Long Memory Process of the Egyptian Stock Market Returns

Maged Shawky Sourial

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Abstract

The paper attempts empirically to investigate market returns volatility persistence in a distinct approach from previous researches on the Egyptian Stock Market (ESM). This by testing for the presence of fractional dynamics, i.e. long memory in ESM's returns. The empirical investigation has been conducted using two methodologies, namely: Fractional Integrated Autoregressive Moving Average (ARFIMA) and Fractional Integrated GARCH (FIGARCH) models. Data used are Egypt's International Finance Corporation global (IFCG) index weekly returns during the period January 1996 till end of June 2001. Empirical results provided evidence that weekly market returns exhibited long memory process. This might be due to slow market's adjustment to new information and the presence of non-synchronous trading due to the large number of inactive stocks listed in the stock exchange. Furthermore, maintaining the +/- 5% circuit breaker imposed in February 1997 might have failed to dampen the volatility in the market, resulting in extending the impact of shocks on market volatility for longer period causing the slow decay. The results imply that technically, in some cases, adopting a contrarian trading rule might not be a profitable strategy, and fundamentally, using ARMA process and/or asset pricing models in modeling ESM's returns need to be reconsidered due to the existence of fractional dynamics with long memory features.

أسلوب الذاكرة الطويلة لعوائد الأسهم في سوق مصر للأوراق المالية

ماجد شوقي سوريال

ملخص

تحاول الورقة تحليل تباطؤ وتذبذب سلاسل عوائد الأسهم في سوق مصر للأوراق المالية بطريقة مختلفة عن تلك المستخدمة في الدراسات السابقة. تقوم الطريقة المقترحة على اختبار وجود ديناميكية كسْرية أو ما يعبَّر عنه بأسلوب الذاكرة الطويلة. يعتمد الاختبار المذكور على نماذج الانحدار الذاتي والمتوسط المتحرّك الكسْرية (ARFIMA) وكذلك على نماذج FIGARCH. وبالاعتماد على بيانات عوائد الأسهم الأسبوعية للفترة ما بين يناير 1996 ويونيو 2001، تبين النتائج أن سلسلة العوائد تتصف بأسلوب الذاكرة الطويلة، وقد يعزى ذلك إلى وجود عدد لا بأس به من الأسهم غيرٍ المتداولة في السّوق. بالإضافة إلى ذلك، فإنه يعتقد أن قاعدة توقف المعاملات عند تذبذب يفوق 5٪ نزولا أو صعودا، والتي شُرِع في تنفيذها منذ شهر فبراير من عام 1997، لم تنجح في ضبط تذبذب العوائد في سوق الأسهم، ممّا نتج عنه تمادي تأثير الصدمات على السوق لفترات طويلة. وهذا يعني أن أي استراتيجيات لشراء الأسهم وتحقيق الأرباح بناءً على نماذج لا تأخذ بعين الاعتبار خاصية الذاكرة الطويلة، على غِرار نماذج ARMA التقليدية، ستكون نتائجها مضلّلة.

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Introduction

Volatility persistence is a subject that has been thoroughly investigated for developed markets. The extent of volatility persistence depends on the long-term dependence known as long memory of asset returns. The presence of long memory of asset returns contradicts the weak form of the Efficiency Market Hypothesis, whereby future asset returns are unpredictable from historical returns.

Number of studies using different methodologies of estimations and frequencies of data show that international market stock returns such as the US stock returns provide no evidence of the presence of long memory (Lo, 1991 using the modified R/S method – where the range (R) of partial sums of deviations of a time series from its mean rescaled by its standard deviation (S). Crato, 1994 using maximum likelihood estimation; Cheung and Lai, 1995, using both modified R/S and spectral regression methods). Expectedly, these studies report that testing efficient market hypothesis for international markets have. resulted to the acceptance of the null hypothesis that such markets are weak and/or semi strong efficient

Despite the fact that emerging markets in the last two decades have attracted the attention of international investors as means of higher returns with diversification of international portfolio risk (Harvey, 1995a; Richards, 1996 and El-Erian and Kumar, 1995), few studies have investigated the issue of volatility persistence using various non-linear estimation models. Emerging markets differ from developed markets in that the former, in most cases, is characterized by lack of institutional development, thinly traded markets, lack of corporate governance and market microstructure distortions that hinder the flow of information to market participants. However, in most of these markets, participants react slowly to information due to lack of equity culture.

This paper focuses on the Egyptian Stock Market (ESM) revisiting the issue of volatility persistence in stock market returns. A study by Mecagni and Sourial (1999) using daily market returns and General Autoregressive Conditional Heterskadesticity (GARCH) in mean models, reports that the effect of shocks to volatility tends to decay within few time lags with the duration of the shock lasting for only a few days. These results have been confirmed by Moursi (1999), using volatility-switching GARCH model on daily market returns, stating that excessive returns volatility, nevertheless, should not pose serious threats to the ESM.

In addition, this paper attempts empirically to investigate market returns volatility persistence in a distinct approach from previous researches by testing for the presence of fractional dynamics, i.e. long memory in ESM's returns. The empirical investigation has been conducted using two methodologies, namely: Fractional Integrated Autoregressive Moving Average (ARFIMA) and Fractional Integrated GARCH (FIGARCH) models. Data used were Egypt's IFC-(International Finance Corporation), global index weekly returns during the period January 1996 till end of June 2001. Empirically, results show that weekly market returns exhibited long memory process, which might have been due to the aggregation of short-term memory in higher frequency. Further, using ARMA process and/or asset pricing models in modeling, ESM's returns need to be reconsidered due to the existence of fractional dynamics with long memory features.

Theoretical Background

The origin of interest in long memory process appears to have come from the examination of data in the physical sciences and preceded interest from economists. Since ancient times, the Nile River has been known for its long-term behavior characteristic. A phenomenon named by Mandelbrot and Wallis (1968) as "Joseph Effect" refers to the prophecy of Joseph that seven years of great abundance would come throughout the land of Egypt to be followed by seven years of famine Seemingly, observations in the remote past relative to the long memory process register high correlations with the observations in distant future.

Relying on this phenomenon, Hurst (1951) investigated the question of how to regularize the flow of the Nile River. In Hurst's empirical investigation, he developed a technique known as the rescaled adjusted range *R/S – Statistic*. The statistic is the range *R* of partial sums of deviations of a time series from its mean rescaled by its standard deviation *S*. However, the shortcoming of this technique is its sensitivity to the short range dependence, implying that any incompatibility between the data and the predicted behavior of *R/S* statistic under the null hypothesis need not come from long memory process, but could merely be a symptom of short-term memory. In this respect, Lo (1991) developed a modification of Hurst's ratio indicating distinction between long- and short-range dependence. Addressing the problem as to whether aggregation in data has any relevant effect on the dependence structure, Granger (1980) proved that aggregation of short-memory process may however, lead to long memory.

Subsequently, several studies have employed long-horizon returns in examining the Random Walk Hypothesis, predictability of asset returns, and the profitability of contrarian strategies. Contrarian strategy is a technical trading strategy that trades in the opposite direction of the market, i.e., it assumes that the majority of investors are wrong as the market approaches peaks and troughs. The importance of long-range dependence in asset markets was first studied by Mandelbrot (1971) who proposed the use of Hurst *R/S-statistic* to detect long-range dependence in economic series. He observed that pricing assets using martingale methods may not be appropriate if the continuous stochastic process would exhibit long memory. Yajima (1985) consequently, confirmed this observation by concluding that statistical inferences concerning asset-pricing models based on standard testing procedures may not be appropriate in the presence of long-memory series.

In retrospect, where the ARMA model (p,q) is a stationary process, the ARIMA model earlier introduced by Box and Jenkins (1970), an equivalent of the former model showed a process that is non-stationary with the time series integrated of order *d* referred to as an integer. The process should be stationary after differencing it *d* times. An extension to this model was formulated independently by Granger and Joyeux (1980) and Hosking (1981) known as the Fractional-ARIMA (ARFIMA) also referred to as fractional dynamics models, in which the time series could be integrated at a fractional value of *d*. More precisely, the time series that is stationary at $-0.5<d<0.5$ is called a Fractional ARIMA(p,d,q) process. The range that is interesting in the context of long-memory process is $0 \leq d < 0.5$;

It may be said that a time series that exhibits long memory process violates the weak form of Efficient Market Hypothesis developed by Fama (1970) whereby the information in historical prices or returns is not useful or relevant in achieving excess returns. Consequently, the Random Walk hypothesis stating that prices or returns move randomly, therefore rejected.

Egyptian Stock Market Overview

In 1992, Egypt revitalized its capital market after a stagnation of almost 40 years of President Nasr nationalization regime that started in the late 1950s. Thereafter, Egypt, one of the emerging markets during the period has been experiencing high performance. The government enacted the Capital Market Law No. 95 in June 1992, which replaced the multiplicity of laws previously regulating the securities market. A computer-based screen trading system was adopted, continuously, an order-driven market having one 4-hour trading session. A circuit breaker has been implemented since late February 1997 if only to dampen the increasing volatility in the market.

Within 1992-2000, the Egyptian Stock Market (ESM) experienced major progress in terms of activity (Table 1). Market capitalization has multiplied more than ten times to reach £E120 billion which is about US$30 billion[(1)] representing 35% of GDP compared to £E10 billion (about US$2.5 billion) representing 8% of GDP. The volume of trading recorded 1.1 billion securities of value at LE 54 billion in year 2000 compared to volume of 30 million securities at approximately 600 million in 1992.

[(1)] Exchange rate used is £E 3.95 per $

Table (1). Selected Indicators of Development for the Egyptian Stock Exchange 1990-2000

	1990	1991	1992	1993	1994	1995	1996	1997	1998	1999
Annual Returns CMAI	-	-	8.5%	22.0%	56.4%	-11.2%	33.0%	19.3%	6.2%	49.0%
EFGI	-	-	-	32.0%	94.3%	-7.9%	35.8%	13.5%	-29.1%	40.2%
HFI	-	-	-	47.0%	92.2%	-21.3%	30.3%	19.5%	-30.5%	35.4%
Number of Companies Listed\1	573	627	656	674	700	746	646	650	870	1033
New equity issues (LE Million)\2	N/A	N/A	N/A	N/A	4,879	11,251	20,378	19,485	35,303	55,573
Market Capitalization (In L.E. Million)	5,071	8,845	10,845	12,807	14,480	27,420	48,086	70,873	83,140	112,331
In percent of GDP	3.8%	6.7%	8.2%	7.4%	7.2%	12.2%	18.8%	25.4%	30.5%	36.8%
Value of trading (LE Million)	341.5	427.8	596.7	568.6	2,557.2	3,849.4	10,967.5	24,219.8	23,364.0	39,086.1
Listed shares and bands	206.2	233.9	371.4	274.9	1,214.0	2,294.2	8,769.2	20,282.4	18,500.6	32,851.0
Unlisted shares & binds (OTC)	135.3	193.9	225.3	293.7	1,343.2	1,555.2	2,198.3	3,937.4	4,863.4	6,235.1
Volume of trading (Million)\2	17.0	22.7	29.6	17.7	59.8	72.2	207.7	372.5	570.8	1,074.1
Listed shares and bonds	14.3	19.2	20.7	13.7	29.3	43.7	170.4	286.7	440.3	841.1
Unlisted shares & bonds (OTC)	2.7	3.5	8.9	4.0	30.5	28.5	37.3	85.8	130.5	233.0
Number of Companies traded	199	218	239	264	300	352	354	416	551	663
Turnover Ratio[3]	6.7	4.8	5.5	4.4	17.7	14.0	22.8	34.2	22.3	29.2
Memo Item: Nominal GDP\4	79,300	98,664	118,288	132,900	173,117	200,408	225,300	251,145	272,405	305,242

Sources: Capital Market Authority, Annual Report, various issues
1\At year end.
2\Shares and bands.
3\Value of trading listed securities as a share (in percent) of market capitalization.
4\Data from Ministry of Planning; In Million L.E.

Throughout the period from 1996 till 2000 (Figure 1), the market was volatile particularly from 1996-1997 at the height of the privatization program in early 1996, at the time the government was selling major stakes as Initial Public Offerings (IPSs). This was followed by a long period of sluggish market. However, in early 2000, the market peaked, recording new highs for most indices due to the sale of four major cement companies to anchor investors. Unfortunately however, the outstanding performance did not continue and the market sloped downwards to record new lows due to deterioration in monetary indicators and tension in the foreign exchange market (Sourial, 2001).

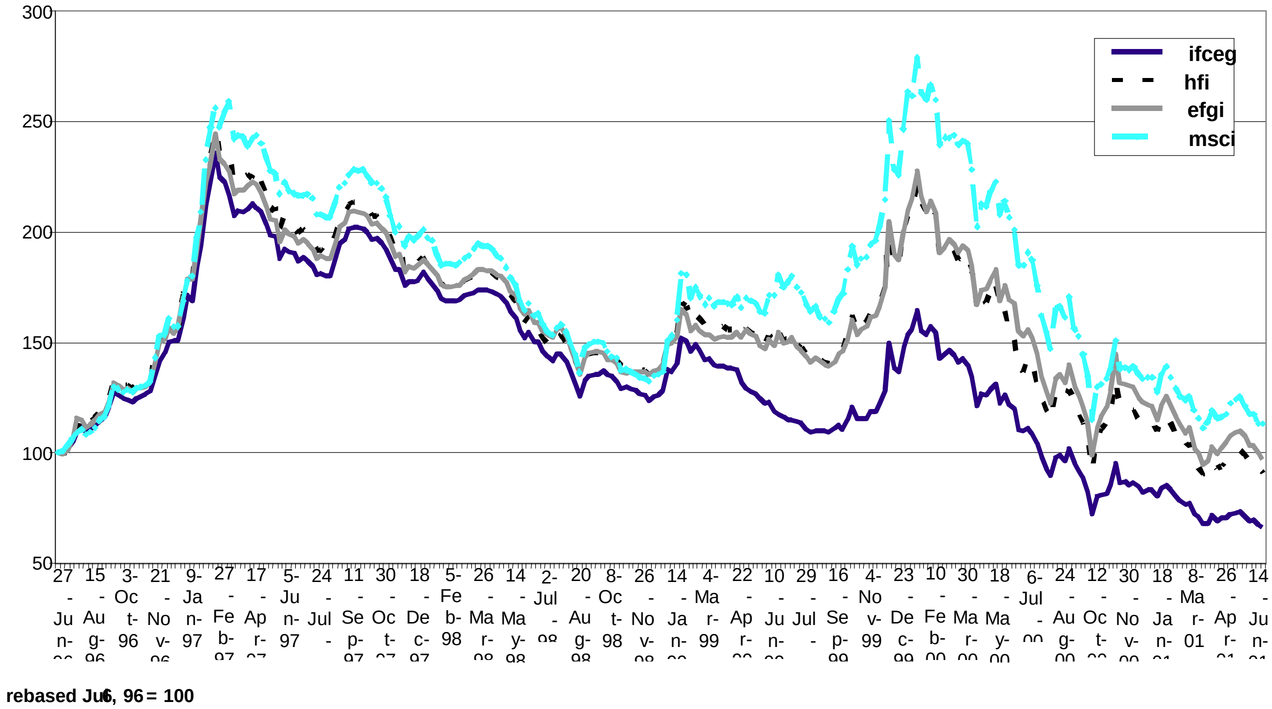


Figure (1).Performance of ESM's various indices

Empirical Methodology:

Empirical investigation was conducted using two known methodologies of fractional integration also known as fractional differencing, namely: (a) Autoregressive Fractional Integrated Moving Average (ARFIMA) model; and (ii) Fractional Integrated General Autoregressive Conditional Heteroscadasticity (FIGARCH) models.

The model of an autoregressive fractional integrated moving average process of order (p,d,q), denoted by ARFIMA(p,d,q), with mean μ , is presented as follows

$$\Phi(L)(1-L)^d(y_t-\mu)=\Theta(L)u_t, u_t \sim IID(0,\sigma_u^2) \qquad \text{Equation (1)}$$

where L is the backward-shift operator, $\Phi(L)=1-\phi_1 L-...-\phi_p L^p$,
$\Theta(L)=1+\vartheta_1 L+....+\vartheta_q L^q$, and $(1\text{-}L)^d$ is the fractional differencing operator defined by the following,

$$(1-L)^d=\sum_{k=0}^{\infty}\frac{\Gamma(k-d)L^k}{\Gamma(-d)\Gamma(k+1)} \qquad \text{Equation (2)}$$

where Γ. denotes the gamma function. The parameter d was allowed to assume any real value. The stochastic process y_t was both stationary and invertible if all roots of $\Phi(L)$ and $\Theta(L)$ lie outside the unit circle and $|d| < 0.5$, while it was non-stationary for $d \geq 0.5$ as it possessed infinite variance. The process was said to exhibit (i) long memory, or long-range dependence, if $d \in (0, 0.5)$ and $d \neq 0$; (ii) intermediate memory (anti-persistence), or long-range negative dependence for $d \in (-0.5, 0)$; and (iii) short memory if $d = 0$ corresponding to stationary and invertible ARMA modeling. For $d \in (0.5, 1)$, the process was mean reverting with no long run impact of an innovation on future values of the process. The significance of ***d*** was tested by *t-statistic* constructed using the theoretical error variance of $\pi^2/6$.

The fractional differencing parameter d was estimated using a semi-parametric procedure suggested by Geweke and Porter-Hudak (1983). The procedure was based on the slope of spectral density function, where $I(\xi)$ is the periodogram of y at frequency ξ as defined by the following,

$$I(\xi)=\frac{1}{2\pi T}\left|\sum_{t=1}^{T}e^{it\xi}\left(y_t-\bar{y}\right)\right|^2 \qquad \text{Equation (3)}$$

The ARFIMA model was estimated using two-stage maximization procedure[(2)] to maximize the log likelihood function (equation 4) suggested by Chung (1999). The first stage maximized the function using simplex method. This method is a search procedure which requires only function valuations, rather than derivatives. It starts by selecting *K+1* points in *K*-space, where *K* is the number of parameters. The geometrical object formed by the connection of these points is called a *simplex*. The second stage maximized the function using Broyden, Fletcher, Goldfrab, and Shanno (BFGS) method based on the estimation results from the simplex maximization method. Press et. al. (1988) described the method as the process that starts with a diagonal matrix, in which each iteration is updated based upon the change in parameters and in the gradient attempting to determine the curvature of the function. The log likelihood function for the sample of T observations considering conditional sum of squares is hereby shown:

$$l(\theta)=0.5\log\left(\sigma^2\right)+0.5\left(\sigma^{-2}\right)\sum_{t=1}^{T}\left[\phi(L)\theta(L)^{-1}(1-L)^d\left(y_t-\pi\right)\right]^2 \qquad \text{Equation (4)}$$

The second methodology, the FIGARCH model, is an extension of the Integrated GARCH models. The GARCH models introduced by Bollerslev (1986) reflect a natural

(2) in conjunction with RATs software procedure for the estimation of fractional integration models.

generalization of the ARCH process initiated by Engle (1982) The GARCH process is expressed as follows,

$$\varepsilon_t \mid \psi_{t-1} \sim N(0, h_t),$$

$$h_t = \alpha_0 + \sum_{i=1}^{q} \alpha_i \varepsilon_{t-i}^2 + \sum_{j=1}^{p} \beta_j h_{t-i} \qquad \text{Equation (5)}$$

where $\boldsymbol{\varepsilon_\tau}$ is a discrete-time stochastic process conditioned on information set $\boldsymbol{\psi_\tau}$ and is obtained from the following linear regression,

$$\varepsilon_t = y_t - x_t' b \qquad \text{Equation (6)}$$

$\boldsymbol{h_t}$ is the conditional variance, and

$$p \geq 0, q > 0,$$

$$\alpha_0 > 0,$$

$$\alpha_i \geq 0, i = 1, \ldots.., q,$$

$$\beta_i \geq 0, i = 1, \ldots, p$$

The process can be represented in terms of distributed lags of past $\boldsymbol{\varepsilon^2_\tau}$ as follows (Appendix 1 for derivation).

$$h_t = \alpha_0 [1 - \beta(L)]^{-1} + \alpha(L)[1 - \beta(L)]^{-1} \varepsilon_t^2 \qquad \text{Equation (7)}$$

On the other hand, the GARCH(*p,q*) process was estimated using Brendt, Hall, Hall and Hausman (1974) with maximum likelihood estimation (BHHH). The log likelihood function for a sample of *T* observations is as follows:

$$L_T(\theta) = T^{-1} \sum_{t=1}^{T} l_t(\theta),$$

$$l_t(\theta) = -0.5\left(\log h_t + \varepsilon_t^2 h_t^{-1}\right) \qquad \text{Equation (8)}$$

It may be observed that the GARCH process attempted to account for volatility persistence. However, the feature may be characterized by a relatively fast decay in volatility persistence. In practice, volatility shows very long temporal dependence especially in emerging market stock returns for reasons already discussed. Consequently, the process exhibited strong volatility persistence when [1-α(L)-β(L)] polynomial contains a unit root, as in the equation:

$$\sum_{i=1}^{q} \alpha_i + \sum_{j=1}^{p} \beta_j \approx 1$$

Based on the above, Baillie, Bollerslev and Mikkelsen (1996) formulated the Fractionally Integrated GARCH (FIGARCH) which combined high temporal dependence with parsimonious parameterization. FIGARCH (*p,d,q*) process is represented as follows: (Appendix 1 for derivation)

$$\sigma_t^2 = \omega + \lambda(L)\varepsilon_t^2 \qquad \text{Equation (9)}$$

where

$$\omega = \alpha_0 [1-\beta(L)]^{-1},$$

$$\lambda(L) = \{1-\phi(L)(1-L)^d [1-\beta(L)]^{-1}\},$$

$$0 \le d \le 1$$

The above process may be expressed as an ARFIMA process in ε^2_τ as follows: (Appendix 1 for derivation),

$$\phi(L)(1-L)^d \varepsilon_t^2 = \alpha_0 + [1-\beta(L)]\upsilon_t \qquad \text{Equation (10)}$$

where

$$\upsilon_t = \varepsilon_t^2 - h_t$$

Data and Statistical Distribution

The ESM performance is represented officially by the financial market regulator, the Capital Market Authority *all-stocks* index (CMAI), in addition to a number of domestic(3) and international(4) indices that monitor ESM performance. The official *all-stocks* CMA index has not been used as it proved its inefficiency in reflecting market performance due to its inclusion of large number of inactive traded stocks. Thus, the empirical investigation was conducted using weekly returns of IFC Global-Egypt index(5). The index was initiated in January 1996 with base value of 100 points which included 32 listed companies representing 51% of total market capitalization. At the end of December 2000, the index had 72 out of 1076 listed companies representing 20% of total market capitalization. Weekly returns were calculated for the index as continuously compounded returns at time t, r_{it}. The natural log difference in the closing market index P_t between two weeks is shown below(6):

$$r_t = \ln\left[\frac{P_t}{P_{t-1}}\right] = \ln(P_t) - \ln(P_{t-1}) \qquad \text{Equation (11)}$$

(3) Two indices published by Egyptian Financial Group-Hermes (EFG and HFI), one by Prime Securities Investments (PIPO) which monitors privatized companies' performance, one by HC Securities and others.

(4) Investable and Global indices published by the International Finance Corporation and MSCI-EM index.

(5) The index includes securities without accounting for the stock's availability to overseas investors. The present coverage of an International Finance Corporation Global (IFCG) Index exceeds 75% of total market capitalization, drawing on stocks in the order of their liquidity.

(6) Dividends were not included in the returns calculation due to lack of data.

The sample consisted of 287 observations starting December 29, 1995 and ending on June 28, 2001. The distributional statistics for the index returns was compared to other three indices such as (i) *actively-stocks indices* Hermes Financial Index (HFI) and Morgan Stanley MSCI-Egypt index; and (ii) *large-capitalization index* Egyptian Financial Group Index (EFGI). Table 2 reflects the following:

- The mean returns of the IFCG-Egypt shows the highest among the indices. According to the t-statistics, mean returns of the four indices proves insignificant from zero at 5% significant level. Medians' returns are negative and confirm the same ranking of the indices, thereby implying skewed series with departure from normality.
- It is evident that the four indices' returns are volatile (Figure 2). This has been confirmed by the ARCH test, where the null hypothesis of returns is homoscedastistic, rejected at 5 and 1% significance levels, using χ^2_1 statistic, in favor of heteroscedasticity in the four indices. In other words, the four indices' returns exhibit volatility clustering with a tendency for large (small) asset price changes to be followed by other large (small) price changes of either sign tending to be time dependent.
- Indices' returns display significant positive skewness where the null hypothesis of skewness coefficients conforming to the normal distribution value of zero is rejected at 1% significance level. This result is in compliance with means greater than the medians.
- The null hypothesis of kurtosis coefficients conforming to the normal distribution value of three is rejected at 5% significance level for the IFCG-Egypt and HFI returns. Thus, the returns of both indices prove to be leptokurtic with their distributions having thicker (fatter) tails than that of a normal distribution. The other two indices EFGI and MSCI (Morgan Stanley Capital Index)-Egypt are platykurtic.
- Results have been confirmed by rejecting the null hypothesis of the bivariate Jarque-Bera test for unconditional normal distribution of the indices' weekly returns.
- The indices returns register significant positive first-order autocorrelation (ρ_1), at 5 and 10% significance levels. The autocorrelation coefficient of the IFCG-Egypt index implies that only 1.3% of the variation in the weekly index returns is predictable using the preceding week's index returns. The EFGI records the highest level of predictability, as 1.6% of the variation in the weekly EFGI returns is predictable using the preceding week's index returns[(7)].

(7) The R^2 of a regression of returns on a constant and its first lag is the square of the slope coefficient, which is the first-order autocorrelation (Campbell *et al,* 1997).

- With respect to Dickey-Fuller[(8)] (1979) and Phillips-Perron[(9)] (1988) unit root statistics, the null hypothesis for both tests that indices returns, using t-statistics, have unit root is rejected in favor of the alternative that the four series are trend stationary process with a degree of predictability.

Table (2). Unconditional Distribution Statistics for the Selected Egyptian Stock Market Monthly Returns

	rifceg	rhfi	refgi	rmsci
Mean(%)	-0.18%	-0.08%	-0.06%	0.05%
t-statistics	-0.93516	-0.40135	-0.27223	0.19336
Median(%)	-0.29%	-0.28%	-0.16%	-0.01%
Standard Deviation(%)	3.28%	3.47%	3.55%	3.94%
Kurtosis	3.21463	3.17817	2.76491	2.3264
Excess Kurtosis	0.21463	0.17817	-0.23509	-0.6736
t-statistics\1	30.692	25.479	-33.618	-79.664
Skewness	0.463	0.438	0.36412	0.28529
t-statistics\2	1059.769	1002.293	833.117	539.840
Jarque-Bera test for normality\3	133.838	129.967	97.76	62.397
First-order autocorrelation coefficient (returns)	0.115	0.125	0.126	0.104
t-statistics	1.957	2.117	2.139	1.681
R-Squared	1.33%	1.55%	1.59%	1.08%
Dickey-Fuller Test	-15.304	-15.064	-15.015	-14.786
Phillips-Perron unit root test	-15.045	-14.897	-14.881	-14.520
ARCH-Test	35.210	33.624	38.765	25.303
Minimum(%)	-12.58%	-13.98%	-14.16%	-15.66%
Maximum(%)	15.44%	15.00%	15.65%	15.51%
Sample Period	96:1-01:6	96:1– 01:6	96:1-01:6	96:6-01:6
Count	287	287	287	261

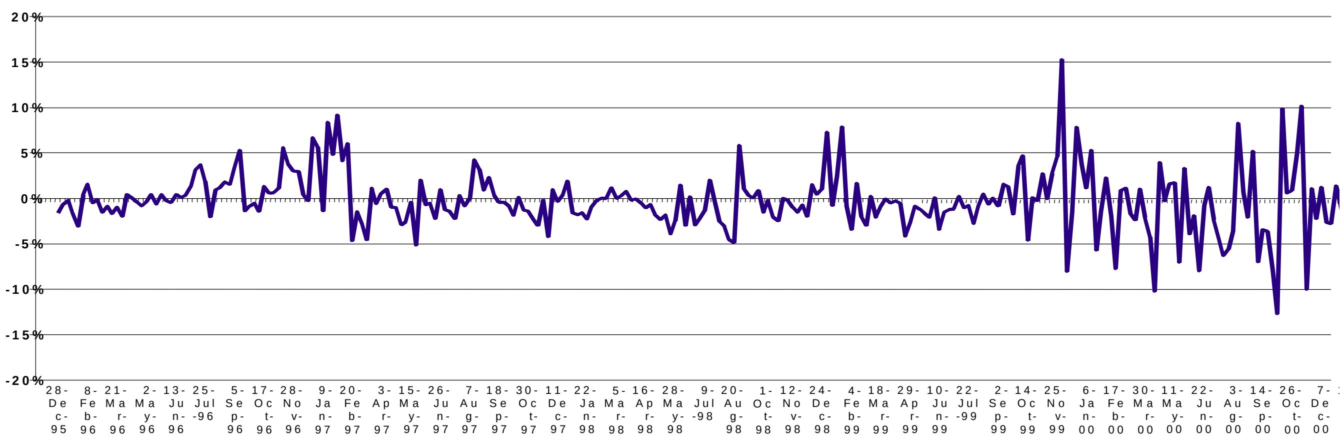
1\t=(K̀-3)\se(K̀)where se (K̀) = square root (24/n).
2\t=(S̀-0)\se(S̀) where se (S̀)=square root (6/n).
3\The Jarque-bera test for normality distributed as chi-square with 2 degrees of freedom. The critical value for the null hypothesis of normal distribution is 5.99 at the 5 percent significance level. Higher test values reject the null hypothesis.

(8) Dickey and Fuller (1979) devised a procedure to formally test for the presence of unit root using three different regressions. In this case, the following regressions with constant (a_0) and trend (t) (3rd regression presented by Dickey-Fuller) is used to test for nonstationarity: $\Delta y_t = a_0 + \gamma y_{t-1} + a_2 t + \sum_{i=2}^{P} \beta_i \Delta y_{t-i+1} + \varepsilon_t$, the null hypothesis is that $\gamma = 0$ for stochastic nonstationary process.

(9) Phillips-Perron non-parametric unit root tests were used because they allow for a general class of dependent and heterogeneously distributed innovations, contrary to other unit root tests

Summarily, the IFCG-Egypt index returns tend to be characterized by positive skewness, excess kurtosis and departure from normality. The index also displays a degree of heteroscedasticity and the series on stationary process trend with degree of predictability. The findings are in conformation with other market indices and consistent with several other empirical studies, in which emerging market returns depart from normality, hence, a rejection of the null hypothesis for a random walk. Mandelbrot (1963) and Fama (1965) shows that unconditional distribution of security price changes to be leptokurtic, skewed and volatility clustered. On the. other hand, Bekaert et. al. (1998) claim that 17 out of the 20 the monthly returns of emerging markets have positive skewness while 19 out of 20 have excess kurtosis resulting to the rejection of normality for more than half of the countries. Similarly, the results are consistent with other empirical studies on the ESM (Sourial, 1997; Mecagni and Sourial, 1999; Mohielden and Sourial 2000; Moursi, (1999).

IFC Global-Egypt Returns



HFI Returns

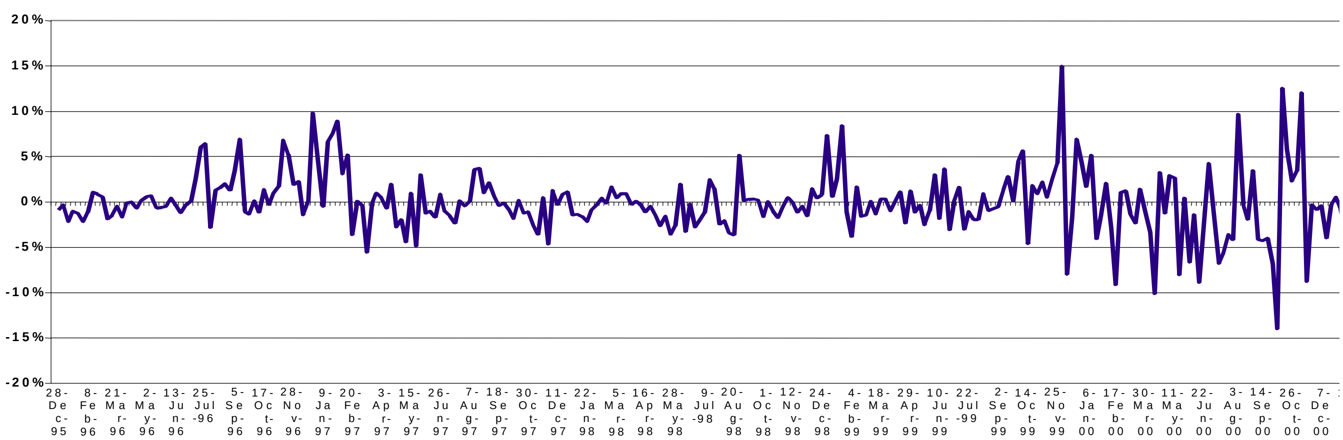


Figure (2).The Egyptian Stock Market Weekly Returns

Empirical Results

The empirical investigation was conducted using parsimoniously ARFIMA (1,*d*,1) model (Equation 1) to test for the existence of long memory process in the weekly IFCG-Egypt returns. The estimation of spectral regression was studied employing different frequencies of periodogram ordinates to evaluate the sensitivity of the results to the choice of the sample size. Data in Table 3 provide the following observations:

- The fractional differencing parameter value experienced minimal changes in value ranging from 0.222 to 0.203 varying the frequency of periodogram ordinates from *T* to *T*5*, .indicating *d-value*'s insensitivity to changes in the frequency of the ordinates.[(10)]
- There is evidence that the IFCG-Egypt weekly returns reveal fractional dynamics with long-memory features. The statistical significance of estimated *d* has been tested twice. The first hypothesis is a two-tailed *t-statistic* testing for H_0: $d = 0$ versus H_1: $d \neq 0$, while the second is one-tailed *t-statistic* testing for H_0: $d = 0$ versus H_1: $d > 0$. The null hypothesis in both tests are rejected in favor of *d-value* being significantly greater than zero statistically. Therefore the process may be said to be stationary which is in line with rejection of the unit root tests exhibiting long-memory process.
- The process may be considered long-range positive dependence as $d \in (0, 0.5)$ and $d \neq 0$. Consequently, the process is not mean reverting and could not be presented using ARMA models.

Furthermore, a parsimonious GARCH(1,1) model (Equation 5) has been estimated using the same data to test for the degree of volatility persistence i.e. $\sum_{i=1}^{q}\alpha_i + \sum_{j=1}^{p}\beta_j \approx 1$ and whether the process would exhibit a strong persistence and an Integrated GARCH (IGARCH) model could be considered or not.

Table (3). Estimates for ARFIMA(1,d,1)Model for ESM Weekly Returns
Using Broyden, Flecher, Goldfrab & Shanno (BFGS) Maximization Method

Nords=	T(287)	T^*2 (574)	T^*3 (861)	T^*4 (1148)	T^*5 (1435)
φ	0.08483 (0.7322)	0.07726 (0.22651)	0.074361 (0.21933)	0.072535 (0.31319)	0.071773 (0.2114)
ϑ	-0.2168 (-1.9159)*	-0.19835 (-0.53728)	-0.19149 (-0.51219)	-0.18756 (-0.82783)	-0.18547 (-0.4969)
d	0.22247 (2.11421)**	0.21063 (2.09405)**	0.20638 (2.05804)	0.20414 (1.02092)	0.202738 (2.07731)**
L (γ)	843.743	841.473	841.683	841.786	841.847

*** Significant at 1 percent, ** significant at 5 percent, * significant at 10 percent.

(10) Sensitivity of *d-value* towards the starting values assigned for the parameters has been tested *(not recorded)* providing evidence of no effect on the estimation results.

The results in Table 4 show that the significance of both α_1 and β_1 provided evidence that conditional volatility was time variant and that there were volatility clustering effects. Apparently, it appeared that shocks tended to persist, with large (small) innovations followed by similar ones. The significance of the parameters implies the existence of long memory process as shown by $\alpha_1 + \beta_1 = 1.04$.

Extending the investigation using FIGARCH (1,*d*,1) model (Equation 9), the model was manipulated to be presented as ARFIMA process (Equation 10). The transformation was to allow for estimating the model using RATS (Regression Analysis of Time Series) econometric software. The process of estimation could be similar to the procedures previously undertaken in estimating ARFIMA(1,*d*,1) process.

Table (4). Estimates for AR(1)-GARCH(1,1) Model for ESM Weekly Returns
Using Brendt, Hall, Hall and Houseman (BHHH) Maximization Method

Variable	AR(1)	$\alpha 0$	$\alpha 1$	$\beta 1$	$\alpha 1+\beta 1$	$L(\theta)$
Coefficient	0.1286	0.00007	0.52329	0.52144	1.04473	888.86
t-statistics	2.05596**	3.4554***	6.12776***	8.6433***		

*** Significant at 1 percent, ** significant at 5 percent, * significant at 10 percent.

Table 5 presents the following results:

- The fractional differencing parameter value records approximately 0.235 with different frequencies of the periodogram ordinates from *T* to *T*5* with exception of frequency for ordinates of *T*4* with value of 0.215. The result is an indication that *d-value* is insensitive to changes in the frequency of the ordinates which is in consonance with the previously estimated ARFIMA process.

- It has been proven that the IFCG-Egypt weekly returns manifest fractional dynamics with long-memory features. The null hypothesis in both tests are rejected in favor of *d-value* which was significantly greater than zero at 5% level for frequency of ordinates equal to *T*, *T*3* and *T*5*. As for frequency of ordinates equal to *T*2*, the first null hypothesis ($d = 0$) is rejected at 15% significance level, while the second null hypothesis ($d > 1$) is rejected at 10% significance level. Similar to the results of the ARFIMA process, frequency of ordinates equal to *T*4* is insignificant from zero. Thus, the process could be considered as a stationary process, and may be said to manifest long-memory process.

Table (5). Estimates for FIGARCH(1,d,1)Model for ESM Weekly Returns
Using Broyden, Flecher, Goldfrab & Shanno (BFGS) Maximization Method

nords=	T(287)	$T^{*}2$ (574)	$T^{*}3$ (861)	$T^{*}4$ (1148)	$T^{*}5$ (1435)
$\alpha 0$	0.01067 (0.13188)	-0.002 (-0.0186)	-0.1726 $(-1.96115)^{**}$	-0.00498 (-0.0313)	-2218 (-0.21066)
$\alpha 1$	0.86517 $(11.0519)^{***}$	0.8665 $(7.5993)^{***}$	0.87184 $(7.3629)^{***}$	0.86834 $(5.9240)^{***}$	0.89948 (7.2896)
$\beta 1$	0.14495 $(2.2616)^{**}$	0.14387 (1.5670)	0.11832 (1.0680)	0.14106 (1.15532)	0.10946 (0.91654)
d	0.2343 $(2.1632)^{**}$	0.2352 (1.5403)	0.23385 $(1.9301)^{*}$	0.2153 (1.07913)	0.23106 $(1.9628)^{**}$
$L(\theta)$	840.824	841.61	841.881	842.016	842.09
$\alpha 1+\beta 1$	1.0101	1.0104	0.9902	1.009	1.009

*** Significant at 1 percent, ** significant at 5 percent, * significant at 10 percent

Conclusion

The paper investigated the issue of volatility persistence in the ESM The investigation was approached empirically by testing for the presence of fractional dynamics, i.e. long memory in ESM's returns, using two methodologies, such as Fractional ARIMA (ARFIMA) and Fractional Integrated GARCH (FIGARCH) models. The investigation was conducted using Egypt's IFC-Global index weekly returns from January 1996 till end of June 2001.

The estimation results of both ARFIMA(1,*d*,1) and FIGARCH(1,*d*,1)models provided evidence that the IFCG-Egypt weekly returns volatility show fractional dynamics with long-memory features, conclusively, after the rejection of both one- and two-tailed *t-statistics* tests. These findings suggest that the estimated *d-value* is significantly greater than zero statistically with the process considered to be long-range positive dependence as $d \in (0, 0.5)$ and $d \neq 0$.

The above results are consistent with the evidence provided by Sourial (1997) using AR(*q*)-GARCH(*p,q*)-M models for distinct data frequencies for the ESM's returns and with Barkoulas *et.al.* (1997) testing for long-memory process in the Greek Stock Market. Thus, the hypothesis that the ESM is weakly efficient is rejected due to long-range dependence in weekly returns. The evidence is consistent with number of emerging market characteristics.

The results also confirm that the aggregation of short-memory process could lead to long memory features. These findings were identified by Mecagni and Sourial (1999) and Moursi (1999) and likewise consistent with Granger's (1980) observations. Hence, using ARMA representation and/or asset pricing models in modeling, ESM returns could not provide relevant results as Mandelbrot (1971) and Yajima (1985) have thereby confirmed.

Expectedly, because of most individual investors lacking the equity culture and with an investment strategy characterized by herd behavior, the market's adjustment to new information is predicted to be low. Moreover, the presence of non-synchronous trading due to the large number of inactive stocks listed in the stock exchange taking advantage of tax exemption, has thereby resulted to dependence of stock returns. as recorded in the Annual Reports on the stock market performance in 1999 and 2000 issued by the Ministry of Economy. Furthermore, maintaining the +/- 5% circuit breaker imposed in February 1997 might have failed to dampen the volatility in the market, resulting in extending the impact of shocks on market volatility for longer period causing the slow decay. The results imply that in some cases adopting a contrarian trading rule might not be a profitable strategy, after all.

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Appendix

Derivation of FIGARCH(*p,d,q)*
From GARCH(*p,q*) process

Starting with GARCH(p,q) process

i. $$h_t = \alpha_0 + \sum_{i=1}^{q} \alpha_i \varepsilon_{i-i}^2 + \sum_{j=1}^{p} \beta_j h_{t-j}$$

using lag operator the above equation will be as follows

ii. $$h_t = \alpha_0 + \alpha(L)\varepsilon_t^2 + \beta(L)h_t$$

iii. $$h_t - \beta(L)h_t = \alpha_0 + \alpha(L)\varepsilon_t^2$$

iv. $$[1-\beta(L)]h_t = \alpha_0 + \alpha(L)\varepsilon_t^2$$

v. $$\therefore h_t = \alpha_0[1-\beta(L)]^{-1} + \alpha(L)[1-\beta(L)]^{-1}\varepsilon_t^2$$

if $[1-\alpha(L)-\beta(L)]$ *polynomial contains unit root i.e.* $\sum_{i=1}^{q}\alpha_i + \sum_{j=1}^{p}\beta_j \approx 1$

$\therefore$ the process is considered Integrated GARCH (IGARCH)

vi. $$[1-\beta(L)]h_t = \alpha_0 + \alpha(L)\varepsilon_t^2$$

vii. $$-\alpha(L)\varepsilon_t^2 = \alpha_0 - [1-\beta(L)]h_t$$

multiply both sides by $[1-\beta(L)]\varepsilon_t^2$

viii. $$[1-\beta(L)]\varepsilon_t^2 - \alpha(L)\varepsilon_t^2 = \alpha_0 + [1-\beta(L)]\varepsilon_t^2 - [1-\beta(L)]h_t$$

ix. $\left[1-\alpha(L)-\beta(L)\right]\varepsilon_t^2=\alpha_0+\left[1-\beta(L)\right]\left(\varepsilon_t^2-h_t\right)$

let $\phi(L)=\left[1-\alpha(L)-\beta(L)\right](1-L)^{-1}$

x. $\phi(L)[1-L]\varepsilon_t^2=\alpha_0+\left[1-\beta(L)\right]\left(\varepsilon_t^2-h_t\right)$

xi. $\phi(L)[1-L]\varepsilon_t^2=\alpha_0+\left[1-\beta(L)\right]\varepsilon_t^2-\left[1-\beta(L)\right]h_t$

xii. $\left[1-\beta(L)\right]h_t=\alpha_0+\left[1-\beta(L)\right]\varepsilon_t^2-\phi(L)(1-L)\varepsilon_t^2$

xiii. $h_t=\alpha_0\left[1-\beta(L)\right]^{-1}+\varepsilon_t^2-\phi(L)(1-L)\left[1-\beta(L)\right]^{-1}\varepsilon_t^2$

xiv. $h_t=\alpha_0\left[1-\beta(L)\right]^{-1}+\left[1-\phi(L)(1-L)\left[1-\beta(L)\right]^{-1}\right]\varepsilon_t^2$

transferring the IGARCH process in equation (xiv) to FIGARCH(p,d,q) process by replacing (1-L) with $(1-L)^d$

xv. $\therefore h_t=\alpha_0\left[1-\beta(L)\right]^{-1}+\left[1-\phi(L)(1-L)^d\left[1-\beta(L)\right]^{-1}\right]\varepsilon_t^2$

for simple representation

xvi. $h_t=\omega+\lambda(L)\varepsilon_t^2$

where

$$\omega=\alpha_0\left[1-\beta(L)\right]^{-1},$$

$$\lambda(L)=\left\{1-\phi(L)(1-L)^d\left[1-\beta(L)\right]^{-1}\right\}$$

from equation (x) , FIGARCH process can represented in the form of ARFIMA process as follows

xvii. $$\varepsilon_t^2=\frac{\alpha_0+\left[1-\beta(L)\right]\left(\varepsilon_t^2-h_t\right)}{\phi(L)(1-L)^d}$$

substitute with ϕ(L) and let $\nu_t=\left(\varepsilon_t^2-h_t\right)$ to formulate the model estimated by RATs

xviii. $$\varepsilon_t^2=\frac{\left[\alpha_0+\left[1-\beta(L)\right]\nu_t\right](1-L)}{\left[1-\alpha(L)-\beta(L)\right](1-L)^d}$$