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Keywords

Empirical, analysis, UAE, stock, market, volatility

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Empirical Analysis of the UAE Stock Market Volatility

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Abstract

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The purpose of this paper is twofold. First, we investigate the volatility characteristics of the UAE stock markets measured by fat tail, volatility clustering, and leverage effects, in order to explore a parsimonious model for the UAE stock market and predict its future performance. Second, we use switching regime ARCH methodology to assess the impact of stock market openness to foreign investors on the market returns and we analyse its observed irregular performance using recently developed methodologies.

Keywords: Stock market volatility, asymmetric GARCH, Markov switching ARCH
JEL Classification Codes: C22; C52; G12

1. Introduction

Modelling and forecasting financial markets volatility has received considerable attention from academic researchers, policy makers and practitioners during the past 25 years and since the appearance of the seminal paper of Engle (1982). The main reason for this enormous interest is because volatility is used as a measure of risk and different participants of the financial markets need this measure for various purposes. For instance, volatility is needed as an input in portfolio management by portfolio managers and investors. It is needed in the pricing of derivatives securities (pricing of options in particular). The well-known option pricing formula of Black-Scholes (1973) requires a measure of stock price volatility. Financial regulators and financial institutions require quantifying the financial risk. One commonly employed method of quantifying financial risk by these regulators and institutions is Value at Risk (VaR). Under parametric methods the volatility of financial asset returns needs to be calculated in order to compute the VaR. Additionally, for the purpose of predicting asset return series, forecast confidence intervals may be time-varying. To obtain accurate confidence intervals, appropriate modelling of volatility of returns may be crucial.

The principal difficulty is that volatility is not constant over time and that financial market volatility exhibits certain characteristics that are specific to financial time series (Bollerslev, 1986 and 1990). Therefore, practitioners and financial econometricians have developed a variety of time-varying volatility models that takes into account these characteristics. Some of these characteristics are: Fat tail, volatility clustering and Leverage effects. Many studies have shown that probability distribution for asset returns often exhibit fatter tails than the standard normal distribution. In addition, financial time series usually exhibit a characteristic known as volatility clustering, in which large changes tend to follow large changes and small changes tend to follow small changes. Volatility clustering suggests a time-series model in which successive disturbances, although uncorrelated, are nonetheless serially dependent. Finally, certain classes of volatility models (asymmetric GARCH models) are also capable of capturing the so-called leverage effect, in which asset returns are often observed to be negatively correlated with changes in volatility. In other words, volatility tend to rise in response to lower than expected returns and tend to fall in response to higher than expected returns. Failure to take into account the above empirical regularities in forecasting stock market volatility may lead to inaccurate forecasts of volatility and returns and therefore may be very costly for the financial market participants.

The financial market volatility of the developed countries have been studied extensively since 1987 stock market crash as well as the volatility of the East Asian stock markets after the East Asian financial crisis. The volatility characteristics of the financial markets in the Middle East are far from being thoroughly analyzed despite their tremendous growth in recent years. The purpose of this paper is twofold. First we investigate the volatility characteristics of the UAE stock markets measured by fat tail, volatility clustering, and leverage effects in order to explore a parsimonious model for the UAE stock market and predict its future performance. Second, we conduct structural change tests for the variance in the selected volatility model to assess the impact of stock market openness to foreign investors on the market returns and analyze its observed irregular performance using recently developed methods of asymmetric GARCH models.

In this paper we present and assess alternative models for the UAE stock market volatility. Section 2 deals with a review on GARCH models and their characteristics. In section 3 we present the main features of the UAE stock markets and their recent evolution. In section 4 we present our empirical results of the stock market volatility and we estimate a switching regime ARCH model that best describes the changing pattern of the stock market volatility due to the implementation of new reforms allowing foreigners to take part in the market. Section 5 concludes our findings.

2. Literature Review on Volatility Modelling

Extensive empirical research has been carried out to investigate the volatility characteristics of the developed countries and for the Far East countries and to developed volatility models that take into account these characteristics. Recently, some studies have examined these characteristics for some of the Central and Eastern European countries and few Latin American countries. We review some of the studies that are related to emerging markets and some recent studies for the developed countries (see Poon and Granger, 2003, for a comprehensive survey on this literature).

Bekaert and Harvey (1998) examined stock market returns of twenty emerging markets and found these returns to be highly non-normal. Seventeen of twenty stock markets exhibit skewness in the returns, and nineteen of twenty were found to be leptokurtic over the investigated period (April 1987-March 1997).

Aggarwal, Inclan, and Leal (1999) explored the stock market volatility of 10 largest emerging markets in Asia and Latin America. They found that shifts in volatility of considered emerging markets is related to important country-specific political, social, and economic events. Moreover, the time-varying stock market volatility is modelled by GARCH models.

Koutmos (1999) and Koutmos and Saidi (1995) found that the conditional variance of Asian stock markets is an asymmetric function of past innovations. Positive past returns are on average 1.4 times more persistent than negative past returns of an equal magnitude. Kasch-Haroutounian and Price (2001), Gilmore and McManus (2001), Poshakwale and Murinde (2001) and Murinde and Poshakwale (2002) investigated the volatility of Central and Eastern European stock markets and found high volatility persistence, significant asymmetry, lack of relationship between stock market volatility and expected return and non-normality of the return distribution to be the basic characteristics of stock market volatility in those countries. In fact, Poshakwale and Murinde find empirical evidence for the presence of conditional heteroscedasticity in Hungary and Poland. Using daily data from 1994 to 1998, they show that the returns of the official indices of the Budapest and the Warsaw stock exchanges can be modelled using a GARCH model. However, the baseline GARCH model fails to account for the entirety of heteroscedastic conditional volatility in the return series. Kasch-Haroutounian and Price (2001) argue that this is due to the presence of asymmetry and non-linearity in the series. They conformed this finding for the Czech Republic, Hungary, Poland, and Slovakia over the 1992/1994 to 1998 period by employing a variety of asymmetric models to the data.

Recently, the traditional linear ARCH and GARCH model has been found inappropriate to describe financial time series mainly because of the presence of non-linearity in the series. For instance, Franses and Van Dijik (1998) show in general that non-linear GARCH models characterize volatility of AEX, DAX, DJI, FTSE and the NIKKEI stock returns far better than traditional GARCH model. Fornari and Mele (1997) employ the asymmetric GARCH model proposed by Glosten, Jagannathan and Runkle (1993) (GJR) and volatility switching GARCH for selected American, French, Japanese and Italian stock market returns. Using daily series, the volatility switching GARCH process is found to capture asymmetries better than GJR model.

3. Characteristics of the U.A.E. Stock Markets

The United Arab Emirates Stock markets were officially established in 2000, before that trading of stocks used to take place over the counter. First, in April 2000, the Dubai financial market (DFM) opened its doors and then in November the Abu Dhabi stock market (ADSM) began its operations. These markets are being supervised by the Emirates Securities and Commodities Authorities (ESCA). Both ADSM and DFM have experienced tremendous growth since their inception both in terms of market capitalization and number of companies listed on these markets. These two markets together form the second largest stock market in the Gulf, following Saudi Arabia’s stock market which has a market capitalization of $646,120.80 million (as of 2005).

The ADSM is the larger of the two markets. The market capitalization of the ADSM was $132,412.89 million in 2005 as compared to $111,992.68 million of DFM. During the same year the number of listed companies in ADSM was 59 while in DFM it was 30. Initially, only the nationals were allowed to purchase the stocks, but starting January 2003 foreigners were also allowed to invest in these markets. The Tables[1] below provide some insightful statistics on the evolution of the ADSM and DFM respectively.

Table A: Abu Dhabi stock market statistics

	2002	2003	2004	2005
Market Capitalization (in Million $)	20,375.76	30,362.51	55,490.40	132,412.89
Number of Listed Companies	24	30	35	59
% Change in Price	6.06	28.32	74.87	64.91
Turnover Ratio	1.78	3.31	8.02	21.53

Table B: Dubai stock market statistics

	2002	2003	2004	2005
Market Capitalization (in Million $)	9,469.52	14,284.23	35,090.90	111,992.68
Number of Listed Companies	12	13	18	30
% Change in Price	20.92	29.11	23.99	136.85
Turnover Ratio	7.26	7.19	39.14	98.49

Several factors have contributed to the growth of U.A.E. economy over the last few years, and consequently this has led to a tremendous growth of the U.A.E. stock markets. Among these factors,

[1] Source: All the data except % change in price was obtained from Arab Monetary Fund. The data for % change in price is obtained from the ADSM.

we find increased oil revenues, a focus on the diversification of economic activities and low interest rates in the region are the main contributing factors. In addition, the repatriation of the Arab money after the 9/11 attack has led to enormous growth in the U.A.E. and other Gulf stock markets.

Despite the recent phenomenal growth, the U.A.E. stock markets are relatively small as compared to the stock markets of the developed countries. The number of listed companies is low, most of the stocks are infrequently traded and the trading volume is low. Moreover, the disclosure of information by the listed companies is not at par with the developed countries. According to Woertz (2006), the GCC markets including U.A.E., are relatively unregulated and have seen lots of hyping, dumping and insider trading. The authorities are however trying to improve the transparency and the informational efficiency of the markets. Several steps have been taken by the ESCA over the last several years to strengthen and expand the stock markets of the U.A.E in relation to their listing, regulatory, trading and settlements procedures.

4. Methodology and Empirical Results

Volatility is a crucial factor in options trading and plays a major role in asset allocation under mean-variance framework. Volatility modelling provides an approach to calculating value at risk of a financial position in risk management, and also can improve in parameter estimation and the accuracy in interval forecast.

It has been observed that volatility reacts differently to a big price increase or a big price drop, referred to as the leverage effect. This feature that was not captured by the previous GARCH type models, and recently EGRACH models were developed to model the asymmetry in volatility induced by big positive and negative asset returns.

Define the conditional mean and variance of asset returns given the information set Ft-1 available at t-1.

$$\mu_t = E(r_t / F_{t-1}),\ \sigma_t^2 = V(r_t / F_{t-1})$$

$$r_t = \mu_t + a_t$$

Let $a_t = r_t - \mu_t$, the innovation at time t. We define a GARCH (p, q) model for a_t as follows:

$$a_t = \sigma_t \varepsilon_t;\ \sigma_t^2 = \alpha_0 + \sum_{i=1}^{p} \alpha_i a_{t-i}^2 + \sum_{i=1}^{q} \beta_i \sigma_{t-i}^2$$

where ε_t is *iid* with zero mean and unit variance.

We use daily data on stock returns of the Abu Dhabi stock market. The data is collected from 2001 to 2005. The econometric estimations of the EGARCH and TARCH models are performed with EVIEWS. The remaining models are estimated with RATS programs.

4.1. EGARCH Model

In order to allow for asymmetric effects between positive and negative asset returns, we consider the exponential GARCH model with weighted innovation defined by,

$$h(\varepsilon_t) = \theta\varepsilon_t + \gamma(|\varepsilon_t| - E(|\varepsilon_t|))$$

The EGARG (p, q) model may be written as follows:

$$a_t = \sigma_t \varepsilon_t;\ \log(\sigma_t^2) = \alpha_0 + \frac{1 + \sum_{i=1}^{q-1} \beta_i B^i}{1 + \sum_{i=1}^{p-1} \alpha_i B^i} h(\varepsilon_{t-1})$$

$$\log\ \sigma_t^2 = -0.667 + 0.955 \log \sigma_{t-1}^2 + 0.336 \left| \frac{\hat{\varepsilon}_{t-1}}{\sigma_{t-1}} \right| + 0.0642 \left(\frac{\hat{\varepsilon}_{t-1}}{\sigma_{t-1}} \right)$$

The presence of leverage effect may be tested by the null hypothesis that the coefficient of the last tem in the regression is negative. The impact is asymmetric if this coefficient is different from zero.

From the results in Table 1, we can not identify a leverage effect based on the EGARCH model.

Table 1: AR (1) with EGARCH (1, 1)

Dependent Variable: RADI Method: ML - ARCH Date: 01/15/07 Time: 16:35 Sample(adjusted): 3 1113 Included observations: 1111 after adjusting endpoints Convergence achieved after 231 iterations				
	Coefficient	**Std. Error**	**z-Statistic**	**Prob.**
C	0.000686	0.000189	3.621813	0.0003
AR(1)	0.214322	0.029487	7.268455	0.0000
Variance Equation				
C	-0.667984	0.040047	-16.68019	0.0000
|RES|/SQR[GARCH](1)	0.336657	0.019286	17.45595	0.0000
RES/SQR[GARCH](1)	0.064244	0.014025	4.580725	0.0000
EGARCH(1)	0.955142	0.003517	271.6151	0.0000
R-squared	0.096048	Mean dependent var		0.001203
Adjusted R-squared	0.091957	S.D. dependent var		0.010107
S.E. of regression	0.009631	Akaike info criterion		-6.964419
Sum squared resid	0.102487	Schwarz criterion		-6.937346
Log likelihood	3874.735	F-statistic		23.48194
Durbin-Watson stat	1.687802	Prob(F-statistic)		0.000000
Inverted AR Roots	.21			

4.2. TGARCH Model

An alternative approach to handle leverage effects is to use the threshold GARCH model as follows:

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

The dummy variable D_{t-i} is an indicator for negative innovations, defined by:

$$D_{t-i} = \begin{cases} 1 & \text{if } a_{t-i} < 0 \\ 0 & \text{if } a_{t-i} \geq 0 \end{cases}$$

$$\sigma_t^2 = 1.96e^{-6} + 0.819\sigma_{t-1}^2 + 0.228\,\hat{\varepsilon}_{t-1}^2 - 0.103(\hat{\varepsilon}_{t-1}I_{t-1})$$

Where $I_{t-1} = \begin{cases} 1 & \text{for negative residulas} \\ 0 & \text{for positive residulas} \end{cases}$

From the estimated TGARCH model, it is shown that the good news has an impact of (+0.228) magnitude and the bad news has an impact of (0.228-0.103=0.115) magnitude.

The latter would have been negative if the leverage effect was significant. Thus, based on the threshold GARCH model, we could not conclude that the bad news in the UAE stock market increases volatility.

4.3. CHARMA Model

This model was developed in the literature to describe the evolution of the conditional variance and used random coefficients to produce conditional heteroscedasticity.

The main difference between ARCH and CHARMA models is that in the latter we use cross-products of lagged a_t in the volatility equation. In asset return series cross-product terms refer to interactions between previous returns. Therefore, it seems reasonable to assume that stock volatility depends on these interactions.

The basic CHARMA model may be represented by:

$$r_t = \mu_t + a_t$$

$$a_t = \sum_{i=1}^{p} \delta_{it} a_{t-i} + \textit{white noise series } (\eta)$$

For instance in a CHARMA (2) model, the conditional variance of a_t is given by:

$$\sigma_t^2 = \sigma_\eta^2 + w_{11}a_{t-1}^2 + 2w_{12}a_{t-1}a_{t-2} + w_{22}a_{t-2}^2$$

We estimate a third-order conditional heteroscedasticity model. The idea is that if cross-products of lagged residuals are significant in the variance equation than CHARMA model would provide a better volatility forecast than the standard ARCH model.

We find the following results:

$$r_t = 2.22e^{-5} + 0.612a_{t-1}^2 + 0.058a_{t-1}a_{t-2} + 0.197a_{t-2}^2 + 0.182a_{t-3}^2$$

Table 2 in the appendix shows the detail results. In particular, there exists an interaction effect as indicated by the significance of the cross-product lagged residuals.

Table 2: AR (1) with TGARCH (1, 1)

Dependent Variable: RADI Method: ML - ARCH Date: 01/11/07 Time: 14:35 Sample(adjusted): 3 1113 Included observations: 1111 after adjusting endpoints Convergence achieved after 36 iterations				
	Coefficient	**Std. Error**	**z-Statistic**	**Prob.**
C	0.000549	0.000184	2.979950	0.0029
RADI(-1)	0.216967	0.030973	7.005034	0.0000
		Variance Equation		
C	1.96E-06	1.79E-07	10.93691	0.0000
ARCH(1)	0.228280	0.022055	10.35070	0.0000
(RESID<0)*ARCH(1)	-0.103554	0.025995	-3.983685	0.0001
GARCH(1)	0.819288	0.008931	91.73081	0.0000
R-squared	0.096780	Mean dependent var		0.001203
Adjusted R-squared	0.092694	S.D. dependent var		0.010107
S.E. of regression	0.009627	Akaike info criterion		-6.964601
Sum squared resid	0.102404	Schwarz criterion		-6.937528
Log likelihood	3874.836	F-statistic		23.68027
Durbin-Watson stat	1.692707	Prob(F-statistic)		0.000000

4.4. VaR-ARCH model

Value at Risk (VaR) is an estimate of the amount by which a financial institution's position in a risk category could decline due to general market movements during a given holding period.

VaR is a measure of loss associated with an extraordinary event under normal market conditions.

Suppose we want to analyse the risk of a financial position for the next s periods. Assume $\Delta V(s)$ is the change in the value of the assets in the financial position from time t to (t + s). In this study, the quantity is measured in UEA Dirham. Let $F_s(x)$ be the cumulative distribution function of $\Delta V(s)$. We define the VaR over the time horizon s with the probability p as:

$$p = \Pr ob\,(\Delta V(s) \le \text{VaR}) = F_s(VaR)$$

The holder of a financial position would suffer a loss when $\Delta V(s) < 0$, and thus VaR assumes a negative value when p is small. It also follows from the definition above that the probability for the financial asset holder to face a loss greater than or equal to VaR is equal to p. This implies that VaR is concerned with tail behaviour of $F_s(x)$.

We use risk-metrics in our VaR calculations as follows:

$$\mu_t = 0,\ \sigma_t^2 = \alpha\sigma_{t-1}^2 + (1-\alpha)r_{t-1}^2$$

Assume we have a long financial position so that loss occurs when there is a gig drop in the asset prices, which means large negative returns. If we set the probability to 5%, then we van use $1.65\sigma_{t+1}$ to measure the risk of the portfolio.

In our computations of the value at the risk for the UAE stock market, we model the volatility of the market returns by means of an integrated GARCH (1, 1) without a drift.

We obtain,

$$\sigma_t^2 = 0.9133\sigma_{t-1}^2 + (1-0.9133)a_{t-1}^2$$

Table 3 presents in detail our computations of the value at risk. In particular, we find that given a 10 million dirham financial position in the UAE stock market, there is a 5 percent chance that the stock holder would face a loss greater than or equal to nearly 2562 dirham.

Table 3: CHARMA model

MAXIMIZE - Estimation by BHHH Usable Observations 1103 Total Observations 1110 Skipped/Missing 7 Function Value 4787.70553209				
Variable	**Coeff**	**Std Error**	**T-Stat**	**Signif**
1. MU	4.81181e-04	1.57896e-04	3.04745	0.00230791
2. A0	2.22269e-05	8.45988e-07	26.27334	0.00000000
3. A1	0.61273	0.05728	10.69638	0.00000000
4. A12	0.05845	0.00505	11.57101	0.00000000
5. A2	0.19752	0.02256	8.75504	0.00000000
6. A3	0.18278	0.01825	10.01266	0.00000000

4.5. Non linear Volatility Model

In this section we use nonlinear models that are applicable to financial time series.

We begin with the estimation of a smoothed threshold AR model for the conditional heteroscedasticity (STAR) as an alternative to traditional linear models. Threshold autoregressive models use piecewise linear models in order to improve the linear approximation. In addition, we use a continuous conditional mean for the stock returns.

The results are presented in the appendix in Table 5. For the log return series, we obtain the following estimation results:

$$\sigma_t^2 = 2.39e^{-5} + 0.58a_{t-1}^2 + 0.36a_{t-2}^2 + \frac{1.81e^{-5} - 0.138a_{t-1}^2}{1+\exp(-100a_{t-1})}$$

In order to analyse the leverage effect, consider the following situations:

- For a large negative shock (a_{t-1} <0), the volatility approaches an ARCH (2):
  $$\sigma_t^2 = 2.39e^{-5} + 0.58a_{t-1}^2 + 0.36a_{t-2}^2$$
- For a large positive shock (a_{t-1}>0), the volatility is now given by a different ARCH (2) model: $\sigma_t^2 = 4.20e^{-5} + 0.44a_{t-1}^2 + 0.36a_{t-2}^2$

We also estimate the smoothed threshold AR model for the simple return series and we obtain the same results (Table 5 in the appendix).

Table 4: VaR-ARCH model

GARCH Model - Estimation by BFGS Usable Observations 1112 Function Value 9993.07041976				
Variable	**Coeff**	**Std Error**	**T-Stat**	**Signif**
1. Mean(1)	7.19113e-06	1.44473e-06	4.97750	0.00000064
2. C	2.23773e-10	4.53690e-11	4.93228	0.00000081
3. A	0.19905	0.02727	7.29805	0.00000000
4. B	0.80098	0.02170	36.91183	0.00000000

5% VaR on 10,000,000 2561.34824
1% VaR on 10,000,000 3622.56369

Table 5: STAR-ARCH (2), log returns

GARCH Model - Estimation by BFGS Convergence in 23 Iterations. Final criterion was 0.0000000 < 0.0000100 Usable Observations 1112 Function Value 4863.70074483				
Variable	**Coeff**	**Std Error**	**T-Stat**	**Signif**
1. Mean(1)	7.08625e-04	1.61792e-04	4.37986	0.00001188
2. C	2.61009e-06	5.35116e-07	4.87762	0.00000107
3. A{1}	0.14856	0.01166	12.73970	0.00000000
4. A{2}	0.07622	0.00609	12.51880	0.00000000
5. B	0.77870	0.01237	62.93664	0.00000000
Linear Regression - Estimation by Least Squares Dependent Variable RETURNS Usable Observations 1112 Degrees of Freedom 1111 T x R**2 18.131				
Mean of Dependent Variable Std Error of Dependent Variable Standard Error of Estimate Sum of Squared Residuals Durbin-Watson Statistic		0.0013075011 0.0101604122 0.0101604122 0.1146929481 1.318533		
Variable	**Coeff**	**Std Error**	**T-Stat**	**Signif**
1. Constant	0.0013075011	0.0003046905	4.29124	0.00001932
MAXIMIZE - Estimation by BFGS LAST CRITERION WAS 0.0176923 Usable Observations 1110 Total Observations 1113 Skipped/Missing 3				
Function Value		4771.77122781		
Variable	**Coeff**	**Std Error**	**T-Stat**	**Signif**
1. B0	1.0660e-03	2.4562e-04	4.34000	0.00001425
2. C	2.3972e-05	3.5204e-06	6.80964	0.00000000
3. A1	0.5869	0.1088	5.39283	0.00000007
4. A2	0.3612	0.0731	4.94191	0.00000077
5. SC	1.8149e-05	6.7700e-06	2.68084	0.00734369
6. SA1	-0.1384	0.1674	-0.82656	0.40848458

Unlike the linear EGARCH and the TGARCH models, the estimated STAR model does provide evidence of asymmetric responses to positive and negative shocks.

4.6. Markov Switching ARCH Model

In this section we estimate a switching autoregressive conditional heteroskedastic time series model for returns on the daily UAE stock market index. The volatility clustering can be detected by persistent periods of different volatility levels and by the dependence on past innovations, taking into account a leverage term to model the asymmetric response of volatility to positive and negative shocks.

It is well known that standard GARCH models usually impute a high degree of persistence to conditional volatility. This persistence may be spurious if the conditional volatility is subject to structural change. Thus we apply the switching ARCH (denoted by SWARCH) model of Hamilton and Susmel (1994) to investigate regime shifts and volatility persistence. Markov switching models (Hamilton 1996) provide a flexible way of dealing with parameter changes in sequentially observed data, like time series data, by assuming that the parameter change is driven by a hidden Markov chain. Our results show that the SWARCH model provides a better description of the data and implies a much lower degree of volatility persistence than the conventional ARCH (2) model.

Figure 2 suggests that the level of volatility in the UAE stock market differs across the sample period. In fact, starting in 2003, we observe much more volatility in the market and this came at the time when a new legislation has been implemented and which allowed foreigners to trade stocks at the UAE local markets. To identify the effect of this new law on the market performance we use a regime-switching ARCH specification to model the evolution of the variance. We introduce a second-order three-state Markov chain with constant transition probabilities, $p_{ij} = prob(s_t = i / s_{t-1} = j)$ where the state of the financial market at time t is denoted by $s_t \in \{1, 2, 3\}$. We therefore define low-volatility, medium, and high volatility states, respectively. The estimations are given in Table 7 in the appendix.

$$\sigma_t^2 = 0.0017 + 0.057 a_{t-1}^2 + 0.054 a_{t-2}^2$$

$$P = \begin{pmatrix} 0.209 & 0.620 & 0.010 \\ 0.161 & 0.337 & 0.651 \\ 0.630 & 0.043 & 0.339 \end{pmatrix}$$

The probabilities in the third row are computed from the constraint, $\sum_j p_{ij} = 1$.

The results in Table 7 show that these probabilities are significant, which leads us to conclude that the SWARCH model forecasts the UAE stock market volatility better than the traditional ARCH model.

Table 6: STAR-ARCH (2), simple returns

MAXIMIZE - Estimation by BHHH
Convergence in 52 Iterations. Final criterion was 0.0000091 < 0.0000100
Usable Observations 1109
Total Observations 1111 Skipped/Missing 2
Function Value 4746.20198409

Variable	Coeff	Std Error	T-Stat	Signif
1. A0	2.7845e-05	8.8527e-07	31.45384	0.00000000
2. A1	0.5702	0.0734	7.77083	0.00000000
3. A2	0.2530	0.0283	8.92988	0.00000000
4. A00	1.6957e-05	3.0021e-06	5.64835	0.00000002
5. A11	-0.0487	0.1250	-0.38989	0.69661519
6. MU	8.2716e-04	2.2679e-04	3.64721	0.00026511

Table 7: Switching ARCH model

Statistics on Series X (daily stock returns)			
Observations 1112			
Sample Mean	0.13075011162	Variance	1.032340
Standard Error	1.01604122313	SE of Sample Mean	0.030469
t-Statistic	4.29124	Signif Level (Mean=0)	0.00001932
Skewness	0.49252	Signif Level (Sk=0)	0.00000000
Kurtosis	9.38897	Signif Level (Ku=0)	0.00000000
Jarque-Bera	4129.37075	Signif Level (JB=0)	0.00000000
MAXIMIZE - Estimation by BHHH Usable Observations 1111			
Function Value		-1350.00085491	

Variable	**Coeff**	**Std Error**	**T-Stat**	**Signif**
1. MU	0.128767	0.004764	27.02955	0.00000000
2. A0	0.001730	0.000155	11.15667	0.00000000
3. A(1)	0.056913	0.010475	5.43334	0.00000006
4. A(2)	0.054143	0.008607	6.29031	0.00000000
5. P(1,1)	0.209446	0.049441	4.23626	0.00002273
6. P(2,1)	0.161576	0.067019	2.41091	0.01591257
7. P(1,2)	0.620075	0.065402	9.48094	0.00000000
8. P(2,2)	0.337465	0.074442	4.53324	0.00000581
9. P(1,3)	0.010000	0.090358	0.11067	0.91187693
10. P(2,3)	0.650954	0.120734	5.39165	0.00000007
11. HV(1)	174.494781	28.125282	6.204203	0.00000000
12. HV(2)	267.833265	39.558264	6.770601	0.00000000

5. Conclusion

In this paper we study the volatility of the UAE stock market using GARCH models and switching regime ARCH models. Our results cast a better performance of the SWARCH models in representing and forecasting the market volatility described by means of low, medium and high volatility episodes. The change in the volatility pattern and the recent irregular behaviour of the stock market came as a result of the introduction of a new regulation allowing foreign investors to participate in the UAE stock markets. Our study shows that this has created an unprecedented high level of volatility and could explain to some extent the recent sluggish performance of the markets.

Furthermore, based on the non linear threshold autoregressive methodology, we identified a significant leverage effect such that a stock price decrease would have a greater impact on subsequent volatility than a stock price increase with the same magnitude.

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Appendix

Figure 1: Descriptive statistics of stock returns

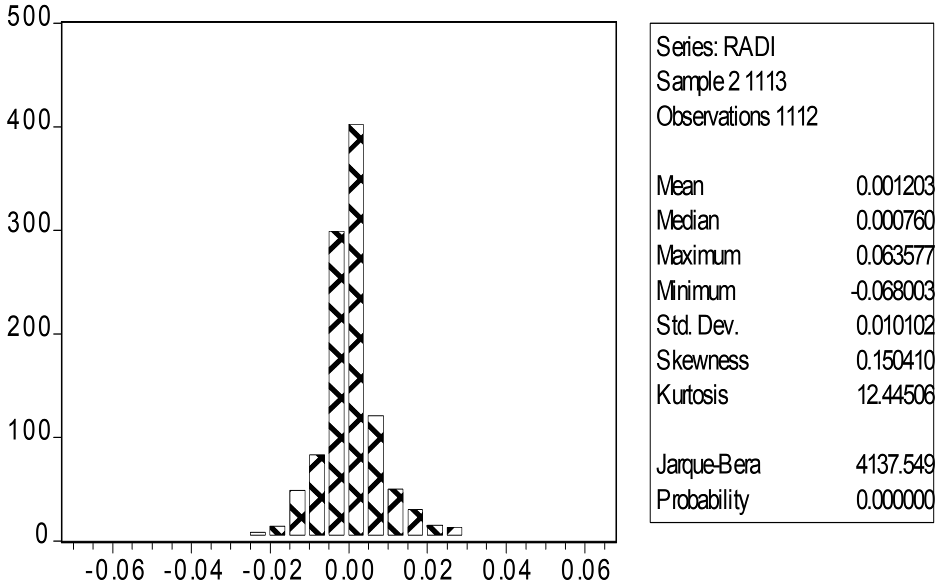

Figure 2: Plot of stock return series