Stock Market Returns, Volatility and Volatility Persistence: Evidence from Emerging Markets

Samer A.M. Al-Rjoub, Khaled Alzubi and Morad Autair *

ABSTRACT

This paper examines the relationship between stock market returns and volatility and extends to measure the degree of persistence in volatility over the period from 1990 through 2002 for selected emerging markets. Using GARCH in mean, Exponential GARCH and by incorporating sudden change in volatility effect in the GARCH/E-GARCH models, the relationship between stock returns and variance was tested. Empirical evidence suggests that contemporaneous returns and volatilities for the majority of the markets are significantly and positively correlated. The volatility proves to be persistent across countries. To account for sudden change in variance, the Iterative Cumulative Sums of Squares (ICSS) are used to identify the points of shifts in volatility. ICSS results are significant, come in accordance with the identified points and confirm that the events and news cause shifts in volatility of stock returns.

JEL Specification: G15, G14.

KEYWORDS: Volatility, Sudden Change.

1. INTRODUCTION

The theoretical relationship between stock returns and their volatility is the major concern of financial economists over the past 20 years. They started by calculating simple data correlations and covariances and ended with sophisticated models that incorporate time varying structures in the variance. Although theory predicts a positive relation between asset returns and their variances, empirical evidences are in conflict. Some researchers found a positive relationship between the degree of the data dispersion around its mean and the stock returns (French, Schwert and Stambaugh, 1987) while others reported a negative relationship (Cheung and Ng, 1992). An ongoing concern is how to model conditional volatility in economic time series. They all agree on the notion that volatility can be decomposed into predictable and unpredictable components (Bollerslev et al., 1992). The major concern is about the predictable component of volatility since the risk premium is a function of it. In this paper we will model volatility and test its persistence by incorporating time varying structure in the time series models. We use both GARCH and E-GARCH models and then we allow for sudden change in variance in these two models. We extend by using the Iterative Cumulative Sum of Squares (ICSS) to account for possible sudden movement in the variance when testing the relationship between stock market volatility and returns. This paper is organized as follows. Section 2 discusses the literature review. Section 3 describes the methodology

Received on 17/4/2005 and Accepted for Publication on 17/11/2005.

and discusses the data and the descriptive statistics. Empirical results are discussed in Section 4. Finally, Section 5 concludes.

2. LITERATURE REVIEW

The volatility and stock returns relationship has been extensively examined for the past two decades with minor attention to the Arab Stock Markets. Most investigations were directed to examine such a puzzle in the developed markets without much attention to emerging stock markets that have grown over the past decade and which own features that distinguish them from other stock markets (Harvey, 1995a).

One of the first authors who examined the relation between stock volatility and stock price is Christie (1982). He starts with the assumption of constant firm volatility and notices that the stock volatility is a positive increasing function of financial leverage. Christie (1982) developed risky debt model and found a significant positive association between equity volatility and financial leverage (significant positive slope coefficient). Accordingly, empirical findings support both hypotheses that equity volatility increases with leverage and that the rate at which leverage affects volatility declines as leverage increases. The findings of the second model that explicitly incorporates interest rates, is in contradiction with a part of a dependent claim that supports the hypothesis of negative interest rate volatility relation.

Duffee (1995) (following the steps of Christie (1982) and other authors) proposes another interpretation for the negative relation between stock returns and changes in stock returns volatility. Duffee (1995) examines the relation between stock returns and firm volatility regressions[1] for monthly and daily data frequencies. He finds a negative contemporaneous relation between stock returns and volatility that is much stronger for highly leveraged firms than for less leveraged firms even when current returns and next month's volatility are taken. Although these empirical findings are generally consistent with leverage explanation, they originate from a discovery that is in conflict with leverage effect from a theoretical standpoint. Pure leverage effect cannot be reconciled with any positive type of relationship between stock returns and volatility.

French *et al*. (1987) found evidence of a positive relation between expected risk premium on common stocks (expected return on a stock less than the risk-free interest rate) and the predictable level of volatility. They used ARIMA and GARCH models, which produce little volatility, claiming that their effects on returns are very different. They discovered a strong negative relation between the unpredictable component of stock market volatility and excess holding period returns. The authors argue that if expected risk premiums have a positive relation with a predictable component of stock volatility then unexpected increase in volatility (and upward revision in predicted volatility) increases future risk premiums and lowers current stock prices, causing a negative contemporary relation between returns and changes in volatility. French *et al*. (1987) are oriented to interpret their result as evidence of positive relation between expected risk premium an ex ante volatility confirming the volatility feedback theory.

A spectacular paper by Engle and Ng (1991), introduced the News Impact Curve to measure how new information is incorporated into volatility; they call it EGARCH; a model that differs from the standard GARCH model in two main respects: First one, EGARCH allows good news and bad news to have a different impact on volatility while GARCH model doesn't. Second, EGARCH model allows big news to have much more impact on volatility than GARCH model. The findings of Engle and Ng (1991) were negative shocks that initiate more volatility than positive shocks and that is particularly apparent for the largest shocks.

Lately, the study by Bomfim (2003) introduced new statistical evidence in the U.S. He concluded that U.S stock prices do respond reliably to macroeconomic news

[1] For monthly data, he used Ordinary Least Squares (OLS) and found that an increase in month's stock return by one percentage point corresponds to about 0.40% increase in that month's volatility.

conveyed by monetary policy decision regarding fund rate. Bomfim (2003) explored the relationship between monetary policy and daily stock returns also, emphasizes the potential impact of unanticipated monetary policy on the volatility of stock returns, using simple Bollerslev (1986) GARCH (1,1) process.

Finally, Aggarwal *et al*. (1999), examine in their study the events that cause large shifts in the volatility of emerging markets. The authors first determine when large changes in the volatility of emerging stock market returns occur and then examine events during the period of increased volatility. The Iterated Cumulative Sums of Squares (ICSS) algorithms are used to identify the point of (shocks) sudden changes in the variance of returns in each market. Aggarwal *et al.* (1999) used a GARCH framework and a combined model with GARCH and sudden change in the variance. Aggarwal *et al*. (1999) found that high volatility in emerging markets is identified by several shifts, and large changes in volatility seem to be related to important local political, social and economic and regional events.

However, whether the relationship is positive or negative the debatable and the empirical findings remain questionable, and the insignificant relationship appears puzzling. In what follows we summarize a sample of empirical studies on the relationship between returns and conditional volatility, which we report in Table (3). Conditional volatility studies typically use GARCH models to measure volatility; while gross volatility refers to the standard deviation of daily returns computed over the course of a month and uses OLS estimation. On the other hand, unspecified label means that asymmetry was modeled but the researchers did not specify the exact cause of asymmetry.

3. METHODOLOGY

GARCH and EGARCH models developed by Bollerslev (1986), Nilsson (1991) and Pagan and Schwert (1990), are used to test for the empirical tests. In addition, we use sudden change in the variance model following the footsteps of Aggarwal *et al*. (1999), in an attempt to examine the impact of news on volatility and stock returns[2] for the selected six Arab Stock Markets[3]. The GARCH model is a reliable approach for studying the stochastic behavior of several financial series, in particular, to explore the changing behavior of volatility over time. Moreover, with GARCH models, the conditional mean and volatility of stock returns are assumed to be predictable[4] using past available information at a given point of time such as past returns and past volatility measures. EGARCH model proposed to capture some specifications that are not covered in GARCH model such as the explanatory power of the nonparametric models, because it reflects the asymmetric relation volatility and past returns. In addition to the impact of news, the leverage effects and volatility feedback effect are examined in this paper too.

Generally, with GARCH models, the conditional mean and volatility of stock returns are assumed to be predictable using past available information at a given point of time. The general format of a standard GARCH model can be written as follows:

$$r_t = \mu + \partial h_t^{1/2} + \varepsilon_t \qquad \ldots(1)$$

$$\varepsilon_t / \Omega_{t-1} \sim N\,(0, h_t)$$

$$h_t = \omega + \alpha\varepsilon^2_{t-1} + \beta h_{t-1}$$

where r_t is the stock market return and h_t is the conditional variance equation.

N represents the conditional normal density with mean zero and variance, $\boldsymbol{h_{t-1}}$ and $\boldsymbol{\Omega_{t-1}}$ is the information available up to time t-1.The GARCH models are used to

[2] Respective finance literature papers which studied the impact of news include Anderson and Bollerslev (1998), Jones, Lamont and Lumsdaine (1998), Culter, Poterba and Summers (1989), Bomfim (2003), and many others.

[3] There is a lack of papers which study the Arab Stock Markets. A recent paper by Dahel (2001) studied the volatility in a number of emerging Arab Stock Markets along with some other newly emerged markets and some developed markets.

[4] See e.g. Harvey (1989), and Keim and Stambaugh (1986).

capture volatility observed in a time series and to comment on the relationship between volatility and return through the sign of ∂. The summation of the coefficients for lag squared errors and lagged conditional variance will determine whether volatility is persistent or not, i.e., if $(\alpha+\beta)$ is close to one volatility is persisting**.**

The contemporary returns and the market based volatilities, which we refer to as the volatility feedback, imply that the excess return on the aggregate market portfolio should be positively and directly proportionally related to the volatility of the market[5]. However, empirical findings have reported consistently positive and significant estimates of the risk premium.[6] On the other hand, empirical evaluation of the relationship between returns and contemporaneous volatility has typically found the volatility feedback to be statistically insignificant, and sometimes even negative[7]. Consequently, testing of volatility feedback effect hypothesis is most frequently performed with GARCH-family models. The volatility feedback theory predicts that the coefficient ∂ should be positive and statistically significant. However, to make meaningful interpretation of empirical results we should recall the findings of French *et al*. (1987), in which they state that this negative relation exists between expected volatility and returns and not solely attributed to the effect of leverage. They interpret this negative relation as an evidence of a positive relation between expected risk and ex ante volatility.

Generally, the GARCH model is used to lock up the persistence of observed volatility in a time series. Specifically, the modification of the model to incorporate the sudden change in variance must be considered. In the next part of our empirical study we use the combined GARCH model and sudden change in variance model. Lastrapes (1989) and Lamoreux and Lastrapes (1990) hypothesized that the presence of ARCH is based upon the hypothesis that daily returns are generated by a mixture of distributions, in which the rate of daily information arrivals is the stochastic mixing variables[8]. In brief, this model employs the Iterative Cumulative Sums of Squares logarithms (ICSS)[9] technique to identify discrete shifts in volatility of spot and future prices series by using a modified GARCH model that incorporates the effect of news on market returns volatility. The modification incorporate the effect of news (e.g. wars, financial crises, policy interactions, etc…). The general format of combined GARCH model and sudden change in variance model can be written as:

$$r_t = \mu + \partial h_t^{1/2} + u_t , \qquad \ldots (2)$$

$$\varepsilon_t/\Omega_{t-1} \sim N\ (0, h_t)$$

$$h_t = \omega + d_1 D_1 + \ldots + d_n D_n + \alpha\varepsilon^2_{t-1} + \beta h_{t-1}.$$

Here the conditional variance equation is modified to capture sudden change in volatility. The dummy variables are introduced into the variance equation of the GARCH model to account for sudden change in variance, where $D_1, \ldots, D_n$ are dummy variables that take a value of 1 for each point of sudden change of variance and 0 otherwise.

In order to account for the news effect, Exponential GARCH is used. E-GARCH was first introduced by Nelson (1991) to allow for lagged shocks to have asymmetric effect on conditional volatility. Empirical evidence found that negative shock in returns leads to larger stock volatility than equivalent positive returns (Black, 1976; Christie, 1982; French, Schwert and Stambaugh, 1987; Schwert, 1990). The general format of EGARCH model can be written as:

---

5 See e.g. (Pindyck, 1984).

6 See e.g. (French, Schwert and Stambaugh, 1987; Campbell and Hentschel, 1992).

7 See e.g. (Campbell, 1987; Glosten, Jagannathan and Runkle, 1993).

8 Related work is develped by Inclan and Tiao (1994) and by Aggarwal et al. (1999).

9 The ICSS technique has been used to identify sudden changes in the variance in stock market returns. A GARCH model with sudden variance change dummy variables is found to significantly lower the persistence of volatility.

$$r_t = \mu + \partial h_t^{1/2} + \varepsilon_t, \quad \ldots(3)$$

$$\varepsilon_t / \Omega_{t-1} \sim N(0, h_t)$$

$$Log(h_t) = \omega + \beta . \log(h_{t-1}) + \gamma \cdot (\varepsilon_{t-j} / \sqrt{h_{t-j}}) + \alpha \cdot [|\varepsilon_{t-1} / \sqrt{h_{t-1}} - \sqrt{2/\pi}|]$$

Where ∂, ε_t, ω, β, γ and α, are parameters to be estimated. Among all the parameters to be estimated, the most relevant to this study are the parameters ∂, γ, α and β because the sign and significance of the parameters directly shed light on the nature of the relationship between volatility and stock returns and other hypotheses.

Moreover, equation (3) describes time variation in the conditional second moment's variance. The values of the parameters γ and α, reflect the conditional variance process to respond asymmetrically to positive and negative shocks in returns , if $\gamma < 0$ (>0), such an asymmetry exists and the variance tends to rise (fall) when the shock is negative (positive). The summation of the coefficients for lag squared errors and lagged conditional variance will determine whether volatility is persistent or not, so if α and β sum up or are close to one then volatility persists.

In the presence of the leverage effect, the coefficient γ should be negative and statistically significant. Intuitively, if $\varepsilon_t < 0$ (negative shock to stock price), then the impact on volatility should be greater than in the case of positive shock to stock price (when $\varepsilon_t > 0$). Cheung and Ng (1992) used a similar model, and found that the relation between stock volatility and stock price is negative and significant for two different sets of data, which they interpret as an indication of leverage effect.

Table 1: Aggregate Market Data for the Arab Capital Markets (1994- 2002).

Year	Market Capitalization (Million U.S. $)	No. of Listed Companies	Value Traded (Million U.S. $)	Share Traded Million Share	Velocity of Circulation (%)	AMF Composite index
1994	72536.71	1089	10513.2	3150.05	14.49	100.00
1995	84619.44	1081	14988.4	9590.30	17.71	108.30
1996	107766.49	1091	30529.6	26621.40	28.33	119.93
1997	145562.02	1184	63894.8	35859.00	43.90	138.45
1998	122872.06	1446	35536.4	15837.30	28.92	104.12
1999	149150.33	1634	35594.2	11865.50	23.86	114.31
2000	148158.38	1634	36538.9	9073.06	24.66	102.21
2001	152230.05	1378	42687.8	23522.50	28.04	100.11
2002	208858.11	1687	65400.1	46086.30	31.31	100.71

Source: Arab Monetary Fund, AMDB, Different issues.

Table 2: Aggregate Gross Domestic Product for the Arab Countries (1994- 2002).

Years	GDP (Million$)	GDP Annual Growth Rate (Current Prices) (%)	GDP Annual Growth Rate (Fixed Prices) (%)
1994	497.00	2.20	3.67
1995	548.40	9.40	2.63
1996	600.90	8.70	3.73
1997	723.00	3.70	2.33
1998	604.00	-3.40	4.21
1999	648.00	6.80	2.28
2000	*729.00*	*12.50*	*4.52*
2001	708.10	-2.90	3.92
2002	716.60	1.20	2.97
	Average growth	**4.24**	**3.36**

Source: Arab Monetary Fund. Unified Arab Economic Report, Different Issues**.**

Table 3: Summary of Selected Empirical Studies on Asymmetric Volatility.

Study (Author(s))	***Volatility Measures***	***Presence of Asymmetry***	***Explanation***
Black (1976)	*Gross Volatility*	*Stocks, portfolios*	*Leverage hypothesis*
Christie (1982)	*Gross Volatility*	*Stocks, portfolios*	*Leverage hypothesis*
French, Schwert and Stambaugh (1987)	*Conditional Volatility*	*Index*	*Time-varying risk premium theory*
Schwert (1990)	*Conditional Volatility*	*Index*	*Leverage hypothesis*
Nelson (1991)	*Conditional Volatility*	*Index*	*Unspecified*
Campbell and Hentschel (1992)	*Conditional Volatility*	*Index*	*Time-varying risk premium theory*
Engle and Ng (1993)	*Conditional Volatility*	*Index (Japan Topix)*	*Impact of news*
Glosten, Jagannathan and Runkle (1993)	*Conditional Volatility*	*Index*	*Unspecified*
Duffee (1995)	*Gross Volatility*	*Stocks*	*Leverage hypothesis*
Bekaert and Harvey (1997)	*Conditional Volatility*	*Index (Emerging Markets)*	*General relationship*
Bekaert and Wu (2000)	*Conditional Volatility*	*Index and Portfolio*	*Leverage hypothesis and Feedback effect*
Brandt and Kang (2001)	*Conditional Volatility*	*Index (CRSP)*	*Leverage hypothesis and Feedback effect*
Brooks and Ragunathan (2003)	*Conditional Volatility*	*Stock Index*	*Spillovers,*

Source: Authors' own collection and the study by Bekaert and Wu (2000).

3.1 Data Description and Methodology

The data available are divided into two sets: The first set consists of a monthly average locally index valued in local currency for six ASM; namely , the Bahrain (BSE); Egypt (ESE) ; Jordan (ASE); Kuwait (KSE); Oman (MSM); and Saudi Arabia (SCM) stock exchanges (see appendix A for detailed information). The second set consists of average weekly and monthly Arab Monetary Fund Database (AMDB) index valued in US dollars for the selected sample study. The descriptive statistics for the local monthly prices index are reported in Table (4). The results somehow differ for the AMBD prices index after eliminating the currency exchange rates effect. Results for AMDB are reported in Table (6). Generally speaking, the monotonic relationship between risk and return are not clear in the data from Tables (4 and 6), but the general note is that both returns and volatility are high, a common ingredient in the making of an emerging market. When testing for normality in the data, Jarque-Bera (J-B) test rejects the null hypotheses of normally distributed returns for all the stock markets. In order to shed light on the correlation between the study stock markets, we calculate the correlation matrix between these markets as shown in Tables (5 and 7). Results show that there is week correlation between these markets which can help for hedging purposes and diversifications among them when decisions are to be taken in case of international diversification. The financial time series data are used to estimate equation 1 through 3 to estimate the mean "mean equation" and the conditional variance "variance equation" which is financially interpreted as follows: the variance is predicted by forming the weighted average of long term average (ω), information about volatility observed in the previous period (α), and the forecasted variance from last period (β). Furthermore, when the sum of GARCH estimated coefficient ($\alpha + \beta$) is very close to one, this indicates that volatility shocks are quite persistent. This model is also consistent with the volatility clustering, where large changes in returns are likely to be followed by further large changes. In order to account for sudden changes in variance the Iterative Cumulative Sum of Squares (ICSS) algorithm is used to specify the time when the sudden change in the variance occures[10]. In a time series, it is assumed that if the variance exhibits inactive movement over a specific time period, then there is a sudden change in variance driven by an event affecting the financial market. This process is repeated through time. After determining these points of sudden changes using ICSS, we incorporate them into our GARCH model. This process is repeated using EGARCH.

3.2 Regression Specifications and Tests

Heteroskedasticity Consistent Covariance to compute the Quasi-Maximum Likelihood (QML) covariances and standard error using the method described by Bollerlsev and Wooldrige (1992) is used for all the regerssion runs. In addition, Correlogram Q-statistics of the standardized residuals are carried out to test for the autocorrelation and partial autocorrelation in the mean equation and to check the specification of the mean equation. If the mean equation is correctly specified, all Q-statistics should be insignificant (p-values more than (0.10)). In addition, the Lagrange Multiplier (LM) test is conducted to determine whether there are additional ARCH terms left in the residuals. If the variance equation is correctly specified, there should be no ARCH left in the residuals[11]. These tests are carried on for all model specifications in order to guarentee accuracy of the results.

4. EMPIRICAL RESULTS

Stock market volatility is measured based on stock returns instead of excess stock returns over the risk-free interest rate[12]. Many researchers, such as Baillie and

[10] See Appendix (B) for the chosen points of sudden change in the variance.

[11] This test was first imposed and carried out by Engle (1982).

[12] Because of the absence of reliable risk-free interest rate for most countries in the Arab countries, we use market index returns instead of excess returns.

Degennaro (1990), Nelson (1991), and Lee, Chen and Rui (2001), have argued that such a practice produces little difference in estimation and the results of the two models in which they are used very similar in either the estimated parameters or the fitted variances. Table (8) reports the results of the GARCH in mean models for the AMDB weekly prices index. It appears that some markets seem to have some autocorrelation in residuals such as KSE and MSM. The parameter ∂ shed the light on the nature of the relationship between stock market returns and their volatility. The coefficient ∂ is positive for all markets but positive and significant at the 5% level only for three markets; namely, ASE, BSE, and KSE and are consistent with the findings of French *et al*. (1987) and Campbell and Hentschel (1992)[13]. The results are generally consistent with many previous works, including Baillie and DeGennaro (1990), Poon and Taylor (1992), Odossion and Lee (1995), and Lee, Chen and Rui (2001). In all the countries of the sample, the coefficients alphas and betas are both significant. The sum of the conditional variance equations coefficients are more than one for KSE, MSM, ESE and SCM stock markets indicating extreme persistence in volatility except for ASE and BSE stock markets where they have lower summation of their coefficients. Table (9) reports the results of GARCH (*p,q*)-M regression for local monthly prices index. Apparently, from the residual tests, autocorrelation still exists in few markets. ARCH-LM tests were carried out and the test results confirmed that there is no additional ARCH effect in the residuals for all markets. Table 9 shows that the volatility is persistent in almost all markets. In five of the six countries series the coefficients alpha and beta are not significant at the same time. They have either the alpha or beta coefficient significant but not both. Volatility is persistent in four markets and statistically significant (ASE, BSE, KSE, and MSM) except for ESE and SCM markets. The sum of the conditional variance equations are more than one for ASE, BSE,KSE, and SCM stock markets indicating extreme persistence in volatility except for ESE and SCM stock markets where they have lower summation of their coefficients.

The results obtained from estimating GARCH models using price index in U.S. dollars are similer to the results obtained for the same period using price index in local currency in explaining the relationship between stock market returns and volatility. Results show negative relationships between stock returns and their volatility for five markets, but, none of ∂ parameters estimated is statistically significant at any conventional level, with the exception of MSM which is significant at ten percent level. This finding is also documented by Nelson (1991).

Table (10) presents the EGARCH estimation for the weekly AMDB prices index. It shows that, the coefficient ∂ is positive in three markets and negative for three other markets but none are statistically significant at any conventional significance level, with the exception of the BSE. In addition, the γ parameters estimation is significant at one percent significance level for only BSE. The sign of γ is positive and negative suggesting an asymmetric response of conditional variances to negative and positive stock returns innovation in these markets. Remarkably, empirical evidence along confirms the findings, which confirm that market volatility responds asymmetrically to positive and negative returns, but unfortunately not always significant. Similar findings are reported by Swhert (1989), Nelson (1991), Glosten et al. (1993), Engle and Ng (1993), Dufee (1995) and Bekaert and Wu (2000).

Table (11) presents the EGARCH (*p, q*)-M estimation for the monthly local prices index. The coefficient ∂ is positive in four markets and statistically significant at five and ten percent level. This may be interpreted as an evidence for a significant positive relationship between stock market returns and volatility in ASM. In all the countries of the sample, the coefficients alpha and beta are both significant. The sum of the conditional variance equation coefficients are more than one for KSE, MSM, ESE, SCM and SCM stock markets indicating extreme persistence in volatility except for ASE stock market where they have lower summation of their coefficients.

13 Poon and Taylor (1992) and Glosten *et al.* (1993) documented positive relationship but insignificant estimates.

It's worth mentioning that the results obtained from estimating GARCH model and EGARCH model are not the same, which are consistent with the findings by Engle and Ng (1991). Moreover, the γ parameter estimates are positive in four markets and are statistically in two. This indicates that there is an asymmetric response of conditional variances to negative and positive stock returns innovations in these markets. Furthermore, leverage effects are found in three markets and statically significant. As a final remark, we perform the estimation using different data frequency. It is conceivable that volatility estimated from weekly data is more precise than GARCH volatility estimated from monthly data simply because of the higher frequency of weekly data[14]. While in some respects, this is precisely one of the points of this paper puzzles simply because volatility estimates from high frequency data must be more reliable than the more complicated volatility estimates from GARCH low frequency data, we would still like to confirm that the results in this paper are not artifacts of the large frequency difference between monthly and weekly data.

The effect of news is examined by specifiying the points of shifts in volatility in the stock market price index returns and by determining the events that are associated with the increase in volatility (see Appendix b). Appendix b lists the estimated number of changes in variance and the point in time of each variance shift using the ICSS algorithm presented by Inclan and Tiao (1994).

Results show that the high volatility markets are marked by several shifts in the variance. As an example, there were twelve significant shifts in volatility in KSE during the study period. The changes in volatility seem to be related to important country political, economic and regional events. As seen from Appendix b, the number of changes in the variance varies from country to country and the number of changes depends upon the frequency of the data[15].

Table (12) presents the results obtained from estimating model (3). The model is estimated after accounting for the shift-dummies in the GARCH model representation to test the impact of sudden changes in the variance on the parameters of the estimated model. The results are as follows: in four out of six markets α and β are both significant in the modified GARCH model , in the two remaining markets namely the ASE and BSE, only β is statistically significant. In addition, the sum of GARCH coefficients is close to one implying extreme persistence in volatility in all markets. Moreover, the statistically significant dummy variable coefficients, found in three markets, imply that "news" affects the volatility of stock returns, a result consistent with the findings of Bomfim (2003), Aggarwal et al. (1999) and Jones et al. (1998).

5. CONCLUSIONS

This paper investigates empirically the relationship between stock market returns and volatility. The paper extends by incorporating the effect of news, the feedback effect , leverage effect, and by utilizing the Iterative Cumulative Sum of Squares (ICSS) algorithm to account for sudden changes in the variance. We assume that the variance exhibits inactive movement over a specific time period, then there is a sudden change in variance driven by an event affecting the financial market. This process is repeated through time.

Throughout this paper we document a positive and significant relationship between volatility and returns in the tested ASM markets. Statistically positive relationship rules in almost all markets. The positive relation implies that, the increase (decrease) in the price index is associated with an increase (decrease) in the volatility of returns. Our findings are consistent with the predictions of many assets pricing models (Sharpe, 1964;

[14] The main results of Andersen and Bollerslev (1997) study hing on the effective use of frequently sample data in constructing accurate ex ante volatility measurement.

[15] More changes were found in the weekly returns than in the monthly returns. For this reason only the weekly data are examined.

Linter, 1965; Metron, 1973). Also they contradict the empirical findings of an insignificant relation reported in the literature (Baillie and DeGennaro, 1990; Nelson, 1991; Poon and Taylor, 1992; Theodossion and Lee, 1995; Lee, Chen and Rui, 2001).

Table 4: Monthly Local Price Index Returns in Local Currency (1994-2003).

	ASE	BSE	KSE	MSM	ESE	SCM
Mean	0.00622	0.00477	0.01610	0.00755	0.01553	0.01887
Median	-0.00130	0.00349	0.01276	0.00673	0.00751	0.01352
Maximum	0.11086	0.13278	0.20254	0.20271	0.25448	0.51984
Minimum	-0.06424	-0.08765	-0.10939	-0.12587	-0.08150	-0.11079
Std. Dev.	0.03675	0.03858	0.05026	0.06031	0.04772	0.07012
Skewness	0.48712	0.20076	0.19791	0.60953	1.97742	3.87027
Kurtosis	2.62541	3.82205	4.27934	4.06002	9.70108	28.6710
Jarque-Bera	4.90262	3.76641	8.070285	11.7439	239.658	2845.71
Probability	0.08618	0.15210	0.017683	0.00282	0.00000	0.00000
Observations	108	108	108	108	95	95

Source: Authors' own calculations.

Table 5: Local Monthly Prices Index Correlation Matrix.

	ASE	BSE	KSE	MSM	ESE	SCM
ASE	1					
BSE	0.2117	1				
KSE	0.2167	0.3956	1			
MSM	0.0837	0.2979	0.3294	1		
ESE	0.0469	0.0362	0.0237	0.1441	1	
SCM	0.1450	0.2010	0.1791	0.0799	0.1468	1

Source: Authors' own calculations.

Table 6: Weekly AMDB Price Index Returns in US Dollar (1994-2003).

	ASE	BSE	KSE	MSM	ESE	SCM
Mean	0.00056	0.00030	0.00118	-0.00015	-0.00202	0.00101
Median	-0.00017	0.00012	0.00030	0.00000	-0.00056	0.00057
Maximum	0.08049	0.13837	0.23391	0.14654	0.20839	0.06810
Minimum	-0.06410	-0.34316	-0.21849	-0.14805	-0.24565	-0.07008
Std. Dev.	0.01615	0.02320	0.02579	0.02631	0.03238	0.01895
Skewness	0.66302	-6.52826	0.01598	0.59561	-0.48223	-0.09744
Kurtosis	6.09677	106.105	30.3655	10.5519	17.6262	5.35959
Jarque-Bera	227.439	216475	15008.6	1171.43	3715.21	97.1641
Probability	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000
Observations	481	481	481	481	415	416

Source: Authors' own calculations.

Table 7: Weekly AMDB Prices Index Correlation Matrix.

	ASE	BSE	KSE	MSM	ESE	SCM
ASE	1					
BSE	0.0737	1				
KSE	0.0568	0.0043	1			
MSM	-0.0152	0.0006	-0.0262	1		
ESE	-0.0171	0.0519	-0.0108	-0.0089	1	
SCM	0.0384	0.0157	-0.0118	0.0820	0.0545	1

Source: Authors' own calculations.

Table 8: GARCH (1,1) Estimation Results Models. The return series (rt) is the AMDB weekly prices index returns. Sample period is from 30:12:1994 - 30:12:2003.

	Equation for Mean		Equation for Variance			Residual Test for Correlation				
	μ	∂	ω	α	β	$\rho_{(1)}$	$\rho_{(8)}$	$\rho_{(12)}$	$\rho_{(24)}$	$\rho_{(36)}$
ASE GARCH(1,1)	-0.45	0.074**	0.01***	0.1526**	0.0067	1.94 (0.17)	5.253 (0.73)	9.64 (0.65)	16.37 (0.88)	25.88 (0.87)
BSE GARCH(1,1)	-2.52***	0.292**	8.784**	0.101***	0.063	0.19 (0.68)	3.12 (0.93)	6.43 (0.89)	11.76 (0.98)	21.62 (0.97)
KSE GARCH(1,1)	-0.004	7.574**	0.002**	0.366**	0.312**	0.43 (0.52)	13.07 (0.11)	15.14 (0.23)	39.14 (0.09)	48.77 (0.08)
MSM GARCH(1,1)	0.068	0.001	.0139**	0.309**	0.754***	3.57 (0.06)	26.76 (0.01)	31.88 (0.01)	56.82 (0.00)	67.38 (0.01)
ESE GARCH(1,1)	-0.002*	0.267	0.0001	0.232**	0.733***	0.05 (0.81)	2.50 (0.96)	8.75 (0.64)	14.20 (0.94)	18.19 (0.99)
SCM GARCH(1,1)	0.144	-0.004	1.156**	0.242***	0.448**	0.08 (0.08)	11.20 (0.19)	13.97 (0.30)	26.93 (0.31)	**35.63** (**0.48**)

Note: (*), (**), and (***) are significant at 10%, 5%, and 1%, respectively. *P* values are in parenthesis.

Table 9: GARCH (1,1) Estimation Results. The return series (rt) is the AMDB local monthly prices index returns. Sample period is from 30:12:1994 - 30:12:2003.

	Equation for Mean		Equation for Variance			Residual Test for Correlation				
	μ	∂	ω	α	β	$\rho_{(1)}$	$\rho_{(8)}$	$\rho_{(12)}$	$\rho_{(24)}$	$\rho_{(36)}$
ASE GARCH(1,1)	-0.044	37.89	0.001*	0.105	0.091	0.46 (0.49)	4.47 (0.78)	8.59 (0.73)	21.40 (0.61)	28.03 (0.82)
BSE GARCH(1,1)	0.22	-0.001	19.98**	0.168*	-0.47*	1.30 (0.25)	3.10 (0.92)	11.08 (0.52)	20.70 (0.65)	40.22 (0.28)
KSE GARCH(1,1)	0.014**	-2.006	0.01***	0.456**	-0.282**	13.28 (0.00)	29.82 (0.00)	61.96 (0.00)	71.19 (0.00)	89.92 (0.001)
MSM GARCH(1,1)	0.018***	-1.811*	0.000	0.436**	0.524***	6.36 (0.02)	18.57 (0.02)	22.70 (0.03)	37.11 (0.04)	41.45 (0.24)
ESE GARCH(1,1)	0.012**	-0.0211	0.000	0.087	0.901***	5.98 (0.03)	9.89 (0.27)	10.40 (0.58)	27.03 (0.57)	27.86 (0.83)
SCM GARCH(1,1)	0.036	-4.881	4.7E-05	-0.034	1.022***	9.48 (0.02)	16.54 (0.04)	14.82 (0.07)	29.18 (0.19)	32.46 (0.63)

Note: (*), (**), and (***) are significant at 10%, 5%, and 1%, respectively. *P* values in parenthesis

Table 10: EGARCH(p,q) Estimation Results. The return series (rt) is the AMDB weekly prices index returns. Sample period is from 30:12:1994 - 30:12:2003.

	Equation for Mean		Equation for Variance					Residual Test for Correlation				
	μ	∂	ω	α	β_1	β_2	γ	$\rho_{(1)}$	$\rho_{(8)}$	$\rho_{(12)}$	$\rho_{(24)}$	$\rho_{(36)}$
ASE EGARCH(1,1)	0.003	-12.82	-22.33**	0.175**	-0.75***	-	-0.0614	0.22 (0.64)	3.37 (0.91)	6.55 (0.88)	11.94 (0.98)	22.08 (0.96)
BSE EGARCH(1,2)	0.002**	-11.03**	-15.26**	0.448***	0.073*	-0.92***	0.223***	2.14 (0.15)	5.36 (0.72)	10.46 (0.58)	28.08 (0.26)	37.64 (0.40)
KSE EGARCH(1,1)	-0.003	6.421	-2.83**	0.57**	0.67***	-	0.101	0.96 (0.33)	14.25 (0.08)	16.30 (0.13)	36.32 (0.08)	49.04 (0.08)
MSM EGARCH(1,1)	-0.0932	-0.013	-0.18**	0.402***	0.95***	-	-0.071	3.57 (0.06)	26.76 (0.001)	31.88 (0.001)	56.82 (0.00)	67.38 (0.001)
ESE EGARCH(1,1)	-0.003	0.814	-1.013	0.347**	0.884***	-	0.047	0.10 (0.74)	2.76 (0.94)	9.39 (0.58)	14.92 (0.92)	18.41 (0.99)
SCM EGARCH(1,1)	0.064	2.642	-3.01*	0.411**	0.664**	-	-0.055	2.94 (0.08)	12.26 (0.14)	14.83 (0.25)	27.41 (0.28)	**36.77 (0.43)**

Table 11: EGARCH(p,q) Estimation Results. The return series (rt) is the AMDB local monthly prices index returns. Sample period is from 30:12:1994 - 30:12:2003.

	Equation for Mean		Equation for Variance					Residual Test for Correlation				
	μ	∂	ω	α	β_1	β_2	γ	$\rho_{(1)}$	$\rho_{(8)}$	$\rho_{(12)}$	$\rho_{(24)}$	$\rho_{(36)}$
ASE EGARCH(1,2)	-4.01*	0.36**	1.39**	0.34**	-0.05	0.388*	0.07	0.12 (0.71)	4.93 (0.73)	7.65 (0.81)	22.18 (0.56)	26.44 (0.87)
BSE EGARCH(1,1)	-0.99	0.088**	0.26***	-0.22**	0.95***	-	-0.039	0.50 (0.81)	2.72 (0.95)	7.85 (0.79)	16.08 (0.88)	27.95 (0.82)
KSE EGARCH(1,1)	-0.09**	1.15**	3.3**	0.60**	-0.23	-	0.159**	15.41 (0.00)	39.52 (0.01)	72.14 (0.00)	78.50 (0.00)	101.73 (0.00)
MSM EGARCH(1,1)	0.018***	-2.5*	-0.72*	0.76**	0.98***	-	-0.099	7.00 (0.01)	18.42 (0.02)	22.41 (0.04)	35.82 (0.06)	40.41 (0.28)
ESE EGARCH(1,1)	-0.022	20.12*	-3.12	-0.26	0.47*	-	0.42	0.92 (0.33)	8.80 (0.35)	12.45 (0.41)	29.16 (0.19)	43.68 (0.17)
SCM EGARCH(1,1)	0.100***	-18.24	-5.06***	-0.27	0.036	-	-0.28*	0.04 (0.82)	2.72 (0.95)	7.85 (0.79)	16.08 (0.88)	27.95 (0.82)

Table 12: Combined GARCH and Sudden Change in Variance Model "The Effect of News".

	Equation for Mean		Equation for Variance			
	μ		ω	α	β_1	***Dum***
ASE GARCH(1,1)	0.0041		0.0001*	-0.014	0.836***	0.0003*
BSE GARCH(1,1)	0.0011		0.0034*	0.094	0.493***	-0.0067**
KSE GARCH(1,1)	-0.0013		0.0001**	0.410*	0.446***	-0.0005*

	Equation for Mean		Equation for Variance			
	μ		ω	α	β_1	***Dum***
MSM GARCH(1,1)	0.0002		0.0001*	0.2561**	0.781***	-0.0005
ESE GARCH(1,1)	-0.0021*		0.0009*	0.289*	0.721***	-0.0002
SCM GARCH(1,1)	0.0011		0.0009**	0.218**	0.555***	-0.0001

Appendix A

Arab Stock Markets Participating in the Arab Monetary Fund Data Base.

Country	Arab Stock Market	Stock Market Code	Opening Date
Bahrain	Bahrain Stock Exchange	BSE	1989
Egypt	Egypt Stock Exchange	ESE	
(1)	Alexandria Stock Exchange	ASE	1888
(2)	Cairo Stock Exchange	CSE	1903
Jordan	Amman Sock Exchange	ASE	1976
Kuwait	Kuwait Stock Exchange	KSE	1962
Oman	Muscat Securities Market	MSM	1989
Saudi Arabia	Saudi Capital Market	SCM	1984

Source: Arab Monetary Fund, AMDB, Different Issues.

Appendix B

Sudden Changes in Variance.

Market	No. of Sudden Change	Period	Events
ASE	**Seven**	11/05/95-06/07/95 18/07/96-22/08/96 04/12/97-25/12/97 02/04/98-23/04/98 28/01/99-01/04/99 02/11/00-23/11/00 09/01/03-27/03/03	
BSE	**Ten**	04/05/95-08/06/95 18/07/96-12/09/96 06/03/97-10/04/97 23/04/98-18/06/98 22/04/99-13/05/99 20/01/00-23/03/00 20/09/01-25/10/01 17/01/02-28/02/02 13/02/03-06/03/03 13/11/03-04/12/03	

KSE	**Twelve**	27/07/95-05/10/95 02/11/95-07/12/95 04/04/96-09/05/96 06/03/97-05/06/97 04/12/97-15/01/98 12/03/98-30/04/98 05/11/98-18/02/99 07/10/99-11/11/99 30/03/00-04/05/00 20/06/02-25/07/02 24/10/02-12/12/02 08/05/03-12/06/03	
MSM	**Twelve**	08/06/95-13/07/95 11/04/96-09/05/96 18/07/96-29/08/96 03/04/97-08/05/97 11/09/97-05/02/98 02/04/98-28/05/98 19/11/98-06/05/99 01/07/99-22/07/99 20/01/00-23/03/00 01/03/01-26/04/01 17/01/02-14/03/02 19/06/03-24/07/03	
ESE	**Thirteen**	05/09/96-07/11/96 05/12/96-16/01/97 18/12/97-22/01/98 07/01/99-25/02/99 25/03/99-24/06/99 09/09/99-04/11/99 03/02/00-20/04/00 21/09/00-23/11/00 19/07/01-23/08/01 13/09/01-25-10/01 25/04/02-06/06/02 18/07/02-12/09/02 18/09/03-06/11/03	
SCM	**Ten**	06/02/97-20/03/97 29/05/97-26/06/97 23/07/98-24/09/98 22/04/99-20/05/99 02/12/99-06/01/00 18/05/00-29/06/00 01/03/01-29/03/01 05/07/01-16/08/01 22/11/01-24/01/02 14/11/02-05/12/02	

REFERENCES

Aggarwal, R. Inclan, C. and Leal, R. 1999. Volatility in Emerging Stock Markets. ***Journal of Financial and Quantitative Analysis***, 34: 33-55.

Andersen, Torben, G. and Bollerslev T. 1997a. Heterogeneous Information Arrivals and Return Volatility Dynamics: Uncovering the Long Run in High Frequency Returns. ***Journal of Finance,*** 52: 975–1005.

Andersen, T. and Bollerslev, T. 1997b. Answering the Critics: Yes ARCH Models Do Provide Good Volatility Forecast, ***Working Paper***, NBER.

Andersen, T. and Bollerslev, T. 1998. Answer the Skeptics: Yes, Standard Volatility Models do Provide Accurate Forecasts. ***International Economic Review***, 39: 885-905.

Andersen, T., Bollerslev, T., Diebold, T. and Ebens H. 2001. The Distribution of Realized Stock Return Volatility. ***Journal of Financial Economics***, 61 (43): 76.

Andersen, T. and Sorensen, B. 1996**.** GMM Estimation of a stochastic Volatility Model: A Monte Carlo study. ***Journal of Business and Economics Statistics***, 14 (3): 328-353.

Arab Monetary Fund Database, Arab Monetary Fund, Different Issues.

Baillie, R. and Bollerslev, T. 1989. Common Stochastic Trends in a System of Exchange Rate. ***Journal of Finance***, 44: 181-167.

Baillie, R. and Degennaro, R. 1990. Stock Returns and Volatility, ***Journal of Financial and Quantitative Analysis***, 25: 203-214.

Baillie, Richard, T. and Bollerslev, T. 1992. Prediction in Dynamic Models with Time-Dependent Conditional Variances. ***Journal of Econometrics,*** 52: 91–113.

Barrett, D. 1996. ***Stock Market Volatility - A Psychological Phenomenon***?, http://www.economics.tcd.ie/ser/1996/barret.htm.

Bekaert, G., Harvey, C.R. 1997. Emerging Equity Market Volatility. ***Journal of Financial Economics***, 43: 29-77.

Bekaert, G. and Wu, G. 2000. Asymmetric Volatility and Risk in Equity Markets, ***The Review of Financial Studies***, 13 (1): 1-42.

Black, F. 1976. Studies of Stock Price Volatility Changes, ***Proceedings of the 1976 Meetings of the American Statistical Association, Business and Economic Statistics Section***.

Bollerslev, T., Engle, R. and Woodridge, M. 1988. A Capital Asset Pricing Model with Time Varying Covariances. ***Journal of Political Economy***, 96: 116-113.

Bollerslev, T., Woodridge, M. 1992. Quasi-Maximum Likehood Estimation and Inference in Dynamic Models with Time Varying Covariances. ***Econometrics Review***, 11: 143-172.

Bollerslev, T., Engle, F. and Nelson, D. 1994. ARCH Models. in ***Handbook of Econometrics,***. 4 (R.F. Engle and D. McFadden, eds.), Amsterdam: North Holland Press.

Bollerslev, T., Chou, Y. and Kroner, F. 1992. ARCH Modeling in Finance: A Review of the Theory and Empirical Evidence. ***Journal of Econometrics,*** 52: 5-59.

Bollerslev, T. 1986. Generalized Autoregressive Conditional heteroskedasticity. ***Journal of Econometrics***, 31: 307-327.

Bomfim, A. and Reinhart, R. 2000. ***Making News: Financial Market Effects of Federal Reserve Disclosure Practices***. Manuscript, Federal Reserve Board.

Bomfim, A. 2003. Pre-announcement Effects, News Effects, and Volatility: Monetary Policy and the Stock Market. ***Journal of Banking and Finance***, 27: 133-151.

Brandt, W. and Kang, Q. 2001. On the Relationship between the Conditional Mean and Volatility of Stock Returns: A Latent VAR Approach, ***Working Paper***, University of Pennsylvania.

Brooks, D. and Ragunthan, V. 2003. Returns and Volatility on the Chinese Stock Markets. ***Applied Financial Economics***, 13: 747-752.

Campbel, Y. and Hentschel, L. 1992. No News is Good News: An Asymmetric Model of Changing Volatility in Stock Returns. ***Journal of Financial Economics***, 31: 281-318.

Changli, H. 2000. Moments and the Autocorrelation Structure of the Exponential GARCH (p,q) Process, ***Working Paper of The Economic Research Institute***, Stockholm School of Economics.

Cheung, Yin-Wong, and Ng, K. 1992. Stock Price Dynamics and Firm Size: An Empirical Investigation. ***Journal of Finance,*** 5: 1985-1997.

Chou, Y. 1988. Volatility Persistence and Stock Valuations: Some Empirical Evidence Using GARCH. ***Journal of***

Econometrics, 3: 279-294.

Chou, R., Engle, F. and Kane, A. 1992. Measuring Risk, Aversion from Excess Returns on a Stock Index. ***Journal of Econometrics,*** 52: 201–224.

Christie, A. 1982. The Stochastic Behavior of Common Stock Variances: Value, Leverage and Interest Rate Effects. ***Journal of Financial Economics***, 10: 407-432.

Dahel, R. 1999. Volatility in Arab Stock Markets, ***Working Paper***, Arab Planning Institute, Kuwait.

Darrat, F., Rahman, S. and Zhong M. 2003. Intraday Trading Volume and Return Volatility of the DJIA Stocks: A Note. ***Journal of Banking and Finance***, 27:2035-2043.

Duffee, R. 1995. Stock Returns and Volatility: A Firm Level Analysis. ***Journal of Financial Economics***, 37: 399-420.

Ederington, H. and Lee, J. 1993. How Markets Process Information: News Releases and Volatility. ***Journal of Finance***, 48: 1161-1191.

Ehrlich, I. 1994. Productivity Growth and Firm Ownership: An Analytical and Empirical Investigation. ***Journal of Political Economy***, University of Chicago Press, 102 (5): 1006-38.

Engle, F. and Ng, V. 1993. Measuring and Testing the Impact of News on Volatility. ***Journal of Finance***, 48/5:1749-1778.

Engle F., Lilien, D. and Robins, R. 1987. Estimating Time Varying Risk Premia in the Term Structure: The ARCH-M Model. ***Econometrica,*** 55: 391–407.

Engle, F. and Granger, C. 1987. Cointegration and Error Correction: Representation, Estimation and Testing. ***Econometrica***, 55: 251-76.

Engle, F. 1982. Autoregressive Conditional Heteroskedasticity with Estimates of the Variance of United Kingdom Inflation. ***Econometrica,*** 50: 987-1007.

French, K., Schwert, W. and Stambaugh, R. 1987. Expected Returns and Volatility. ***Journal of Financial Economics***, 19: 3-29.

Glosten, R., Jagannathan, R. and Runkle, D. 1993. On the Relation between the Expected Value and the Volatility of Nominal Excess Return on Stocks. ***Journal of Finance***, 48: 1779-1801.

Hansen, P. 1982. Large Sample Properties of Generalized Method of Moments Estimators. ***Econometrica,*** 50: 1029-1054.

Harvey, C. 1989. Time-Varying Conditional Covariances on Tests of Asset Pricing Models. ***Journal of Financial Economics,*** 24: 289–317.

Inclan, C. and Tiao, G. 1994. Use of Cumulative Sums of Squares for Retrospective Detection of Changes of Variance. ***Journal of the American Statistical Association,*** 89: 913-923.

Jones, C., Lamont, O. and Lumsdaine, R. 1997. Macroeconomic News and Bond Market Volatility. ***Journal of Financial Economics***, 47:315-337.

Lamoureux, C., Lastrapes, W. 1991. Heteroskedasticity in Stock Return Data: Volume versus GARCH Effect. ***Journal of Finance***, 45: 221-229.

Lastrapes, D. 1989. Exchange Rate Volatility and U.S. Monetary Policy. ***Journal of Money, Credit and Banking,*** 21: 66-77.

Lee C., Chen G. and Rui O. 2001. Stock Returns and Volatility on China's Stock Markets. ***Journal of Financial Research***, 24 (4): 523-543.

Linter, J. 1965. The Valuation of Risky Assets and the Selection of Risky Investments in Stock Portfolios and Capital Budgets. ***Review of Economics and Statistics,*** 47: 13-37.

Mecagni and Sourial. 1999. The Egyptian Stock Market: Efficiency Tests and Volatility Effects. ***IMF Working Paper***, (April, 1999).

Megginson, W. and Netter, J. 2001. From State of Market: A Survey of Empirical Studies of Privatization. ***Journal of Economic Literature***, 39: 321-389.

Merton, R.C. 1973. An Intertemporal Capital Asset Pricing Model. ***Econometrica,*** 41: 867-887.

Merton, C. 1980. On Estimating the Expected Return on the Market. ***Journal of Financial Economics***, 8: 323-361.

Nelson, D. 1991. Conditional Heteroskedasticity in Asset Returns: A New Approach. ***Econometrica***, 59: 347-370.

Newey, W. 1985. Generalized Method of Moments Specification Testing. ***Journal of Econometrics,*** 29: 229-256.

Pagan, A., Schwert, W. 1990. Alternative Models of Conditional Stock Volatility. ***The Journal of Econometrics***, 45: 267-90.

Pindyck, S. 1984. Risk, Inflation, and the Stock Market. ***American Economic Review***, 76: 1142-1151.

Poon, S. and Taylor, S. 1992. Stock Returns and Volatility: An Empirical Study of the UK Stock Market. ***Journal of Banking and Finance***, 16: 37-59.

Qi, L. Jian, Y. and Cheng, H. 2003. The Relationship between Stock Returns and Volatility in International Stock Markets. ***Working Paper***, Texas A & M University, and Private Enterprise Research Center.

Schwert, W. 2002. Stock Volatility in the New Millennium: How Wacky is Nasdaq? ***Journal of Monetary Economics***, 49: 3-26.

Schwert, W. 1989. Why Does Stock Market Volatility Change Over Time? ***Journal of Finance***, 5: 1115-1153.

Schwert, W. and Seguin, S. 1990. Heteroskedasticity in Stock Returns. ***Journal of Finance,*** 45: 1129-1155.

Sharpe, F. 1964. Capital Asset Prices: A Theory of market Equilibrium Under Conditions of Market Risk. ***Journal of Finance***, 19: 425-442.

Tauchen, G. 1987. Statistical Properties of Generalized Method of Moments. ***Journal of Business and Economic Statistics,*** 4: 397-425.

Theodossiou, P. and Lee, U. 1995. Relationship between Volatility and Expected Returns Across International Stock Markets, ***Journal of Business Finance and Accounting***, 22: 289-300.

Unified Arab Economic Report, Arab Monetary Fund, Different Issues.

Wooldridge, M. 1990. A Unified Approach to Robust, Regression-based Specification Tests, ***Econometric Theory***, 6: 17-43.

التذبذب في عوائد الأسهم : دليل من الأسواق الصاعدة

سامر الرجوب وزملاؤه*

ملخص

تفحص هذه الدراسة العلاقة بين عوائد الأسهم و التذبذب فيها، بالإضافة الى قياس" استمرار التذبذب" في الفترة الواقعة بين 1992 و2002 لأسواق ست دول صاعدة. تم استخدام اسلوب GARCH in mean وExponential GARCH كما تم فحص هذه النماذج بعد تعديلها "للتغيير المفاجئ" خلال تلك الفترة.

دلت النتائج الإحصائية على وجود العلاقة النظرية بين العائد والمخاطرة للأسواق قيد الدراسة. وبعد التعديل لاحتمالية أي تغيير مفاجئ في التباين خلال فترة الدراسة باستخدام طريقة Iterative Cumulative Sums of Squares (ICSS) بقيت العلاقة الإيجابية المستمرة بين العائد والمخاطرة موجودة.

Samer A.M. Al-Rjoub
Assistant Professor of Finance, Department of Banking and Finance, Hashemite University, Zarqa, Jordan.

Khaled Alzubi
Assistant Professor of Finance, Department of Banking and Finance, Hashemite University, Zarqa, Jordan.

Morad Autair
Arab Bank, Irbid-Jordan.

تاريخ استلام البحث 2005/4/17، وتاريخ قبوله 2005/11/17.