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Value-at-Risk Analysis in the MENA Equity Markets: Fat Tails and Conditional Asymmetries in Return Distributions

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Abstract

In this paper, we examine the forecasting performance of the Value-at-Risk (VaR) models in the MENA equity markets. We use the Asymmetric Power ARCH model to analyze four MENA emerging markets, namely Egypt, Jordan, Morocco, and Turkey. While most empirical studies focus only on holding a long position of a portfolio, in this paper, we consider a short position in each market. In the process, we find that the returns have significantly fatter tails than the normal distribution and therefore introduce the Asymmetric Power ARCH model to estimate the value-at-risk in each market. Then, we explore the impact of asymmetry in the conditional variance and fat-tailed distributions on measuring Value-at-Risk. We find that the VaR estimates based on the Student APARCH model are more accurate than those generated using Normal APARCH models, and therefore a proper risk assessment should not neglect both the long memory and tail behavior in these markets. 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.

Keywords: Asymmetric Power ARCH model; MENA equity markets; Value at Risk models

JEL classification: C14/ C15/G15

Highlights

- We examine the forecasting performance of the Value-at-Risk (VaR) models in the MENA equity markets.
- We use the Asymmetric Power ARCH model to analyze four MENA markets
- We focus on holding a long position and a short position of a portfolio.
- It is found that the VaR estimates based on the Student APARCH model are more accurate.
- Our results should be useful to investors, bankers, and fund managers.

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 (1995) 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 (1995) 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 indicate 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 context 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. One approach that can be used to estimate the VaR focuses on modelling the tail of the distribution.

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). 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 repatriation 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, other markets like Egypt, Morocco, and Turkey have no restrictions on foreign investors[2]. 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.

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

[2] For an overview of the equity markets in some Middle Eastern countries and issues related to market efficiency and organizational structure, look at Bekaert and Harvey (1995,1997), Errunza (1994), El Erian and Kumar (1995), Al-Loughani (1995) and Al-Loughani and Moosa (1997), Claessens et al. (1995), Ghysels & Cherkaoui (2003) and Appiah-Kusi & Menyah (2003).

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 stock market 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 comparative underdevelopment of MENA stock markets has focused the minds of many MENA exchanges in upgrading their trading infrastructure and systems. For example, Egypt revitalized its capital market by adopting a computer-based screen trading system, a circuit breaker and has one 4-hours trading session. Starting in 2002, the Egyptian Stock Exchange expanded the price boundaries imposed on daily movements of listed shares which are accompanied by applying trading halt for a period of 30 minutes, 45 minutes or until the end of the trading session. In Jordan, the Securities Law, No. 23 introduced in 1997, involved institutional changes in the capital market, the use of electronic trading system, and elimination of obstacles to investment. By 2000, the Amman Stock Exchange (ASE) began implementing new directives to secure settlement of trades and provide assurance to dealers of timely settlements and by 2001, S&P revised its outlook on Jordan's long-term foreign currency rating to positive from stable and the Amman Stock Exchange 's performance was the strongest in the Middle East. In Morocco, the reforms started earlier and 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 Casablanca Stock Exchange (CSE). As a result, the CSE was included in the

IFC Emerging Market database in 1996 together with stock exchanges from two other countries, Egypt and Russia. 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. Other improvements were introduced and include adopting the international accounting standards and improvements in the information dissemination process (e.g. the CSE created its own website to provide market participants with information regarding corporate developments on timely basis). 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, 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, Turkey agreed to strengthen its banking system and accelerate privatization, which later had its impact on the stock market performance.

Overall, these markets showed a noticeable change over the years. This change 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. Further, 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.

The purpose of this paper is to use the Asymmetric Power ARCH model to analyze four emerging MENA markets, namely Egypt, Jordan, Morocco, and Turkey. We extend previous studies by providing a more extensive and systematic study of these markets in several aspects. First, we provide an extensive analysis of the financial and economic characteristics of these markets. Second, we apply the Asymmetric Power ARCH model for each market taking into consideration the asymmetric and fat tails distribution. Third, we estimate the maximum daily loss in each market by computing the Value-at-Risk based on the estimated models. And fourth, using different performance measures, we backtest each model to determine its use and credibility. Overall, we find that the VaR measures based on the normal distribution have a difficulty in modeling large positive and negative returns, and the incorporation of the fait-tailed distribution with the Asymmetric Power ARCH improves on the performance of normal based models. Overall, the VaR estimates based on our proposed models are found to be important 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. Further, we argue about some factors that are likely to influence the dynamics and risk management in these markets. These include accounting standards, market size, financial liberalization, improvements in microstructure (e.g. adopting automated trading system), quality of information, and the enforcement of insider trading regulations. 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.

The paper is organized as follows. Section 2 provides a literature review related to the MENA equity markets. Section 3 presents the empirical methodology. Section 4 presents the data and its properties. Section 5 provides the estimation results with the value-at-risk analysis. Section 6 contains a summary of our findings and concluding remarks.

Literature Review

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. Abraham et al. (2002) examined the random walk properties of three Gulf stock markets - Kuwait, Saudi Arabia, and Bahrain - after correcting for infrequent trading. They could not reject the random walk hypothesis for the Saudi and Bahrain markets, however, the Kuwaiti market failed to follow a random walk even after the correction. Abdmoulah (2009) tested the weak market efficiency form by using the GARCH (1,1) for 11 Arab stock markets and found all markets to be inefficient. Al Janabi, Hatemi-J and Irandoust (2010) tested the informational efficiency of stock markets of the countries of the Cooperation Council of the Golf (GCC) and their empirical results showed that markets are efficient vis-à-vis the price of oil and gold, while Jorg (2010) rejected the random walk hypothesis for these markets, but with some differences for weekly and monthly data. Lagoarde-Segot and Lucey (2008) investigated the informational efficiency of seven emerging MENA stock markets. They analyzed the impact of market development, corporate governance and economic liberalization. Their results concluded with heterogeneous levels of efficiency in the MENA stock markets, and their efficiency index seems to be affected mostly by market depth and corporate control. By contrast, variables linked to the overall economic liberalization process do not seem to have explanatory power. Lagoarde-Segot and Lucey (2008) showed that Turkey and Israel showed the strongest evidence of weak-form efficiency. These markets were followed by Jordan, Tunisia and Egypt, with Lebanon and Morocco lagging behind. They associated that with the fact that Turkey and Israel are endowed with more liquid and capitalized stock markets and have well-developed financial systems.

In terms of market integration and co-movements with other markets, 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. Arouri and Nguyen (2010) considered the correlations between some MENA equity markets (mainly GCC markets) and the World stock market. Their study showed that the degree of cross-market co-movements changed over time and has considerably increased since 1994, while Cheng et al. (2010), found weak evidence of regional co-movement in the MENA region. They also found that the MENA stock markets are largely segmented from global markets. Aloui and Hkiri (2014) examined the short term and long term dependencies between the stock market returns for the GCC countries during the period 2005-2010 using the wavelet squared coherence analysis. They found frequent changes in the pattern of the co-movements among those markets after 2007, and an increasing strength of dependence during the last financial crisis. Garham and Nikkinen (2012) studied the co-movement of the MENA region stock market with U.S. stock market for the period 2002–2010. Using the wavelet coherence approach with simulated confidence bounds, the authors pointed out a modest degree of co-movement between the U.S. stock market and MENA markets.

Recently, more attention has been given to the MENA region in terms of studying its characteristics, behavior and volatility dynamics. We go over some of the recent literature, detailing the importance of these markets for risk management, portfolio analysis and market efficiency. For example, Hammoudeh and Li (2008) examined the sudden changes in volatility for five Gulf area Arab stock markets using the iterated cumulative sums of squares (ICSS) and analyzed their impacts on the estimated persistence of volatility. They found that most of the Gulf Arab stock markets are more sensitive to major global events than to local regional factors. For example, the 1997 Asian crisis, the collapse of oil prices in 1998 after the crisis, the adoption of the price band mechanism by OPEC in 2000, and the September 11th attack have been found to have consistently affected the Gulf markets.

Brooks (2007) studied a set of emerging markets including those from the MENA region using the Asymmetric Power ARCH model and explored the applicability of the model to those markets. His key findings were as follows. First, unlike developed markets where a power term of unity and a conditional standard deviation model appears to be appropriate, emerging markets demonstrate a considerably greater degree of power values. Second unlike developed markets where non-normal conditional error distributions appear to fit the data well, there are a set of emerging markets for which estimation problems arise with the conditional *t* distribution, and a conditional normal distribution appears to be the preferred option. Third, the degree of volatility asymmetry appears to vary across markets, with the Middle Eastern and African markets having very different volatility asymmetry characteristics to those of the Latin American markets.

Nikkinen *et al*. (2008) used data from 53 equity markets including the MENA markets to investigate the short term impact of the September 11 attacks on markets' returns and volatility. Their findings indicate that the impact of the attacks results in significant increases in volatility across regions and over the study period. However, stock returns experienced significant negative returns in the short-run but recovered quickly afterwards. Nevertheless, they find that the impact of the attacks on financial markets varied across regions and implied that the less integrated regions (i.e., MENA) are with the international economy, the less exposed they are to shocks. They found that the MENA region provides investors with the highest returns and the lowest volatility, in which it shows statistically significant higher stock returns and lower volatility compared with each of the other regions. In the post-September period, the MENA region maintained the lowest volatility compared with other regions, either shortly after the attacks or even over a longer period. In terms of stock returns, MENA shows statistically significant positive stock returns after the attacks compared with each region without exception. In longer periods, the MENA region seems to underperform other regions significantly for 3 months following the attacks. And over a 6- month period following the attacks the MENA region still underperforms other regions.

Lagoarde-Segot and Lucey (2007) investigated the potential diversification benefits in the MENA region using local currencies and dollar transactions. They concluded that these markets should attract more portfolio flows in the future. Analyzing the patterns of portfolio weights across optimization methodologies allowed the authors to make certain deduction concerning the country level risk-to-return trade-off. For instance, market attractiveness in Morocco and Tunisia seems to be primarily driven by low risks rather than high returns. Morocco obtains indeed the highest weights when returns are not taken into account, and where risk is assimilated to downside deviation. The opposite situation is found in Jordan and Israel. Portfolio allocations in these two countries are very small when the optimization techniques relies on downside risk minimization, and overall, these two markets seem to display both high returns and risks, in line with the standard view for emerging markets. Interestingly, portfolio allocations in Egypt seem to be very sensitive to the selected measure of risk. This suggests the predominance of upwards volatility in the Egyptian market, a not surprising feature considering the last decade's massive capitalization increases in the Egyptian market. Portfolio allocations are the most unstable in Turkey, and this dynamic might reflect the multiplier impact of the 2001 crisis on downside volatility in the Turkish market.

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 . There is also more evidence that emerging markets may be less informationally efficient, and their industrial organization is often quite different from that in developed economies. 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. Further, the industrial organization found in these markets is often quite different from that in developed economies. All of these conditions and others may contribute to a different behavior in the dynamics of these markets.

Empirical Methods: Value-at-Risk models

The Value-at-Risk (VaR) 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 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. All these motivate the use of alternative models to forecast VaR measures, namely more advanced parametric methods that take into account those shortcomings.

The Riskmetrics

It is known that volatility in financial markets tends to exhibit clustering behavior, with periods of high and then low volatility. This type of behavior was first captured by Engle (1982) through the use of an autoregressive conditional heteroskedastic (ARCH) process. In the ARCH model, the variance is modeled as a linear function of lagged squared prediction errors. Bollerslev (1986) subsequently generalized the ARCH process so that the conditional variance is not only a function of past errors, but also of lagged conditional variances. A GARCH *(p,q)* process can be specified as:

$$\sigma_t^2 = \alpha_0 + \sum_{i=1}^{q} \alpha_i \varepsilon_{t-i}^2 + \sum_{i=1}^{p} \beta_i \sigma_{t-i}^2 \qquad (1)$$

where ε_t^2 is the sample variance, and σ_t^2 is the conditional variance, both at time t.

The best-known parametric VaR model is J.P. Morgan's RiskMetrics, and its most simple form, it can be shown that the basic RiskMetrics model is equivalent to a normal Integrated GARCH (IGARCH). That is we are able to estimate the optimal conditional variance by a GARCH *(1,1)* model with zero constant and the parameters α and β summing to unity. Imposing such a restriction gives the Integrated GARCH (IGARCH) model of $r_{t+1} = \mu + e_{t+1}$ with e_{t+t}/I_t following a normal distribution $N(0, \sigma_t^2)$ and

$$\sigma_t^2 = \lambda \sigma_{t-1}^2 + (1-\lambda)\varepsilon_{t-1}^2 \qquad (2)$$

$$R_t^* = -Z_\alpha \sqrt{\sigma_t^2} + \mu \tag{3}$$

$$VaR_t = W_0 Z_\alpha \sqrt{\sigma_t^2} \tag{4}$$

where R_t^* denotes the lowest rate of return at α% level, and Z_α is the left quantile at α% for the normal distribution at a particular confidence level. The parameter λ is known as the decay factor, determining how fast the weight on past observations decays. The higher the value of λ, the slower is the rate of decay and the more the weight is given to the more distant observations. In the RiskMetrics specifications, the autoregressive parameter is set at a pre-specified value λ=0.94 with daily data and to 0.97 with weekly data. This makes the estimation simple, since there are no remaining parameters to estimate.

The long side of the daily VaR is defined as the VaR level for traders having long positions in the relevant equity index: this is the usual VaR where traders incur losses when negative returns are observed. Correspondingly, the short side of the daily VaR is the VaR level for traders having short positions, i.e., traders who incur losses when stock prices increase.

The Asymmetric Power ARCH model

Ding et al. (1993) have introduced a relatively new class of Power ARCH (PARCH) model which estimates the optimal power term within the model. So, rather than imposing a structure on the data, the PARCH model allows a power transformation term inclusive of any positive value and so permits a virtually infinite range of transformations. Thus, this model incorporates the standard class of ARCH model which specifies the use of a squared term in that the conditional variance is specified as a function of past squared residuals and variances. The Power ARCH model incorporates the Taylor (1986) GARCH model which relates the conditional standard deviation as a function of past lagged absolute residuals and standard deviations.

The general asymmetric power GARCH model introduced by Ding et al. (1993) specifies σ_t as of the form:

$$\sigma_t^d = \alpha_0 = \sum_{i=1}^{p} \alpha_i (| \varepsilon_{t-i} | + \gamma_i \varepsilon_{t-i})^d + \sum_{i=1}^{q} \beta_i \sigma_{t-i}^d \qquad (5)$$

where α_i and β_i are the standard GARCH parameters, γ_i are the leverage parameters and *d* is the parameter for the power term.

The models discussed above have assumed a symmetrical response of volatility to innovations in the market, while empirical evidence suggests that positive and negative returns to the market of equal magnitude may not generate the same response in volatility (see Nelson, 1990). Glosten et al. (1993) provided one of the first attempts to model leverage effects using a model which utilizes a GARCH type conditional variance specification. In this GJR-GARCH model, the power term and beta conform to the conventional GARCH restrictions (d=2 and β_i is free) however α_i is specified as $\alpha_i(1+\gamma_i)^2$ and the leverage term is restricted to $-4\alpha_i\gamma_i$. Although not originally specified by Glosten et al. (1993), one may also specify a GJR-ARCH type model by restricting beta to be zero in the standard GJR-GARCH framework (i.e. $d=2,\beta_i=0,\alpha_i(1+\gamma_i)^2$ and the leverage term is restricted to $-4\alpha_i\gamma_i$). Another leverage effect ARCH model which is less restrictive then the GJR-GARCH and GJR-ARCH model may be specified. Engle's original ARCH model may be extended to create a leverage ARCH model by allowing γ_i to take on positive values (i.e $|\gamma_i|\leq 1$) in the σ_t^d equation. Further, a leverage GARCH model is obtained by extending Bollerslev's original GARCH model to include a leverage term.

The Taylor ARCH and GARCH models may also be extended in this way to include asymmetric effects. The TARCH model of Zakoian (1994) is defined where α_i is free, d=1 and $|\gamma_i|\leq 1$ (we restrict $\beta_i=0$). Further, a leverage term in the Taylor GARCH model creates a generalized TARCH model. Finally, the A-PGARCH model may be restricted by setting $\beta=0$ to create an A-PARCH model. For full details and proofs of this nesting process see Ding et al. (1993) and Hentschel (1995).

The simple APARCH (1,1) model can be represented as:

$$\sigma_t^d = \alpha_0 + \alpha_1(|\varepsilon_{t-1}| + \gamma_1\varepsilon_{t-1})^d + \beta_1\sigma_{t-1}^d \quad (6)$$

For the normal APARCH model, the one-step ahead VaR is computed as for the RiskMetrics model except the computation of the conditional standard deviation σ_t is given by (the above equation) evaluated at its maximum likelihood estimate.

The Student Asymmetric Power ARCH (Student APARCH) model

The convenience of a normal distribution is powerful inducement for its use in VaR analysis, but this does not necessarily make its use appropriate. Previous empirical studies on VaR (Van den Goorbergh and Vlaar, 1999; Giot and Laurent, 2003) have shown that models based on the normal distribution usually cannot fully take into account the "fat tails" of the returns. To alleviate this problem, the Student-Asymmetric Power ARCH is introduced:

$$e_t = \varepsilon_t\sigma_t \quad (7)$$

where ε_t is drawn from an IID *t(0,1,v)* distribution and σ_t is defined as in (6). For the student APARCH model, the VAR for long and short positions is given by $\mu_t + st_{\alpha,v}\sigma_t$ and $\mu_t + st_{1-\alpha,v}\sigma_t$ with $st_{\alpha,v}$ being the left quantile at α% for the standardized Student t distribution with (estimated) number of degrees of freedom *v* and $st_{1-\alpha,v}$ is the right quantile at α% for this same distribution. Note that because $Z\alpha=-Z_{1-\alpha}$ for the normal distribution and $st_{\alpha,v}=-st_{1-\alpha,v}$ for the Student distribution, the forecasted long and short VaR will be equal in both cases[3].

Data and Empirical Results

[3] To account for the excess skewness and kurtosis, Lambert and Laurent (2001) proposed to extend the Student distribution by adding a skewness parameter, by re-expressing the skewed-Student density in terms of the mean and the variance. Other asymmetric Student densities have been proposed by Hansen (1994) and Paollella (1997).

We specifically study four emerging markets, namely, Egypt, Jordan and Morocco. While not geographically located in MENA, the study will also include Istanbull's stock market of Turkey. The sample data covers the sample period from May 1, 2005 to April 26, 2012. 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 1 summarizes the statistical properties of the returns: we show the first four moments, the autocorrelation coefficients at lag one and the Ljung and Box test statistic for autocorrelation in returns and squared returns. All series exhibit a positive mean returns (except that for Jordan) and high variability as indicated by the standard deviation. Turkey is the most volatile market within the sample. Considering the autocorrelation of returns, at lag one the Egyptian market has the highest coefficient at 0.127 and is significant at the 5% level. We observe also two stylized facts for return series which has universal validity, as documented in the survey by Pagan (1996). The first stylized fact is the non-normality 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(12) test statistics showing strong autocorrelation in squared returns. Further, we tested the series for stationarity by implementation of KPSS tests proposed by Kwiatkowski et al. (1992) for the null hypothesis of I(0). We considered two tests, denoted by Const and Trend based on a regression on a constant, and on a constant and time trend, respectively. The results showed again that the null hypothesis is strongly rejected for the level series, while it is accepted for return series at the levels of significance. We considered also two proxies of daily volatility: the squared and absolute returns to investigate their long memory properties. We employed diverse long-range memory tests and consequently found that the four markets volatilities to be well described by a fractionally integrated process[4].

Estimation results

We estimate the Power ARCH model with the possible normal and *t*-distributions. Both models are presented in Tables 2 and 3. The estimated mean and variance of each market falls in line with those provided in Table 1, where the conditional mean is positive for each market (except again for Jordan) and a conditional positive standard deviation. The autoregressive effect in the volatility specification is the strongest for Jordan, followed by that of Turkey, Egypt and then Morocco. That suggests a strong memory effect in each market. All the estimated coefficients are significant whether in the case of using a normal or a *t*-distribution. γ_1 is negative for Egypt and Jordan and positive for Morocco and Turkey, but not significant. That indicates a leverage effect for negative returns in the conditional variance specification for that of both Egypt and Jordan, but a leverage effect for positive returns for that of Morocco and Turkey. The δ is greater than 1 for all markets and different from 2, but not significant in each case. This suggests that, instead of modeling the conditional variance (GARCH), it is more relevant in this case to model the conditional standard deviation. This result is in line with those of Taylor (1986), Schwert (1990) and Ding, Granger and Engle (1993) who indicate that there is a substantially more correlation between absolute returns than squared returns, a stylized fact of high frequency financial

[4] Results from unit roots and long memory tests are available from author upon request.

returns- often called "long memory"[5]. In fact, Ding et al. (1993) applied the Power ARCH model to US stock returns data and found that the model provided a good fit of the data. The optimal power term was found to be 1.43. Hentschel (1995) who proposed a more general class of PARCH model and also applied it to US stock market data, found the optimal value for the power term was found to be 1.524. Brooks et al. (2000) considered the applicability of this model to a wider range of stock market data and found that the model provided a good fit of the data, and the average optimal power term was 1.3 across all of the indices tested with the highest power term of 2.4 for the Singapore index and the lowest being 0.912 for the German DAX index.

Table 2 also includes some test statistics to check the adequacy of this model (i.e., Asymmetric Power ARCH with normal distribution). We are referred to the output of the Box-Pierce test on standardized residuals and squared residuals and the RBD test. These tests indicate that this specification is not appropriate for our sample data. Indeed this model is unable to consider the stylized facts of this sample data, such as asymmetry and fat tails in the return volatilities. Table 3 proceeds with accounting for the fat tails in estimating the Asymmetric Power ARCH with a student distribution.

Comparing the likelihoods of the two models (i.e., APARCH with normal and *t*-distributions) suggests that the additional flexibility of the Power ARCH with *t*-distribution is empirically relevant. The estimates of the degrees of freedom (DF) are all significant for each market, which implies that the fat tailed *t*-distribution is needed to fully model the distribution of returns. In fact, Turkey, Egypt and Morocco display much larger kurtosis and exhibit fatter tails than those of the Jordanian market. Likelihood ratio tests clearly favor the APARCH with *t*-distribution compared to the one using a normal distribution. Finally, the APARCH model succeeds in taking into account the dynamical structure exhibited by the

[5] Ding et al. (1993) found that the absolute returns and their power transformations have a highly significant long-tem memory property as the returns are highly correlated. For example, significant positive autocorrelations were found at over 2700 lags in 17054 daily observations of the S&P 500.

returns and volatility of the returns as the Ljung-Box on the standardized residuals and squared standardized residuals are mostly nonsignificant at the 5% level.

Backtesting the VaR estimates

Model accuracy is important to all VaR model users. For example, regulatory-capital requirements link explicitly the magnitude of the market-risk capital requirements to the accuracy of each institution model (Cassidy and Gizycki, 1997). However, as noted by Diebold and Lopez (1996), it is unlikely that forecasts from a model will exhibit all the properties of accurate forecasts. Thus, evaluating VaR estimates solely upon whether a specific property is present may yield only limited information regarding their accuracy. In this paper, the proposed models for each market are tested with a VaR level α which ranges from 5% to 0.25%. That is the quantiles we use are 0.95, 0.975, 0.99, 0.995, and 0.9975. However, we only report the results for 0.95, 0.99 and 0.9975. The models performance is then assessed by computing the failure rate for the returns. By definition, the failure rate is the number of times returns exceed (in absolute value) the forecasted VaR. If the VaR model is correctly specified, the failure rate should be equal to the per-specified VaR level. In this paper, we define the failure rate f_l for the long trading positions, which is equal to the percentage of negative returns smaller than one-step-ahead VaR for long positions. Consequently, we define f_s as the failure rate for short trading positions as the percentage of positive returns larger than the one-step-ahead VaR for short positions.

Since the computation of the empirical failure rate defines a sequence of yes/no observations, it is

possible to test $H_0: f = \alpha$ against $H_1: f \neq \alpha$, where f is the failure rate (estimated by $\hat{f}$, the empirical failure

rate). At the 5% level and if T yes/no observations are available , a confidence interval for f is given by

$\hat{f} \pm 1.96\sqrt{\hat{f}(1-\hat{f})/T}$. This test is called the Kupiec (1995) LR test when the hypothesis is tested using a likelihood ratio test. The LR statistic is $LR = -2\log(\frac{\alpha^N(1-\alpha)^{T-N}}{\hat{f}^N(1-\hat{f})^{T-N}})$ where N is the number of VaR violations, T is the total number of observations and α is the theoretical failure rate. Under the null hypothesis that f is the true failure rate, the LR test statistic is asymptotically distributed as a $\chi^2(1)$.

Despite the use of VaR measure as a risk management tool, it has however some drawbacks. One of these is that it is not a coherent measure of risk in the sense of Artzner, Delbaen, Eber, and Heath (1999). A somewhat related measure of risk is the so-called Expected Shortfall (ES) (see Scaillet, 2000). Expected shortfall is defined as the expected value of the losses conditional on the loss being larger than the VaR. It measures the degree to which events in the tail of the distribution typically exceed the VaR measure by calculating the average number of these outcomes to their corresponding VaR measures . The expected short-fall for the long position is computed as the average of the observed returns smaller than the long VaR, while the expected short-fall for the short position is computed as the average of the observed returns larger than the short VaR.

Besides the failure rate, another relevant VaR model should feature a sequence of indicator functions (VaR violations) that is not serially correlated. with the new variables $Hit_t(\alpha)=I(y_t<VaR_t(\alpha))-\alpha$ and $Hit_t(1-\alpha)=I(y_t<VaR_t(1-\alpha))-\alpha$, Engle and Manganelli (1999) suggest to test jointly that:

A1: $E(Hit_t(\alpha))=0$ (respectively $EHit_t(1-\alpha))$ in the case of long trading positions (short trading positions);

A2: $Hit_t(\alpha)$ (or $Hit_t(1-\alpha))$ is uncorrelated with the variables included in the information set.

According to Engle and Manganelli (1999), testing A1 and A2 can be done using the artificial $Hitt=X\lambda+\varepsilon t$, where X is a $T \times K$ matrix whose first column is a column of ones, the next p columns are $Hit_{t-1}, \ldots\ldots Hit_{t-p}$ and the k-p-1 remaining columns are additional independent variables (including the VaR itself). Engle and Manganelli (1999) also show that under the null A1 and A2, the Dynamic Quantile test statistic $\frac{\hat{\lambda}' XX' \hat{\lambda}}{\alpha(1-\alpha)}$ asymptotically as a $\chi^2(k)$, where $\hat{\lambda}$ λ is the OLS estimate of λ.

Complete VaR results for the two models are reported in Tables 4, 5 for the Normal APARCH model and 6 and 7for the APARCH model with a *t*-distribution. Overall, the VaR models based on the normal distribution has a difficulty in modeling large positive and negative returns. These results can be explained by the fact that the MENA equity markets are not normally distributed. Indeed, the entire time-series sample is skewed and fat-tailed; therefore, the symmetric normal distribution has no ability to improve the VaR and ES results.

The symmetric Student APARCH model sometimes improves on the performance of normal based models, however, its performance is still not satisfactory in some cases. Its performance is even worse than normal based models. The reason is that the critical values of the Student distribution are very large in this case, which leads to a high level of long and short VaR: the model often rejected because it is too conservative. Nevertheless, by looking at the tables and comparing both models, the P-values for the null hypothesis of both test are often smaller than 0.05, especially when α is below 1%. Secondly the student *t*-distribution APARCH model performs well as there are no many P-values smaller than 0.05. Thus, the switch from the normal distribution to the skewed Student distribution yields a significant improvement in the VaR performance of the model set for the realized volatility. Jordan is the exception, since the Normal APARCH model used in generating the in-sample VaR forecasts performs better than the *t*-distribution APARCH model (i.e., look at the P-values for long and short positions in comparing the two models).

Conclusion and Implications

Methods that are used to measure VaR 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 Power ARCH model to model equity markets in the MENA region and then use the filtered residuals from these models to measure the Value-at-Risk (VaR) in each market. The Asymmetric Power ARCH model with the *t*-distribution makes it possible to concentrate on the behavior of volatility observations in these markets and account for the fat tails in them. Comparing these models, we find that the VaR measures based on the normal distribution have a difficulty in modeling large positive and negative returns. However, the incorporation of the fait-tailed distribution with the Asymmetric Power ARCH improves on the performance of normal based models. Overall, the VaR estimates based on our proposed models are found to be important 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.

Our results are linked to some factors that are likely to influence the dynamics and risk management in these markets. These factors include accounting standards, market size, financial liberalization, improvements in microstructure (e.g. adopting automated trading system), quality of information, and the enforcement of insider trading regulations. For example, to achieve international comparability in accounting disclosure, MENA countries have amended their national accounting standards to converge with the international set of financial reporting and accounting standards. Thus, all the countries under investigation, currently, pass the transparency criteria and other criteria of market quality set by FTSE. Regulatory framework that maximizes equality among stock market shareholders is important to minimize the asymmetric information and, thus, to ensure market efficiency. The principle of equitable treatment of shareholders (e.g. prohibition of market manipulation and insider dealing) is partially implemented in Turkey, partially observed in Egypt, largely observed in Jordan and materially not observed in Morocco[6].

Other factors include (1) tight symmetric price limits imposed on daily movements of stock prices as they delay price discovery process (for example ±5% imposed on daily movements of stock prices in Egypt, (2) limited information available to market participants about corporations' development due noncompliance with mandatory disclosure requirements, (3) and information asymmetry among market participants because of selective disclosure and self-dealing. For example, starting in 2002, the Egyptian Stock Exchange expanded the price boundaries imposed on daily movements of listed shares which are accompanied by applying trading halt for a period of 30 minutes, 45 minutes or until the end of the trading session if the weighted average price of stocks hit the limits of ±10%, ±15% or ±20% respectively, when compared to their opening prices. In Morocco, the exchange was characterized by a lack of transparency (local accounting standard were employed), small number of individual investors, and extreme illiquidity represented by non-trade of many stocks for several consecutive weeks (Ghysels and Cherkaoui, 2003;). However, extensive series of reforms, deregulations and privatization have taken place in recent years which has been reflected in the market size and liquidity. In Jordan, periods of inefficiencies were detected when the Jordanian exchange was overvalued by the end of 2005 because of spillover effect from oil-producing regional neighbours (i.e. Saudi Arabia and Kuwait) experiencing sharp increase in oil prices. However, a process of price correction took place when Arab investors from Gulf countries had withdrawn

[6] Lagoarde-Segot and Lucey (2008) debated that the extent of weak-form- efficiency in the MENA stock exchanges is mainly explained by differences in stock market development (e.g. market capitalization, and turnover ratio) and corporate governance (e.g. disclosure and shareholder protection).

considerable funds from Jordan to cover their financial positions in their domestic markets after the sharp decline in stock prices in Saudi Arabia and other Gulf stock markets. Overall, the conclusion reached here conforms to the view that these markets are going through many market developments, which will impact their market dynamics and the risk management tools implemented in these markets.

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Table 1 : Summary Statistics of daily returns

	Egypt	Jordan	Morocco	Turkey
Mean	0.0107	-0.046	0.034	0.024
S.D	1.849	1.330	1.227	2.54
Skewness	-1.054	-0.694	-0.339	-0.265
Kurtosis	11.217	11.134	6.309	3.916
J.B.	5409.40* (0.000)	5118.91* (0.000)	857.75* (0.000)	1173.12* (0.000)
ρ_1	0.127	0.058	0.200	0.058
ρ_2	0.014	0.009	0.003	0.192
ρ_3	0.072	0.018	-0.022	-0.005
Q(12)	50.03*	20.21*	87.53*	23.01*
ρ_{s1}	0.175	0.118	0.245	0.125
ρ_{s2}	0.055	0.181	0.136	0.149
ρ_{s3}	0.049	0.164	0.086	0.145
$Q_s(12)$	1132.50*	445.51*	323.16*	459.20*

Notes: J.B. is the Jarque-Bera normality test statistic with 2 degrees of freedom; 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. * indicates significance at 5% level.

Table 2: Asymmetric Power ARCH Estimates with Normal distribution for MENA equity markets

	Egypt	Jordan	Morocco	Turkey
Cst(M)	0.051(1.369)	-0.048*(-1.878)	0.025(1.164)	0.023**(4.234)
Cst(V)	0.061(1.506)	0.026(1.161)	0.119**(2.622)	0.300(1.307)
APARCH (Alpha1)	0.037*(2.418)	0.0272*(2.408)	0.243*(2.624)	0.164*(4.44)
GARCH(Beta1)	0.938*(42.68)	0.940*(29.39)	0.325*(2.739)	0.768*(12.00)
APARCH (Gamma1)	0.263(1.462)	-0.622(-0.899)	0.089(1.125)	0.236(1.143)
APARCH(Delta)	1.27*(3.185)	1.52*(2.326)	1.49*(3.114)	0.778(1.200)
LogLik	-3533.10	-1148.28	-996.05	-2638.23
Q(10)	21.117(0.020)	24.36(0.006)	41.36(0.000)	9.44(0.491)
$Q_s(10)$	14.49(0.069)	6.705(0.568)	14.92(0.060)	3.99(0.857)
Nyblom test of stability	1.13	2.628	1.462	0.491
Tse (2002) RBD (5)	2.662(0.752)	2.089(0.836)	6.401(0.269)	1.335(0.931)

Notes: Estimation results for the volatility specification of the Normal APARCH model on the daily returns of Egypt, Jordan, Morocco and Turkey. *T-Statistics* are reported in parentheses. Q(10) and $Q_s(10)$ are, respectively the Ljung-Box Q-statistic of order 10 computed on standardized residuals and squared standardized residuals. Numbers reported in parentheses for Q(10) and $Q_s(10)$ are the corresponding probabilities. RBD (5) is the residual based diagnostic for conditional heteroskedasticity using 5 lags. * indicates significance at the 1% level. ** indicates significance at the 5% level. *** indicates significant at the 10% level.

Table 3: Asymmetric Power ARCH Estimates with *t*- distribution for MENA equity markets

	Egypt	Jordan	Morocco	Turkey
Cst(M)	0.0552*(2.865)	-0.030*(-3.166)	0.043*(2.288)	0.176(1.621)
Cst(V)	0.0667*(3.066)	2.150*(3.976)	0.113*(2.745)	0.398(1.624)
APARCH (Alpha1)	0.322*(4.131)	0.120**(1.929)	0.258*(3.295)	0.142*(3.659)
GARCH(Beta1)	0.669(8.622)	0.840*(29.39)	0.448*(3.292)	0.798*(14.75)
APARCH (Gamma1)	-0.0012(-0.014)	-0.0793(-0.260)	0.089(1.157)	0.313**(1.994)
APARCH(Delta)	1.062*(4.150)	1.45(0.802)	1.515*(2.959)	1.12*(2.487)
Student (DF)	5.055*(6.634)	2.053*(33.83)	5.079*(6.61)	6.623*(4.912)
LogLik	-909.89	-883.35	-956.29	-2614
Q(10)	21.07(0.021)	15.05(0.049)	40.94(0.00)	14.16(0.051)
$Q_s(10)$	15.55(0.049)	29.35(0.00)	15.54(0.049)	13.629(0.048)
Nyblom test of stability	2.709	7.153	2.443	0.707
Tse (2002) RBD (5)	44.634(0.000)	71.60(0.000)	67.99(0.000)	61.086(0.000)

Notes: Estimation results for the volatility specification of the *t*-Student APARCH model on the daily returns of Egypt, Jordan, Morocco and Turkey. *T-statistics* are reported in parentheses. Q(10) and $Q_s(10)$ are, respectively the Ljung-Box Q-statistic of order 10 computed on standardized residuals and squared standardized residuals. Numbers reported in parentheses for Q(10) and $Q_s(10)$ are the corresponding probabilities . RBD (5) is the residual based diagnostic for conditional heteroskedasticity using 5 lags. * indicates significance at the 10% level. ** indicates significance at the 5% level. *** indicates significant at the 1% level.

Table 4 : In-Sample Value-at-Risk backtesting: Failure Rate, Kupiec LRT, and Dynamic Quantile Test of Engle and Manganelli (1999)- Short positions for APARCH Estimates with Normal distribution

	Egypt				
Quantile	Failure Rate	Kupiec LRT	Dynamic Quantile Test	ESF1	ESF2
0.95	0.962	3.290(0.069)	8.168 (0.317)	1.413	1.487
0.990	0.981	5.608(0.0178)	14.53(0.042)	1.610	1.239
0.9965	0.991	7.899(0.005)	14.75(0.039)	1.911	1.176
	Jordan				
0.95	0.955	0.767(0.381)	27.25(0.000)	2.253	1.726
0.990	0.979	8.305(0.004)	19.50(0.007)	3.093	1.634
0.9975	0.986	22.47(0.000)	75.25(0.000)	3.606	1.581
	Morocco				
0.95	0.950	0.0156(0.900)	2.928(0.891)	1.664	1.431
0.990	0.983	3.364(0.066)	13.03(0.073)	2.175	1.352
0.9975	0.990	10.45(0.001)	57.52(0.000)	2.695	1.282
	Turkey				
0.95	0.955	0.767(0.381)	5.798(0.563)	8.228	1.394
0.990	0.986	0.977(0.322)	10.53(0.160)	12.41	1.384
0.9975	0.993	3.682(0.054)	11.71(0.110)	15.59	1.375

Notes: P-values for the null hypothesis f_1=α (i.e. failure rate for the long trading positions is equal to α)

and f_s=α (i.e. failure rate for the short trading positions is equal to α. α is equal successively to 5%, 1%, and 0.25%). ESF1 and ESF2 represent the expected shortfall as explained by Hendricks (1996). In the Dynamic Quantile Regression, p is set to 5.

Table 5 : In-Sample Value-at-Risk backtesting: Failure Rate, Kupiec LRT, and Dynamic Quantile Test of Engle and Manganelli (1999)- Long positions for APARCH Estimates with Normal distribution

	Egypt				
Quantile	Failure Rate	Kupiec LRT	Dynamic Quantile Test	ESF1	ESF2
0.05	0.055	0.553(0.456)	7.113(0.417)	-1.631	1.354
0.010	0.023	13.10(0.000)	31.92(0.000)	-1.975	1.185
0.0025	0.007	5.646(0.017)	61.13(0.000)	-2.266	1.151
	Jordan				
0.05	0.047	0.178(0.672)	19.42(0.007)	-1.816	1.372
0.010	0.0163	3.364(0.066)	6.391(0.494)	-2.329	1.204
0.0025	0.008	7.899(0.005)	24.01(0.001)	-2.900	1.131
	Morocco				
0.05	0.044	0.767(0.381)	16.55(0.020)	-1.560	1.375
0.010	0.008	0.345(0.556)	1.022(0.994)	-2.588	1.553
0.0025	0.007	5.646(0.017)	10.90(0.142)	-2.710	1.345
	Turkey				
0.05	0.045	0.523(0.469)	16.62(0.019)	-8.702	1.372
0.010	0.0194	6.903(0.008)	15.92(0.025)	-10.75	1.194
0.0025	0.009	10.40(0.001)	19.44(0.007)	-11.48	1.111

Notes: P-values for the null hypothesis $f_1=\alpha$ (i.e. failure rate for the long trading positions is equal to α)

and $f_s=\alpha$ (i.e. failure rate for the short trading positions is equal to α. α is equal successively to 5%, 1%, and 0.25%). ESF1 and ESF2 represent the expected shortfall as explained by Hendricks (1996). In the Dynamic Quantile Regression, p is set to 5.

Table 6 : In-Sample Value-at-Risk backtesting: Failure Rate, Kupiec LRT, and Dynamic Quantile Test of Engle and Manganelli (1999)- Short positions for APARCH Estimates with *t*- distribution

	Egypt				
Quantile	Failure Rate	Kupiec LRT	Dynamic Quantile Test	ESF1	ESF2
0.95	0.958	1.401(0.236)	8.910(0.259)	1.335	1.474
0.990	0.990	0.063(0.801)	1.052(0.993)	1.826	1.221
0.9965	0.998	1.101(0.294)	1.261(0.989)	1.442	1.037
	Jordan				
0.95	0.925	10.98(0.000)	44.15(0.000)	1.771	2.124
0.990	0.983	3.365(0.066)	19.19(0.007)	3.387	1.863
0.9975	0.995	0.833(0.	3.00(0.8850	5.497	1.516
	Morocco				
0.95	0.949	0.000(0.982)	4.895(0.672)	1.647	1.515
0.990	0.987	0.479(0.488)	7.590(0.370)	2.391	1.323
0.9975	0.995	0.833(0.361)	2.781(0.904)	2.420	1.164
	Turkey				
0.95	0.958	1.401(0.236)	5.686(0.5760	8.487	1.447
0.990	0.990	0.063(0.801)	2.201(0.947)	13.53	1.361
0.9975	0.996	0.118(0.730)	0.329(0.999)	16.85	1.331

Notes: P-values for the null hypothesis f_1=α (i.e. failure rate for the long trading positions is equal to α)

and f_s=α (i.e. failure rate for the short trading positions is equal to α. α is equal successively to 5%, 1%, and 0.25%). ESF1 and ESF2 represent the expected shortfall as explained by Hendricks (1996). In the Dynamic Quantile Regression, p is set to 5.

Table 7 : In-Sample Value-at-Risk backtesting: Failure Rate, Kupiec LRT, and Dynamic Quantile Test of Engle and Manganelli (1999)- Long positions for APARCH Estimates with *t*- distribution

	Egypt				
Quantile	Failure Rate	Kupiec LRT	Dynamic Quantile Test	ESF1	ESF2
0.05	0.059	1.706(0.191)	7.115(0.417)	-1.577	1.382
0.010	0.0152	2.430(0.119)	14.87(0.037)	-1.911	1.135
0.0025	0.002	0.085(0.769)	0.142(0.999)	-2.657	1.104
	Jordan				
0.050	0.089	25.71(0.000)	51.51(0.000)	-1.489	1.711
0.010	0.009	0.063(0.801)	1.856(0.967)	-2.867	1.506
0.0025	0.002	0.085(0.769)	0.227(0.999)	-4.094	1.054
	Morocco				
0.050	0.046	0.327(0.567)	15.26(0.032)	-1.533	1.408
0.010	0.007	0.880(0.348)	1.323(0.987)	-2.710	1.438
0.0025	0.003	0.118(0.7300	0.782(0.997)	-2.602	1.169
	Turkey				
0.050	0.053	0.209(0.647)	15.85(0.026)	-8.311	1.371
0.010	0.013	0.977(0.322)	3.179(0.867)	-11.38	1.171
0.0025	0.002	0.085(0.7690	0.247(0.9990	-14.89	1.087

Notes: P-values for the null hypothesis f_1=α (i.e. failure rate for the long trading positions is equal to α)

and f_s=α (i.e. failure rate for the short trading positions is equal to α. α is equal successively to 5%, 1%, and 0.25%). ESF1 and ESF2 represent the expected shortfall as explained by Hendricks (1996). In the Dynamic Quantile Regression, p is set to 5.