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CHAOS AND NON-LINEARITY IN THE SAUDI STOCK MARKET

Key Words

Saudi Share Index; Low-Dimensional Chaotic Dynamics; GARCH; TGARCH; Volatility; Long Memory.

Abstract

This study investigates the statistical properties of the Saudi nominal stock returns using weekly data for the period March 1985- December 1997. The study provides estimates of GARCH and TGARCH models for the full sample and the sub-periods prior to and after the price correction occurrence at the end of 1992. The study takes into account the effect of the Gulf war and the shift in volatility observed in the first sub-period. It is demonstrated that the observed significant effect of bad news in stock returns on volatility for the whole sample is mainly due to the second sub-period. While the statistics of the semi-parametric of Geweke and Porter-Hudak (1983), denoted by GPH test indicate that the stock returns exhibit no long-memory for the various sample periods considered, the results of the BDS test, Brock, Dechert and Scheinkman (1987), generally point to the presence of low- dimensional chaotic dynamics in the sub-period prior to the price correction.

Introduction

The interest in developing a stock market in Saudi Arabia is not newly borne; it goes back as far as 1935 when the society of Saudi Arabia experienced the floatation of the Arabian Automobile Company. This was necessary to provide the cash that match up with the increasing pressure on the company to import more automobiles. Since then and up to 1975, there have been a few attempts to privatize certain companies such as electricity and cement. Apart from these few attempts at privatization, which were initiated by a small number of self-interest investors, the idea of

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establishing an organized stock market that encompasses more players came into practice towards the beginning of the 1980's. During the 1970's, and in particular after the first oil shock, the oil prices reached unprecedented levels which generated a surplus of oil proceeds in the hand of the government. To share this windfall with the public, the government established certain tactics for distributing the oil wealth. One method is the engagement in massive infrastructure projects necessary for economic development. Another way of filtering out wealth, which sparked the interest of people in the stock market, is by offering shares to the public at par value that is much less than the market.

The Saudi share index is prepared by the National Center for Financial and Economic Information at the Ministry of Finance. It is published in weekly format for the period from March 1985 to December 1997. It comprises 71 companies distributed among various sectors of the economy. These sectors are Agriculture, Banking, Cement, Electricity, Industry and Services. Trading in Shares is limited to Saudi nationals.

The general index starts decreasing slowly from the initial value and up to the beginning of January 1987 where it starts to rise in a slow base up to the end of July 1990. Due to the isolation of the Saudi stock market, the great crash of August 1987 in the major international stock markets did not affect the index. After August 1989 when the Iran-Iraq cease-fire came into effect the base of growth of the index started to accelerate. This growth was, however, interrupted by Iraq's invasion of Kuwait. Although the Gulf crisis started in August 1990 and lasted until the third week of February 1991, the impact of this crisis on the market was felt in the last three weeks of August 1990 only, where the index dropped sharply registering high negative returns. However, the rapid deployment of armed forces of the coalition led by the US to dislodge the Iraqis out of Kuwait assured the psychology of the market as early as the first week of December 1990. Since then the index started to ascend signaling the restoration of confidence in the post-crisis economy of the kingdom. This index continued rising over the year 1991 to reach its climax in the second week of May 1992 and stayed high until the fourth week of September of the same year. After that the index started to show symptoms of a crash. The intervention of the government was inevitable and, therefore, it is instituted that the maximum limit of daily price change for a single stock from its opening level is 10%, and if it moves towards this limit trading in that stock faces suspension for the day. The Saudi stock market is essentially driven by liquidity and it is similar in character to the Japanese market where valuation concept is secondary to speculative trading (Banafe,1993). Therefore, the institutional change was aimed at stabilizing the unconditional volatility of the stock returns. The collapse in the prices observed at the end of 1992 is regarded as a price correction and it is attributed to several factors. One major factor is the proliferation of shares in the banking sector. Some investors responded by cashing in their holdings and heavily oversubscribed in these primary issues in anticipation of higher speculative returns and better corporate earnings in this sector (Banafe, 1993). This move spread the risk of capital loss across other sectors and, therefore, some investors transfered their holdings to deposits satisfied with the returns of the risk-free interest rate. Another factor which contributed to the occurrence of the correction phase was the "Fatwa" issued by some religious leaders declaring that while interest rate was Islamically prohibited, speculation was not any different from gambling, which is also frowned upon by Islamic laws. This left some investors with land, real estate sector, and other trading activities as the only available instruments for absorbing their liquidity.

In this study we investigate the time series characteristics of the Saudi stock market using weekly data, from Saturday morning to Thursday midday, for the period 1985 to 1997. In particular the stock returns will be modeled using GARCH and TGARCH. The sensitivity of the estimated parameters to change in the sample period is uncovered by estimating these models for the sub-periods prior to and after the price correction observed at the end of 1992. To investigate the chaotic behavior of the stock market, all standardized residuals of the estimated models for the various sample periods will be subjected to testing for left-over non-linearity using Brock, Dechert and Scheinkman (1987) as well as to the consistency test for heteroscedasticity of Pagan and Sabau (1988). Therefore, this study is divided into further three sections. Section 2 provides descriptive statistics including testing for stationarity and long memory. Section 3 presents GARCH and TGARCH models used in estimation and discusses the results, while concluding remarks are given in Section 4.

Descriptive statistics

The nominal stock returns are calculated as the logarithmic difference in the index. Table 1 shows the descriptive statistics for the stock returns. The table contains the statistical analysis for the full sample period and the other two sub-samples. The full sample (R_t) is from week 1 of March 1985 to week 4 of December 1997. The first sample ($R1_t$) is from week 1 of March 1985 to week 4 of September 1992, which is the sub-period prior to the price correction. The second sample ($R2_t$) is from week 5 of September 1992 to week 4 of December 1997, which is the sub-period after the price correction has occurred. It is obvious from the results that all three samples do not resemble the normal distribution. The test statistics of Jarque-Bera indicate the rejection of the null hypothesis of normality. The probability (prob)-values of Ljung-Box test statistics for the returns series denoted by Q(n) and for the returns squared series denoted by Qsq(n) indicate that the presence of dependence in the first and higher moments is possible. With the exception of Q(20) and Qsq(50) for the second sample the prob-values of these statistics for the three samples indicate, respectively, the presence of serial correlation and significant heteroscedasticity.

Table 1
Descriptive Statistics

	R_t W1/March/1985 W4/Dec./1997	$R1_t$ W1/March/1985 W4/Sept./1992	$R2_t$ W5/Sept./1992 W4/Dec./1997
Max	0.079	0.072	-0.079
Min	-0.087	-0.074	-0.087
Mean	0.001	0.002	-0.0003
Standard deviation	0.017	0.016	0.018
Skewness	0.059	0.063	0.0106
Kurtosis	6.94	6.82	6.89
Jarque- Bera	417.8	232.4	165.9
Q(5)	0.00	0.00	0.006
Q(10)	0.00	0.00	0.051
Q(20)	0.00	0.00	0.130
Q(50)	0.00	0.00	0.024
Q(100)	0.00	0.00	0.016
Qsq(5)	0.00	0.00	0.00
Qsq(10)	0.00	0.00	0.00
Qsq(20)	0.00	0.002	0.00
Qsq(50)	0.00	0.003	0.162
Qsq(100)	0.00	0.00	0.045

Notes:- Q(n) and Qsq(n) are, respectively, are the prob-values of the Ljung-Box statistics for returns and returns squared series up to the n^{th} order.

Prior to presenting the estimated models it is necessary to investigate the statistical properties of the index for the three sample periods. The data in log-levels of the index itself and the returns series are tested for the presence of unit roots. In particular we consider the following null model:

$$X_t = \mu + \rho X_{t-1} + u_t \quad (1)$$

and the following alternative model:

$$X_t = \mu + \beta(t - T/2) + \rho X_{t-1} + u_t \quad (2)$$

where X_t represents the variable under consideration, μ is the drift parameter, u_t is a zero mean serially uncorrelated and mutually independent disturbance term.

Under the null hypothesis it is assumed that $\rho = 1$ and $\beta = 0$, i.e. X_t is non-stationary integrated time series of order one, denoted by $X_t \sim I(1)$, while under the alternative hypothesis it is assumed that ρ is less than one, i.e. the series is stationary around a deterministic trend. Therefore, to test for unit roots, the following regression is adopted:

$$\Delta X_t = \mu + \beta t + \gamma X_{t-1} + \sum_{i=1}^{k} \lambda_i \Delta X_{t-i} + \upsilon_t \quad (3)$$

where Δ is the first difference operator, t is a time trend and υ_t is a covariance stationary random error. The k-lags in the above regression are required to purge out serial correlation and to avoid over-under-parameterization k is determined on the basis of three-information criterion as well as the Lagrange multiplier test of the twelfth order for serial correlation (LM12). The three-information criterion used are Akaike Information Criterion (AIC), Schwarz Bayesian Criterion (SBC), and Hannan-Quinn Criterion (HQC). In the above regression if $k = 0$ then the test is the known Dickey-Fuller test denoted by (DF), while if $k \neq 0$ it is the augmented Dickey-Fuller test denoted by (ADF), (Dickey and Fuller, 1979). To reject the null hypothesis, it is necessary that the t-ratio of γ be statistically significant. The distribution of this test is non-standard and the critical values are tabulated by Fuller (1976) and they are reproduced for various significance levels at the end of Table 2. The calculated DF statistics reported in this table shows that in the case of the log-level of the index itself and for the three sample periods, the null hypothesis of a unit root can not be rejected. On the other hand, these statistics in the case of the returns series for the three periods do not permit rejecting the stationarity of these series. These conclusions seem to be valid regardless of the information criterion used.

Although the results of Table 2 indicate that the stationarity of the stock returns can not be rejected, there is a possibility that the returns series

Table 2
Testing for Unit Roots

Series	ADF	Criterion	k	LM12
a_t	-1.96	AIC	6	15.5 (0.214)
	-1.88	SBC, HQC	3	16.5 (0.169)
R_t	-7.82	AIC	5	15.0 (0.243)
	-11.0	SBC, HQC	2	15.1 (0.235)
$a1_t$	-2.82	AIC	7	9.35 (0.673)
	-2.64	SBC, HQC	3	17.2 (0.141)
$R1_t$	-5.14	AIC	6	10.8 (0.544)
	-8.03	SBC, HQC	2	17.7 (0.124)
$a2_t$	-0.602	AIC, SBC, HQC	1	9.89 (0.625)
$R2_t$	-13.2	AIC, SBC, HQC	0	9.89 (0.625)

Notes: a_t is the log of the Index itself for the whole period, $a1_t$ and $a2_t$ are the log of the index for the first and second period, respectively, while R_t, $R1_t$ and $R2_t$ are the corresponding returns series. LM12 is the Lagrange multiplier test of the twelfth order for serial correlation. AIC, SBC and HQC are the three-information criterion mentioned in the text. Critical values for sample size ∞ are taken from Fuller (1976):

1%	2.5%	5%	10%
-3.96	-3.66	-3.41	-3.12

may exhibit long-memory, i.e. the series is characterized by an autoregressive fractionally integrated moving average denoted by AFRIMA (p, d, q). For valid inferences to be drawn this possibility has to be investigated. It is noted in this literature, e.g. Sowell (1990) and Diebold and Rudebusch (1991), that the standard tests for unit roots such as DF test may have low power against fractional alternatives. In this study, the two step procedure of Geweke and Porter-Hudak (1983) denoted by GPH is used to detect fractional integration in the stock returns. This class of stochastic models, which exhibit long-term dependence, is introduced by Granger and Joyeux (1980) and Hosking (1981) and has the property of capturing non-periodic cyclicality of strongly dependent process. To introduce the test, consider the model:

$$\Phi(1-L)^{d} R_t = \Theta(L)\varepsilon_t \equiv u_t \qquad (4)$$

where L is the lag operator and the parameter d measures the order of fractional integration. If d = 0 then this corresponds to a unit root in the log-level of the series. Expanding $(1- L)^d$ around non-integer, yields:

$$(1-L)^{d} = \sum_{i=1}^{\infty}\Gamma(k-d)L^{k}/\Gamma(k+1)\Gamma(-d) \qquad (5)$$

where $\Gamma(.)$ is the gamma function. The flexibility of the AFRIMA model given by (4) is shown by its ability to encompass a wide range of time series models including ARIMA as a special case where (d) takes real values.

The strong dependency arises when $0 < d < 0.5$. In such case R_t is stationary and invertible and its autocorrelations p_k decay hyperbolically. This rate of decay to zero in this case is much slower than the geometric decay of a stationary ARMA process. Because of this property of strong dependency between distinct observations, the AFRIMA process is coined in this literature by long-memory process. In fact, for $|d| \leq 0.5$, the autocorrelations of equation (4), as $k \to \infty$, has the property:

$$\rho_k \approx \{(-d)!/(d-1)!\}k^{2d-1} \tag{6}$$

and it is obvious that if (d) is positive then the sum of autocorrelations becomes unbounded, while if it is negative, the sum collapses to zero.

The spectral density of R_t is given by:

$$f_R(\omega) = |1 - exp(-i\omega)|^{-2d} f_u(\omega)$$
$$= |2Sin(\omega/2)|^{-2d} f_u(\omega) \tag{7}$$

where $f_u(\omega)$ is the spectral density of the stationary process ut. Taking the logarithms of (7), assuming the availability of a sample size T for R_t, and evaluating at the harmonic ordinates $\omega_j = 2\pi_j/T, j = 0, ..., T-1$, we get:

$$ln\{f_R(\omega_j)\} = ln\{f_u(0)\} - dln\{4Sin^2(\omega_j/2)\}$$
$$+ln\{f_u(\omega_j)/f_u(0)\} \tag{8}$$

The last term may be dropped as negligible if attention is restricted to low-frequency ordinates, say $j \leq K \ll T$. Adding the periodogram at ordinate j, denoted by I (ω_j), to both sides of (8), yields:

$$ln\{I(\omega_j)\} = ln\{f_u(0)\} - dln\{4Sin^2(\omega_j/2)\},$$
$$j = 1, ..., K \tag{9}$$

which may be written in the following linear form:

$$ln\{I(\omega_j)\} = \beta_0 + \beta_1 ln\{4Sin^2(\omega_j/2)\}$$
$$+\zeta_j, j = 1, ..., K \tag{10}$$

where β_0 is the constant, β_1 is the negative slope and ζ_j are independently and identically distributed.

A consistent and asymptotically normal estimate of the differencing parameter (d) may be obtained by applying OLS on the second step model shown above. The asymptotic variance of the error term is given by $\pi^2/6$ and it is imposed to raise efficiency. The identification of the short memory-process, i.e. ARMA part is not a prerequisite for this semi-parametric test. The importance of this test is that it may pick up fractal structure in a time series based on spectral analysis of its low-frequency dynamics. This is so because the test uses only a fraction of the first frequencies. Noting that K is a function in T, and if we assume that the fraction of low-frequency ordinates used is T^{η} *then* $K = T^{\eta}$.

The OLS t-statistic may be used for valid inference regarding the value of the parameter (d). It should be noted, however, that if T^{η} is small this gives rise for imprecise estimation of (d) due to limited degrees of freedom, while if T^{η} is large this contaminates the estimation of (d) due to the inclusion of high or medium frequencies. It is argued that the normality of (d) is dependent on ignoring the (l) for smallest low frequencies (Robinson, 1995). While there is no valid criterion to make the choice of both (l) and (η), we take the liberty of using l = 0, 1, 3, 5, 7 and η = 0.40, 0.50, 0.55, 0.6. The results of using the above procedure to test the stock returns for fractional integration for the three sample periods are reported in Table 3. Specifically the table shows the estimated d-parameters and their asymptotic standard errors to make direct inferences possible. It is obvious from the table that the null hypothesis of the fractional differencing parameter (d) not different from zero can not be rejected regardless of the values of (l) and (η). This gives direct support to the result of DF reported above.

Therefore, we may conclude that stock returns for the three periods exhibit no long-memory. This conclusion is consistent with the general findings of Lo (1991) and Cheung and Lai (1995) using the modified classical Hurst-Mandelbrot re-scaled range (RS) test for long-memory.

After establishing the stationarity of the nominal stock returns with no evidence of long-memory, we present the estimated time series models for the stock returns in the following section.

Garch Models of the Saudi Stock Returns:

Several models are experimented with to model the Saudi nominal stock returns. The most general specification is given by:

$$R_t = \alpha_0 + \sum_{i=1}^{n} \alpha_i R_{t-i} + \gamma D_{1t} + \varepsilon_t;$$

$$\varepsilon_t | \Omega_{t-1} \sim N(0, h^2) \qquad (11)$$

$$h_t^2 = \beta_0 + \beta_1 \varepsilon_{t-1}^2 + \beta_2 h_{t-1}^2 + \beta_3 k_{t-1} \varepsilon_{t-1}^2 + \beta_4 D_{2t} \qquad (12)$$

where: D_{1t} is a dummy variable that takes the values of 1 for the weeks 3, 4 and 5 of August 1990 and 0 elsewhere. D_{2t} is a dummy variable that takes the value 1 for the period from week 2 September 1991 to week 4 September 1992 and 0 elsewhere. k_t is a dummy variable that takes the value 1 if ε_t is negative and 0 elsewhere. With reference to equations (11) and (12) all estimated models reported in this study are defined as follows:

Table 3
The Estimated d-Parameters and their Asymptotic Standard Errors for the Stock Returns Using GPH Procedure

Series	η	No. of Obs.	l			
			0	03	05	07
R_t	0.4	14	0.130	0.200	-	-
			(0.371)	(0.799)		
	0.5	26	0.070	0.070	0.090	0.110
			(0.168)	(0.265)	(0.382)	(0.543)
	0.55	36	0.050	0.040	0.050	0.060
			(0.111)	(0.160)	(0.211)	(0.272)
	0.6	49	0.040	0.030	0.030	0.040
			(0.070)	(0.093)	(0.116)	(0.141)
$R1_t$	0.4	12	0.110	0.180	-	-
			(0.323)	(0.757)		
	0.5	21	0.080	0.110	0.160	0.280
			(0.138)	(0.234)	(0.363)	(0.561)
	0.55	27	0.050	0.060	0.080	0.100
			(0.093)	(0.144)	(0.205)	(0.287)
	0.6	36	0.030	0.020	0.020	0.020
			(0.057)	(0.081)	(0.108)	(0.140)
$R2_t$	0.4	10	0.110	0.230	-	-
			(0.310)	(0.866)		
	0.5	17	0.070	0.120	0.220	0.350
			(0.131)	(0.246)	(0.421)	(0.760)
	0.55	22	0.050	0.080	0.090	0.170
			(0.085)	(0.141)	(0.220)	(0.334)
	0.6	29	0.030	0.050	0.060	0.050
			(0.050)	(0.075)	(0.106)	(0.144)

Notes: - (l) are the numbers of low-frequencies omitted. For various definitions of the sample periods see Table 1.

Model 1: OLS regression of eq. (11) with $\gamma = 0$.

Model 2: GARCH (1, 1) with $\gamma = 0$, $\beta_3 = \beta_4 = 0$.

Model 3: GARCH (1, 1) with $\gamma = 0$, $\beta_3 = 0$ and $\beta_4 \neq 0$.

Model 4: TGARCH (1, 1) with $\gamma = \beta_4 = 0$.

Model 5: TGARCH (1, 1) with $\gamma = 0$ and $\beta_4 \neq 0$.

Model 6: OLS regression of eq. (11) with $\gamma \neq 0$.

Model 7: GARCH (1, 1) with $\gamma \neq 0$, $\beta_3 = \beta_4 = 0$.

Model 8: GARCH (1, 1) with $\gamma \neq 0$, $\beta_3 = 0$ and $\beta_4 \neq 0$.

Model 9: TGARCH (1, 1) with $\gamma \neq 0$ and $\beta_4 = 0$.

Model 10: TGARCH (1, 1) with $\gamma \neq 0$ and $\beta_4 \neq 0$.

The dummy variable D_{1t} is intended to capture the effect of the sudden invasion of Kuwait by the Iraqi regime. This crisis is shown in the returns series by large negative returns for the last three weeks of August 1990. The persistence of this event for a longer period is questionable since the government and some major players intervened immediately to suck up the excess supply of shares due to the panic in the market and, therefore, preventing it from a major collapse. The calamity of this event disappeared immediately after the intention of dislodging Saddam out of Kuwait was declared by the allied forces. In fact the psychology of the market improved tremendously as soon as January 1991. This event, therefore, was a short lived one with respect to the Saudi stock index and may be regarded as completely exogenous. Models denoted by TGARCH are the threshold autoregressive conditional heteroscedasticity; see Nelson (1991), Bollerslev *et al* (1992), Engle and Ng (1993) and Glosten *et al.*, (1993). These types of models are used to test those downward movements (bad news) in the market followed by higher volatility than upward movements (good news) of the same magnitude. It is noted that bad news in stock returns has greater impact on volatility than good news and, therefore, β_3 is expected to be positive. Also in such models β_1 represents the impact of good news, while $\beta_1 + \beta 3$ represent the impact of bad news. The dummy variable D_{2t} is added to capture the change in the level of conditional volatility. It is known that the period represented by this dummy and mentioned above has witnessed the return of huge capital that fled off the country during the Gulf crisis and found in the stock market the appropriate instrument for holding liquidity. Since the issued shares were ordinary shares, few investors competed intensely to get the maximum shares to secure in the least a chair in the executive board of the respective firm with its very high expected returns. This intensive competition drove the index to very high psychological levels they had never reached before. It is, therefore, expected that the level of the conditional variance has shifted upward for those 52 weeks of the life of the index.

The autoregressive term in equation (11) is included to account for the significant autocorrelations observed in the returns series. In order to investigate the impact of structural change the above models are estimated for three sample periods. It is worth noting that several specifications for the three samples including different values of (n), various orders of ARMA models, different lag lengths for the GARCH model and various competing GARCH models are tried. The final results that could not be improved are reported in Tables 4 and 5 for the full sample and in Table 8 for the sub-samples. The three tables show also the calculated values of the diagnostic checking conducted on the OLS residuals and on the standardized residuals of the GARCH and TGARCH models. These are the skewness, kurtosis and the normality test. The Q(n) and Q^2(n) statistics, respectively, are the prob-values for the Ljung-Box statistic of the OLS residuals and squared residuals up to the n^{th} order of serial correlation. For the various specifications of GARCH and TGARCH models the reported prob-values of the Q(n) and Q^2(n) are for the same statistic of the standardized residuals and squared standardized residuals, respectively, up to the n^{th} order of serial correlation. The standardized residuals and squared standardized residuals are the standard residuals and squared standard residuals, respectively, divided by their one-step-ahead conditional standard deviation. The distribution of these statistics is χ^2 with (n) degrees of freedom under the null of no serial correlation.

The results of Tables 4, 5 and 8 show that the GARCH coefficients including the constant terms are highly significant as indicated by the calculated asymptotic t-values. This feature seems to be shared by the coefficients of the estimated TGARCH models. The results of these tables show that the order of the autoregressive term for the full sample is longer than its counterparts for the two sub-samples. In particular AR(6) is found to be an essential requirement to remove linear dependence and thus allowing the convergence of the maximum likelihood for the full sample, while AR(3) and AR(1) is found to be sufficient for the first and the second sample, respectively.

Furthermore, the residuals and the standardized residuals of all estimated models are subjected to the test of left-over non-linearity developed by Brock, Dechert and Scheinkman (1987), denoted by BDS. This test is explained as follows: Let X_t (t = 1,...,T) be a univariate time series within an n-dimensional deterministic economic model. X_t in this context may represent the stock returns or OLS residuals or the standardized residuals obtained from the models presented above. Now an m-dimensional vectors, or m-histories, can be defined in the manner:

$$X_t^m = (X_t, X_{t+1}, ..., X_{t+m-1}) \qquad (13)$$

where X_t is referred to as m-history and the parameter m is the embedding dimension. To measure the distance

(ϵ) between two histories, this is given by the correlation integral:

$$C_{m,T}(\epsilon) = (2/T_m^2 - T_m) \sum_{t=1}^{T} \sum_{s=1}^{T} I_\epsilon (\epsilon - \| X_t^m - X_s^m \|), t \neq s \quad (14)$$

where:

$\| X_t^m - X_s^m \|)$ is the Euclidean norm between X_t^m and X_s^m and $I_\epsilon = 1$ if, $\| X_t^m - X_s^m \|) > 0$, 0 otherwise.

Grassberger and Procaccia (1983) defined the correlation integral as the cumulative distribution function of (ϵ^m):

$$C_{m,T}(\epsilon) = p(\epsilon^m < \epsilon) \quad (15)$$

Therefore, under the null hypothesis that X_t is iid and for fixed (m) and (ϵ):

$$C_{m,T}(\epsilon) \to C_{1,T}(\epsilon)^m, as T \to \infty \quad (16)$$

and it follows that the conditional probability for two trajectories to stay within a distance (ϵ) for (m-1) periods, and assuming independency of $(\epsilon_{t,s})$, is given by:

$$p[(\epsilon^m \leq \epsilon)|(\epsilon^{m-1} \leq \epsilon)] = C_{m,T}(\epsilon)/C_{m-1,T}(\epsilon) = C_{1,T}(\epsilon) \quad (17)$$

which is the correlation integral at embedding dimension 1.

The empirical distribution function for the inter-history distances can be used to provide estimate for $C_{m,T}(\epsilon)$. This is achieved by selecting $\epsilon_k = \sigma\delta^{k-1}$, (k = 1,...,K), where $0 < \delta < 1$ and σ^2 is the sample variance, the estimate $C_{m,T}(\epsilon_k)$ is given by the proportion of distances less than (ϵ_k).

Using the theory of U-statistics by Brock *et al.* (1987), we arrived at the following normalized estimatable statistics:

$$P^m = \{[C_{m,T}(\epsilon)/C_{m-1,T}(\epsilon)] - C_{1,T}(\epsilon)\}/(\sigma_p/T^{1/2}) \quad (18)$$

$$W^m = \{C_{m,T}(\epsilon) - C_{1,T}(\epsilon)^m\}/(\sigma_w/T^{1/2}) \quad (19)$$

The statistic given by (18) is the conditional probability statistic, while equation (19) is the BDS test. The BDS test is also called the Wing statistic due to the shape of plotting $C_{m,T}(\epsilon)$ and $C_{1,T}(\epsilon)^m$ against ϵ. The asymptotic distribution of BDS under iid and its power against specific alternatives using Monte Carlo experiments has been extensively studied and useful summaries are provided by Brock *et al.* (1991). Also it is demonstrated by Brock *et al* (1987), Baek and Brock (1988) and Liu (1989), that BDS statistics remain valid if X_t is the resulting residuals from regression models. This statistic, therefore, may be used as a diagnostic test where models with left-over non-linearity may be dismissed as they are functionally misspecified. In this paper the BDS statistics are reported for m = 2, 3, 4, 5 and $\epsilon = \sigma, 0.5\sigma$. Large estimated values of BDS statistics indicate non-linearity. Further simulation results and applications by inter alia, Liu (1989), Brock and Baek (1991), Brock *et al.* (1991), Hsieh (1991), Liu *et al.* (1992) and Asseery

(1999, 2000), indicate that BDS statistic is highly powerful in detecting departure from non-linearity. It is worth noting that large estimated BDS values may occur when the null hypothesis of independent and identical distribution is violated or that the finite distribution under the null is poorly approximated by the asymptotic normal distribution. Also the strong rejection of iid by BDS statistics is consistent with the presence of low-dimensional ‘‘regular’’ chaotic dynamics. Additionally, the study uses the consistency test for heteroscedasticity due to Pagan and Sabau (1988), denoted by PS. This test involves running the regression:

$$R_t^2 = a + bh_t^2 + u_t \qquad (20)$$

where R_t^2 is the log of stock returns rate of change squared, h_t^2 is the conditional variance estimated in the GARCH or TGARCH model, (a) is the intercept and (b) is the slope. Under the null hypothesis of GARCH capturing most data non-linearity the intercept must equal zero and the slope is expected to be equal one. The Wald statistics are used in this study for testing such hypothesis.

The prob-values of Q statistics for the OLS residuals reported in Tables 4, 5 and 8 are all insignificant, indicating that these orders of autoregression are capable of eliminating all linear dependence observed in the returns series of the three samples reported in Table 1. This gives some comfort that these orders of autoregression are not misspecified. With the obvious exceptions all the parameters of these autoregressive schemes for the three samples are positive and statistically significant. As it is noted earlier in Table 1 the prob-values of the returns squared series of the full sample indicate a significant heteroscedasticity and it is, of course, transmitted to the residuals of the OLS. To allow formally for short-term dependence and conditional heteroscedasticity the Models 2 to 5 are estimated for the full sample and the results are reported in Table 4.

All estimated models show that the coefficients of GARCH are statistically significant and poses the correct theoretical signs, but the sum of the coefficients is less than unity indicating the rejection of integrated generalized autoregressive conditional heteroscedasticity, denoted by IGARCH model. Model 3 shows that change in volatility did occur in the Saudi stock market as indicated by the significance of β_4. While the estimated coefficient of bad news β_3 is insignificant in Model 4, it still has the correct sign. A stronger support for the hypothesis that bad news has a greater impact on returns than good news is given by Model 5 where a change in the level of volatility is allowed for. It

Table 4
The Results of Estimating the Stock Returns for the Full Sample Period (R_t) without the Gulf War Dummy

Coefficients	Model 1	Model 2	Model 3	Model 4	Model 5
α_0	0.006	0.008	0.008	0.007	0.006
	(0.915)	(1.30)	(1.39)	(1.15)	(1.00)
α_1	0.211	0.229	0.228	0.243	0.244
	(5.33)	(4.88)	(4.90)	(5.18)	(5.36)
α_2	0.052	0.105	0.098	0.101	0.091
	(1.28)	(2.34)	(2.21)	(2.22)	(2.02)
α_3	0.106	0.098	0.103	0.110	0.123
	(2.62)	(2.19)	(2.31)	(2.39)	(2.75)
α_4	0.019	0.011	0.004	0.010	0.007
	(0.479)	(0.269)	(0.110)	(0.226)	(0.164)
α_5	-0.040	-0.064	-0.038	-0.056	-0.031
	(-0.982)	(-1.56)	(-0.947)	(-1.34)	(-0.751)
α_6	0.114	0.090	0.101	0.107	0.114
	(2.89)	(2.19)	(2.63)	(2.53)	(2.85)
γ					
β_0		0.0006	0.0006	0.0005	0.0004
		(12.6)	(12.0)	(10.0)	(8.00)
β_1		0.199	0.181	0.121	0.073
		(3.55)	(3.85)	(2.24)	(2.03)
β_2		0.579	0.573	0.490	0.661
		(13.2)	(14.3)	(17.1)	(12.2)
β_3				0.086	0.140
				(1.39)	(2.59)
β_4			0.001		0.001
			(10.0)		(14.3)
LL	1724.7	1753.6	1763.8	1753.4	1765.8
Skewness	0.213	0.091	3.88	0.166	0.130
Kurtosis	7.01	6.77	42.2	6.73	6.97
Normality	432.5	397.1	49069.7	371.9	421.3
Q(5)	1.00	0.931	0.132	0.994	0.847
Q(10)	1.00	0.914	0.174	0.944	0.987
Q(20)	0.899	0.691	0.012	0.844	0.837
Q(50)	0.603	0.487	0.00	0.604	0.504
Q(100)	0.117	0.268	0.00	0.396	0.163
Qsq(5)	0.00	0.030	0.089	0.026	0.00
Qsq(10)	0.00	0.121	0.079	0.104	0.00
Qsq(20)	0.00	0.530	0.106	0.467	0.00
Qsq(50)	0.00	0.411	0.00	0.337	0.001
Qsq(100)	0.00	0.025	0.00	0.034	0.00

Notes:- Numbers in brackets are t-statistics, LL are the values for Log-Likelihood and numbers of Q(n) and Qsq(n) are the same as in Table1.

Table 5
The Results of Estimating the Stock Rreturns for the Full Sample Period (R_t) with the Gulf War Dummy

Coefficients	Model 6	Model 7	Model 8	Model 9	Model 10
α_0	0.009	0.001	0.001	0.001	0.009
	(1.36)	(1.83)	(1.93)	(1.65)	(1.57)
α_1	0.175	0.193	0.195	0.210	0.215
	(4.45)	(4.15)	(4.21)	(4.49)	(4.81)
α_2	0.035	0.071	0.064	0.073	0.066
	(0.878)	(1.63)	(1.49)	(1.65)	(1.52)
α_3	0.109	0.096	0.100	0.110	0.120
	(2.76)	(2.21)	(2.34)	(2.45)	(2.78)
α_4	0.026	0.013	0.011	0.009	0.006
	(0.656)	(0.310)	(0.264)	(0.207)	(0.151)
α_5	-0.037	-0.061	-0.041	-0.050	-0.027
	(-0.940)	(-1.48)	(-1.03)	(-1.19)	(-0.666)
α_6	0.112	0.102	0.104	0.112	0.116
	(2.90)	(2.50)	(2.73)	(2.71)	(2.95)
γ	-0.049	-0.049	-0.050	-0.050	-0.050
	(-5.15)	(-7.23)	(-7.25)	(-6.57)	(-6.34)
β_0		0.0003	0.0004	0.0003	0.0003
		(6.00)	(8.00)	(6.00)	(6.00)
β_1		0.174	0.172	0.110	0.068
		(3.78)	(3.73)	(2.34)	(2.06)
β_2		0.717	0.663	0.749	0.725
		(19.9)	(18.4)	(22.0)	(22.7)
β_3				0.075	0.131
				(1.60)	(2.85)
β_4			0.001		0.001
			(14.3)		(14.3)
LL	1737.9	1770.3	1781.3	1770.6	1784.4
Skewness	0.375	0.362	0.350	0.444	0.243
Kurtosis	6.86	5.51	5.97	5.55	4.55
Normality	411.0	181.1	247.5	193.6	70.2
Q(5) p-val	0.998	0.629	0.995	0.921	0.966
Q(10) p-val	1.00	0.765	1.00	0.974	0.996
Q(20) p-val	0.868	0.468	0.862	0.759	0.880
Q(50) p-val	0.327	0.110	0.373	0.223	0.348
Q(100) p-val	0.092	0.187	0.217	0.341	0.536
Qsq(5) p-val	0.00	0.025	0.00	0.017	0.004
Qsq(10) p-val	0.00	0.050	0.00	0.033	0.021
Qsq(20) p-val	0.00	0.312	0.00	0.216	0.147
Qsq(50) p-val	0.00	0.015	0.00	0.007	0.092
Qsq(100) p-val	0.00	0.002	0.00	0.002	0.009

Notes:- See notes to Table 4.

is clear from this result that the effect of negative signs on the level of volatility is double the effect of good news. It is evident from the estimated coefficients β_4 that before the price correction, the level of volatility shifted up by approximately 3 times its normal level. The calculated diagnostic statistics show that while Model 5 registered the highest Log Likelihood (LL), all models have excess kurtosis. Although the Jarque-Bera statistics indicate the rejection of the null of normally distributed residuals for all models, Model 3 seems to perform the worst. The reported prob-values of Q statistics, conducted on the residuals of OLS and the standardized residuals of Models 2-5, show that short term and long term serial autocorrelations are rejected with the exception of the standardized residuals of Model 3 where a trace of long term dependency is found. The prob-values of the Qsq, on the other hand are significant at the 5% level in the case of Model 2 and 4 for the 5^{th} and 20^{th} orders only. For Model 3 the prob-values are significant at the 10% up to the 20^{th} order, and only after that the prob-values are significant at the 1% level. It is interesting to note from the results of this table that the prob-values of Qsq statistics for the Models 2-4 are significant only at low and high orders, which may be indicative of the existence of some structure in the standardized residuals. These models, and even when a shift in volatility is accounted for, failed to produce a systematic pattern for these statistics to be decisive about the existence of such structure. Only Model 5 seems to be successful in uncovering the presence of such structure after accounting for both bad news and a shift in the level of volatility. In this case the prob-values of Qsq at the various orders considered are significant at the 1% level. This means that linearity of the standardized residuals in this case is strongly rejected. The performance of these models with respect to testing for non-linearity becomes essential rather than complementary to Qsq statistics. The calculated BDS and PS statistics for the full sample are shown in Table 6 and 7, respectively. The results of Table 6 shows that linearity is rejected at the 5% level for all values of (m) and for $\epsilon = 0.5\sigma, \sigma$ in the case of the returns series and the residuals of OLS. For the standardized residuals of Model 2 non-linearity is not rejected even at the 10% level by BDS statistics. The Wald statistic of PS test also follows this direction. For Model 3 BDS statistics reject linearity at the 5% for all dimensions except when m = 5 and for $\epsilon = 0.5\sigma$, where the rejection level is 10%. Also in this case the statistic of PS test rejects linearity at the 5% level. For Model 4 the statistic of PS test strongly can not reject non-linearity while BDS statistics point to the presence of non-linearity at only low levels of significance and dimensionality. The PS statistic of Model 5 rejects linearity at the 10% level only while the rejection of non-linearity is stronger in the case of BDS statistics. It is evident, therefore, that GARCH (1, 1) model masks some structure and relying upon Qsq statistics only may lead to different conclusions.

Models 6 to 10 where the base regression includes explicitly a dummy variable for the weeks of the Gulf war mentioned above are estimated and the results are reported in Table 5. The effect of including this dummy is shown by pushing the sum of the estimated GARCH coefficients nearer to unity. The estimated coefficient of this dummy is significant through all the estimated models. The negative sign of this coefficient indicates a reduction in the unconditional mean by 5% during the war weeks. In terms of excess kurtosis, these models seem to perform better than the models without the war dummy reported in Table 4. The prob-values of Q statistics in this table point to the rejection of short and long term autocorrelation for all estimated models. On the other hand the prob-values of Qsq are all significant at the 1% level in the case of Models 6 and 8. For the rest of the models these values are statistically insignificant at the 5% only at the 20^{th} order. Again these statistics point to some neglected structure in the standardized residuals. Looking at Table 7, the calculated Wald statistics of PS test indicate that the power of rejecting the null hypothesis of GARCH capturing most of data non-linearity decreases while moving from Model 7 to Model 10. The statistics of this test, however, seem to follow the conclusion of Qsq that non-linearity can not be rejected. Similar conclusion may be observed at the 5% or the 10% level in the calculated BDS statistics reported in Table 6 for these models with the exception of Model 10 where these statistics clearly reject non-linearity at the 5% level. In view of the behavior of these statistics discussed above for the full sample it is not impossible to dismiss the possibility that the Gulf war is responsible for the so often rejection of the iid residuals by these tests. The thorough reading between the lines of these statistics may infer that this failure may be due to the presence of two regimes within the whole sample with the possibility of one being IGARCH.

To investigate this possibility various models are estimated for the two samples mentioned earlier and the results are reported in Table 8. The estimated parameters of the autoregressive are all significant and have positive signs. The only exception is α_1 where its significance is lowered by the introduction of the war dummy. While the prob-values of Q statistics for the first sample reveals that autocorrelation is rejected only at low orders of the test, the prob-values of Qsq shows traces of non-linearity. The re-

Table 6
BDS Statistics for the Full Period

Series	ϵ	m			
		2	3	4	5
R_t	0.5σ	7.40	9.02	10.1	10.6
	σ	7.05	8.15	8.72	9.10
Model 1	0.5σ	5.91	7.22	7.70	8.21
	σ	5.52	6.27	6.62	6.81
Model 2	0.5σ	1.77	1.77	1.50	1.23
	σ	1.35	1.50	1.37	1.17
Model 3	0.5σ	3.44	3.72	3.64	3.50
	σ	3.85	3.98	3.73	3.63
Model 4	0.5σ	2.16	2.19	2.05	1.80
	σ	2.24	2.15	1.83	1.53
Model 5	0.5σ	3.68	3.93	4.13	3.61
	σ	3.91	3.95	3.69	3.45
Model 6	0.5σ	5.45	6.84	7.27	7.60
	σ	4.76	5.83	6.19	6.46
Model 7	0.5σ	1.47	1.74	1.91	1.98
	σ	1.55	2.02	2.06	2.03
Model 8	0.5σ	2.61	3.18	2.97	2.57
	σ	2.81	3.31	3.18	2.86
Model 9	0.5σ	1.92	2.13	1.77	1.42
	σ	1.75	1.98	1.72	1.33
Model 10	0.5σ	1.71	1.92	1.62	1.21
	σ	1.43	1.64	1.37	0.923

Notes:- The definition of the various models and the description of the test are given in the text of this section. Critical values for 500 observation, 95% and 90% quantiles, respectively, are taken from Brock *et al* (1991), Table C.3:

$\epsilon =$	0.5σ	-2.25	-2.38	-2.62	-3.16
	2.46	2.74	3.01		3.67
$\epsilon =$	σ	-2.07	-2.02	-2.00	-2.02
	2.18	2.26	2.26		2.32
$\epsilon =$	0.5σ	-1.93	-2.02	-2.22	-2.66
	1.98	2.25	2.42		2.98
$\epsilon =$	σ	-1.74	-1.73	-1.71	-1.71
	1.81	1.83	1.87		1.94

Table 7
The Wald Statistics of PS Test

Model 2	Model 3	Model 4	Model 5	Model 7	Model 8	Model 9	Model 10
2.58	6.60	1.25	5.23	8.89	6.59	5.23	4.55
(0.275)	(0.037)	(0.528)	(0.073)	(0.012)	(0.037)	(0.073)	(0.103)

Notes: These statistics are for testing the hypothesis H_0: $a =$ o; b = 1, where these coefficients are the result of regression (20). Numbers in brackets are the significance levels.

jection is more apparent once the war dummy is included. Again the inclusion of this dummy may have undone the mask that non-linearity is hidden behind. Several results seem to emerge when comparing Model 7 with Model 2 in the same table. One result is that the coefficient of the conditional variance in Model 7 has risen significantly rendering the sum to be close to unity. This indicates that the hypothesis of IGARCH characterizing the first sample can not be ruled out. This implies that shocks do not die out but effect the level of volatility forever. Another interesting result is revealed by Model 8 and it is related to the argument of Deibold (1986) which stresses that fluctuations in GARCH constant may be responsible for persistence in volatility observed in the literature. The sum of GARCH coefficients dropped from 0.95 in Model 7 to 0.85 in Model 8. Here the magnitude of the drop in the sum after accounting for the known shift in the conditional variance is not consistent with that found in the simulation results reported by Lamoureux and Lastrapes (1990) as an elaboration on Deibold's argument. Although it is argued that persistent volatility as implied by finding IGARCH may be the spurious result of neglected structural change, our results definitely lend no support. The results of testing for nonlinearity for the first and second samples using BDS and PS tests are reported in Tables 9 and 10, respectively. The BDS statistics for the first sample show that non- linearity is not rejected at the 5% for the return series itself and Models 1 and 6. For Model 2 there is evidence of non-linearity at the 10% when $\epsilon = \sigma$ and m = 2, 3. The result of PS test for this model, however, strongly rejects non-linearity. The reverse of this result occurs in the case of Model 7 where at the 5% all BDS statistics reject non-linearity while it is accepted by PS test. For Model 8 which has the highest LL and the lowest kurtosis, PS test rejects linearity at the 1% level. The only support for this rejection given by BDS statistics is at the 10% level when $\epsilon = \sigma$ and m = 3.

For the second sample, the results reported in Table 8 show that the order of autoregression is not consistent with that of the first sample. This low order, however, seems to remove all short and long term dependency observed in the return series of this sample. The coefficients of both GARCH and TGARCH models are all significant and posses the right theoretical signs. Also at the 5% level non- linearity is rejected for both models as indicated by the prob-values of Qsq. The BDS statistics reported in Table 9 indicate that while non- linearity is not rejected at the 5% in the case of OLS residuals and the returns series itself, GARCH and TGARCH models are capable of producing iid residuals.

Table 8
The Results of Estimating the Stock Returns for the Sub-Periods ($R1_t$) and ($R2_t$)

Coefficients	First Period: Models:					Second Period: Models:		
	1	2	6	7	8	1	2	4
α_0	0.001	0.001	0.002	0.001	0.002	-0.0003	0.002	0.0007
	(1.33)	(1.59)	(2.17)	(2.01)	(2.24)	(-0.026)	(0.201)	(0.073)
α_1	0.156	0.142	0.082	0.072	0.079	0.234	0.343	0.343
	(3.06)	(2.39)	(1.62)	(1.26)	(1.41)	(3.94)	(4.61)	(4.93)
α_2	0.144	0.190	0.108	0.116	0.127			
	(2.82)	(3.25)	(2.19)	(2.06)	(2.31)			
α_3	0.170	0.159	0.185	0.161	0.172			
	(3.35)	(2.62)	(3.78)	(2.88)	(3.09)			
γ			-0.052	-0.052	-0.051			
			(-5.87)	(-8.27)	(-7.73)			
β_0		0.0004		0.0001	0.0003		0.0007	0.0006
		(6.45)		(1.69)	(4.84)		(8.75)	(7.50)
β_1		0.123		0.106	0.103		0.294	0.114
		(2.32)		(2.04)	(2.15)		(2.70)	(1.50)
β_2		0.721		0.842	0.724		0.497	0.587
		(16.0)		(18.7)	(16.8)		(6.72)	(9.17)
β_3								0.202
								(2.10)
β_4					0.001			
					(4.50)			
LL	1051.0	1058.5	1067.7	1078.8	1088.9	683.5	702.2	702.3
Skewness	0.119	0.058	0.588	0.597	0.467	0.510	0.051	0.141
Kurtosis	6.45	7.66	5.83	5.48	4.92	6.74	4.99	4.69
Normality	188.6	343.2	148.6	119.7	71.7	152.8	43.5	31.8
Q(5)	0.572	0.762	0.452	0.544	0.596	0.760	0.548	0.566
Q(10)	0.133	0.168	0.064	0.095	0.109	0.844	0.565	0.548
Q(20)	0.111	0.222	0.026	0.109	0.092	0.849	0.570	0.564
Q(50)	0.014	0.057	0.001	0.010	0.014	0.622	0.304	0.350
Q(100)	0.066	0.164	0.088	0.162	0.223	0.386	0.557	0.530
Qsq(5)	0.001	0.183	0.019	0.518	0.087	0.00	0.051	0.110
Qsq(10)	0.005	0.350	0.001	0.151	0.010	0.00	0.165	0.119
Qsq(20)	0.027	0.587	0.00	0.051	0.002	0.00	0.449	0.364
Qsq(50)	0.120	0.639	0.00	0.037	0.002	0.010	0.660	0.596
Qsq(100)	0.002	0.025	0.275	0.854	0.520	0.008	0.535	0.628

Notes:- See notes to Table 4.

Table 9
BDS Statistics for the Two Sub-Periods

Series	ϵ	m			
		2	3	4	5
1st period					
$R1_t$	0.5σ	6.22	7.86	8.82	9.61
	σ	6.05	6.99	7.33	7.95
Model 1	0.5σ	5.09	6.23	7.64	8.50
	σ	4.87	5.22	5.45	5.86
Model 2	0.5σ	2.29	2.53	2.93	3.13
	σ	2.21	2.03	1.99	2.06
Model 6	0.5σ	4.21	5.29	6.37	7.59
	σ	3.74	4.52	4.73	5.25
Model 7	0.5σ	1.15	1.29	0.913	0.924
	σ	1.28	1.61	1.42	1.24
Model 8	0.5σ	1.55	1.98	1.65	2.07
	σ	1.84	2.20	1.98	1.95
2ed period					
$R2_t$	0.5σ	3.99	4.49	5.20	5.03
	σ	4.06	4.73	5.30	5.23
Model 1	0.5σ	3.84	4.62	5.06	5.07
	σ	3.54	4.14	4.83	5.01
Model 2	0.5σ	0.001	0.062	-0.456	-0.405
	σ	-0.347	-0.235	0.258	0.315
Model 4	0.5σ	1.04	1.09	0.872	-0.033
	σ	0.460	0.493	0.828	0.854

Notes:- The definition of the various models, the sub-periods, and the description of the test are given in the text of this section. Critical values for 250 observations, 95% and 90% quantiles, respectively, are taken from Brock etal (1991), Table C.2:

$\epsilon=$	0.5σ	-2.64	-2.92	-3.37	-4.11
		2.98	3.23	3.84	4.98
$\epsilon=$	σ	-2.15	-2.17	-2.17	-2.18
		2.27	2.37	2.39	2.56
$\epsilon=$	0.5σ	-1.24	-2.47	-2.87	-3.49
		2.35	2.59	3.02	3.88
$\epsilon=$	σ	-1.88	-1.87	-1.89	-1.89
		1.86	1.91	1.98	2.10

Table 10
The Wald Statistics of PS Test for the Two Sub-Periods

1st period:			**2ed period:**	
Model 2	**Model 7**	**Model 8**	**Model 2**	**Model 4**
0.921	7.02	9.83	2.94	0.521
(0.631)	(0.030)	(0.007)	(0.230)	(0.771)

Notes: See notes to Table 7.

This conclusion is supported by the statistics of PS test reported in Table 10, which indicate that the hypothesis of capturing all non- linearity observed in the returns series by Models 2 and 4 can not be rejected. It is interesting to note that β_3 in Table 8 is positive and statistically significant only for the second sample indicating that bad news effect observed in Tables 4 and 5 for the whole sample is mainly due to the second sample.

Concluding Remarks

Using weekly data over the period 1985 to 1997, the study provides analysis to the time series characteristics of the Saudi stock market. The study shows that stock returns for the whole sample period as well as the two sub-periods prior to and after the occurrence of the price correction at the end of 1992 exhibit no long-memory. For the three sample periods the study presents the estimated models for the stock returns using GARCH and TGARCH. The results of the non-linearity tests conducted on the standardized residuals of these estimated models for the whole period, generally, suggest that they are not iid. It is demonstrated, however, that this failure to produce iid standardized residuals is mainly due to the sample period prior to the price correction. For this sub-period the results suggest the presence of low-dimensional chaotic "regular' dynamics in stock returns. For the sample period after the price correction the results of the estimated models show that stock returns is characterized by low level of volatility and non-linearity is rejected by all tests considered. The estimated models of this second sub-period strongly indicate that bad news effect observed in the estimated models of the whole sample is attributed mainly to this sub-sample. The estimated models strongly indicate that bad news effect observed more than good news does.

The overall results of estimation clearly suggest the significance of the Gulf war dummy. This dummy bares the negative sign indicating a reduction in the unconditional mean. Importantly, the results show that the hypothesis of a shift in the level of volatility for the period 02/09/1992-04/09/1992 can not be rejected as indicted by the significance of the coefficient of the dummy included in the conditional variance to pick up such effect. In fact the magnitude of this coefficient suggests that volatility has increased approximately 3 times its normal level during this period in the life of the Saudi stock returns.

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الملخص

الفوضى واللاخطية في سوق الأسهم السعودية

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هذه الدراسة تفحص الخصائص الإحصائية للعوائد الاسمية للأسهم السعودية باستخدام بيانات أسبوعية، للفترة من مارس ١٩٨٥م حتى ديسمبر ١٩٩٧م. وتقدم الدراسة تقديرات نماذج GARCH وTGARCH لجميع الفترة الزمنية والفترات الجزئية قبل ظهور التصحيح السعري وبعده في نهاية عام ١٩٩٢م. و تأخذ الدراسة فى الحسبان أثر حرب الخليج والانتقال في التقلب Volatility الملاحظ في الفترة الجزئية الأولى. وتوضح النتائج أن ما يلاحظ من أثر للأخبار السيئة على عوائد الأسهم من حيث التقلب في الفترة الزمنية كاملة يعود للفترة الجزئية الثانية. وعلى الرغم من أن الاختبار شبه البارامتيري لـ Geweke and Porter-Hudak (1983) الذي يرمز له بالرمز GPH ، يشير إلى عدم وجود ذاكرة طويلة في عوائد الأسهم لجميع فترات العينة المعتبرة، فإن نتائج اختبار Brock, Dechert and Scheinkman (1987) الذي يرمز له بالرمز BDS، تشير بشكل عام إلى وجود ديناميكيات فوضى من الحجم المنخفض في الفترة الجزئية السابقة لحدوث التصحيح السعري.

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