$Q(12)$	24.99	19.21	39.12	24.09
ρ_{s1}	0.052	0.098	0.188	0.333
ρ_{s2}	0.139	0.050	0.060	0.265
ρ_{s3}	0.081	0.005	0.051	0.217
$Q_s(12)$	195.26	100.74	97.02	350.42
Total (+)	41	43	33	612
Total (-)	43	22	28	653
max	7.38	7.43	6.25	22.02
min	-6.77	-6.98	-4.77	-27.01

Notes: J.B. is the Jarque-Bera normality test statistic with 2 degrees of freedom with the corresponding p-values; ρ_k is the sample autocorrelation coefficient at lag k with asymptotic standard error $1/\sqrt{T}$ and $Q(k)$ is the Box-Ljung portmanteau statistic based on $k-$squared autocorrelations. ρ_{sk} are the sample autocorrelation coefficients at lag k for squared returns and $Q_s(12)$ is the Box-Ljung portmanteau statistic based on $12-$squared autocorrelations.

Table 3: Tests for stationarity in the level and return series

KPSS Statistic					Critical values		
	Egypt	Jordan	Morocco	Turkey	0.1	0.05	0.01
	Level series						
Const	74.41*	79.06*	98.21*	14.60*	0.347	0.463	0.739
Trend	19.56*	15.17*	26.20*	14.07*	0.119	0.146	0.216
	Return series						
Const	0.259	0.232	0.729	0.102	0.347	0.463	0.739
Trend	0.145	0.096	0.086	0.073	0.119	0.146	0.216

Notes: * indicates significance at the 5% level of the null hypothesis of $I(0)$ against long-memory alternatives.

Table 4: Results of the Hill Estimator for daily returns of MENA equity markets (upper tail)

	order statistic m			
Country	110	120	130	140
Egypt	2.757	2.408	2.236	2.01
	(2.346, 3.385)	(2.059, 2.866)	(1.929,2.757)	(1.662,2.477)
Jordan	1.745	1.714	1.564	1.539
	(1.497,2.112)	(1.426,2.135)	(1.355,1.828)	(1.276,1.920)
Morocco	2.183	2.175	2.164	2.016
	(1.859,2.586)	(1.849,2.504)	(1.769,2.643)	(1.770,2.403)
Turkey	2.307	2.369	2.472	2.397
	(1.943,2.833)	(2.025,2.780)	(2.137,2.959)	(2.158,3.018)

Notes: m is the order statistic. Numbers in parentheses are the confidence intervals for α for 5% significance level and based on 100 boostrap simulations

Table 5: Results of the Hill Estimator for daily returns of MENA equity markets (lower tail)

	order statistic m			
Country	110	120	130	140
Egypt	2.704	2.609	2.542	2.340
	(2.385, 3.392)	(2.235, 3.184)	(2.178, 3.235)	(1.894,2.704)
Jordan	2.192	2.109	2.069	2.030
	(1.837,2.659)	(1.818,2.532)	(1.817,2.495)	(1.704, 2.389)
Morocco	2.981	2.948	2.638	2.500
	(2.436,3.768)	(2.431,3.558)	(2.190,3.190)	(2.125,2.965)
Turkey	2.325	2.262	2.164	2.112
	(1.971,2.822)	(1.899,2.884)	(1.855,2.562)	(1.774,2.616)

Notes: m is the order statistic. Numbers in parentheses are the confidence intervals for α for 5% significance level and based on 100 boostrap simulations

Table 6: Estimated daily percent returns with the corresponding time to return for long and short positions (left and right tails)

Time to return	Egypt	Jordan	Morocco	Turkey
	Long positions (left tails)			
5	-7.57	-4.75	-4.40	-18.17
10	-8.46	-5.74	-5.37	-21.15
25	-9.64	-7.29	-6.91	-25.51
50	-10.52	-8.67	-8.33	-29.18
75	-11.04	-9.59	-9.27	-31.49
100	-11.41	-10.29	-9.99	-33.20
	Short Positions (right tails)			
5	7.43	6.33	5.41	19.74
10	8.30	7.77	7.04	22.98
25	9.45	10.03	9.91	27.70
50	10.32	12.07	12.80	31.62
75	10.83	13.42	14.85	34.08
100	11.19	14.45	16.49	35.89

Notes: The table reported the scale of risk and expected extreme returns for each country. According to the general extreme value theory, the significance level will be determined by $\alpha_{GEV} = 1 - n/\widetilde{t}$ and accordingly for 250 trading days per year and 5 years time period, the significance level will be 98,24%.

Table 7: Value at Risk Estimates in the MENA equity Markets

Portfolio	VaR 99%	VaR 99,6%	VaR 99,9%
	Method: Gaussian Distribution		
Egypt	3.776	4.294	4.990
Jordan	2.003	2.282	2.657
Morocco	1.893	2.153	2.504
Turkey	8.968	10.231	11.931
	Method: Historical Simulation		
Egypt	4.310	5.625	6.403
Jordan	2.117	3.218	6.194
Morocco	2.199	2.624	4.467
Turkey	10.222	3.916	22.009
	Method: Extreme Value Distribution		
Egypt	4.133	5.355	7.108
Jordan	1.087	2.889	4.367
Morocco	1.866	2.615	4.035
Turkey	8.669	11.414	15.882

Notes: the table provides the one day VaR estimates in the MENA equity markets, based on Gaussian (variance-covariance), historical simulation and extreme value distribution. For example, a value of 4.133 according to the extreme value distribution, means that the stock return in Egypt will not exceed 4.13% in one day 99% of the time.