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Abstract

This research investigates the presence of structural breaks in the indices of the Egyptian stock market using the Bai-Perron strcutural breaks test. The indices used are the EGX 30, the EGX 70, the EGX 100, and the EGX 20. The presence of long memory is then investigated using the GPH test and the modified GPH test by Andrews and Guggenberger for the full sample and the identified break periods for each index. Finally, an EGARCH model is estimated for the full sample and each break period. Structural breaks were identified triggered by the subprime crisis and the world financial crisis for three indices. Structural breaks triggered by events of the Egyptian revolution were accurately identified for one index. For the daily returns of the EGX 30, EGX 70, and the EGX 100 long memory is found to be spurious while for the EGX 20 long memory in returns is more apparent. For volatility, real long memory is present in the EGX 30, the EGX 70, and the EGX 20, while spurious long memory is present in the EGX 100 because of the presence of periods exhibiting strong anti-persistence. The EGARCH parameters for the full sample were found to be significantly different from the specifications for the break periods for each index. It is concluded that structural breaks are clearly present in the indices of the Egyptian stock market and have considerable impact on the dynamics of daily returns and volatility.

Key words: The Egyptian exchange, long memory, GPH, structural breaks, EGARCH.

JEL Classification Code: C14, C32, C58, D53, G17

1. Introduction

The concept of long memory was first formulated by Hurst (1951) in his ground-breaking work on hydrology while studying river flow data of the Nile. Long memory can be defined as the presence of dependencies in a time series between distant observations in the past and distant observations in the future. The autocorrelation function in a time series exhibiting long memory decays hyperbolically. Interestingly, Mandelbrot and Wallis (1968) described the long-range dependence in a time series as the “Joseph Effect” in reference to the Prophet Joseph who foretold that the land of Egypt will enjoy seven years of abundance followed by suffering seven years of famine. Mandelbrot (1971) was among the first to acknowledge the existence and implications of long memory in economic time series. Since then, extensive research has been conducted on the application of long memory models in macroeconomics, asset pricing, stock returns, exchange rates, and interest rates. The most fundamental implication of long memory in stock returns and volatility concerns the efficient market hypothesis proposed by Fama (1970). Weak-form market efficiency implies that current and future observations are independent of past observations. Therefore, the presence of long memory would challenge the validity of weak-form market efficiency. In a weakly efficient market, assets are priced using martingale methods which would clearly not be valid in the presence of long memory. Long memory implies a degree of predictability in stock returns enabling investors and portfolio managers to develop methodologies not based on the random walk model. If long memory does indeed exist in a time series of stock returns, then the entire concept of weak-form market efficiency would have to be abandoned and investment approaches that have been used for decades would have to be reversed. However, detecting and confirming the presence of long memory can be quite illusive.

Early research investigating long memory in economic time series applied the rescaled range (R/S) statistic proposed by Hurst (1951). This involved dividing the difference between the largest and smallest values in the observations over a certain segment by the standard deviation of the observations during the same segment. A significant deficiency of the R/S-statistic is its sensitivity to short-range dependence. Since stock market returns may exhibit short-term dependencies, long memory properties identified by the R/S statistic may be an outcome of short-term memory in the returns. Kandel and Stambaugh (1989) asserted that the long-run predictability of stock returns uncovered by several researchers may not be long-run in the time series, but may be the result of short-range dependence. Also, Kim, Nelson, and Startz (1991), Richardson (1993), and Richardson and Stock (1989) suggested that indications of long-term dependence may be spurious. Another common method for investigating long memory is the Geweke and Porter-Hudak (GPH) test which is a semi-parametric approach based on spectral regression. Since long memory processes can be characterized by a fractionally integrated process with the degree of integration having values less than one but greater than zero, the GPH test estimates the differencing parameter which would provide an indication on the underlying memory process of the time series. Since the GPH has certain shortcomings, several modifications have been proposed including that of Smith (2005), Robinson and Henry (1999), Andrews and Guggenberger (2003) and many others.

Structural breaks in a time series can greatly impact the statistical properties of the series. A statistical property such as long memory may be apparent for a certain sample, but a closer investigation would reveal that the long memory property results from structural breaks or slow regime switching in the time series. Such a result is referred to as spurious long memory. Therefore, it is critical to test for structural breaks to uncover non-stationarities in the time series. Structural breaks methods are numerous and may test for a single break in the time series or may test for multiple breaks. Among them are the CUSUM, ICSS, Bai-Perron, and Zivot-Andrews test.

This research investigated the impact of structural breaks on the long memory property in market returns and volatility for the Egyptian stock market using the Egyptian Exchange EGX 30, EGX 70, EGX 100, and the EGX 20 indices. Also investigated were the changes in the GACRH parameters during the break periods. The presence of long memory in market returns would cast serious doubt on the validity of weak-form market efficiency, requiring investors to abandon random walk approaches in modeling the dynamics of market returns. Accurate modeling of the long memory property in volatility would have significant implications for risk management, portfolio optimization, derivatives pricing, and the calculation of the value-at-risk (VaR).

The remainder of this paper is organized as follows: Section 2 presents a literature review. Section 3 describes the data set. Section 4 describes the methodology. Section 5 presents the empirical findings and Section 6 presents the summary and conclusion.

2. Literature Review

Extensive research has been conducted on modeling long memory in economic time series in both developed and developing markets across different frequencies with mixed results. In general, long memory properties seem to be market specific with stronger presence in emerging markets. This outcome is expected since emerging markets are less efficient. Also, long memory in volatility is more pervasive than long memory in returns across both developed and developing markets. For developed markets, Lo (1991) applied the modified R/S-statistic to daily and monthly stock returns of value- and equal-weighted indices from the Center for Research in Securities Prices (CRSP). He found no evidence of long-range dependence in any of the indices once short-range dependence is taken into account. Cheung and Lai (1995) applied the modified rescaled range test and the fractional differencing test to the Morgan Stanley Capital International stock index data for eighteen countries. They found little support for long memory in international stock returns. Jacobson (1996) applied the modified rescaled range statistic proposed by Lo (1991) to return series from five European countries as well as the United States and Japan. He reported that none of the returns exhibited long-term dependence. Henry (2002) tested a set of monthly stock index returns for long memory using parametric and semi-parametric estimators The semi-parametric approaches provided strong evidence of long memory in the South Korean returns and some evidence of long range dependence in the German, Japanese and Taiwanese market returns. MacMillan and Thupayagale (2008) examined long memory in equity returns and volatility for South Africa using the ARFIMA-FIGARCH model. They reported that volatility exhibits a predictable component, while returns do not. Blasco and Santamarina (1996) studied memory patterns of returns in the Spanish stock market. They found no convincing evidence of long-range memory. Sadique and Silvapulle (2001) reported evidence of long memory in the stock returns of the Korean, Malaysian, Singapore and New Zealand stock markets. Bilel and Nadhem (2009) investigated long memory in stock returns of G7 countries by applying a wide range of parametric and semi-parametric estimators. They reported some evidence for positive long memory in 5 of the 7 series considered. Kang and Yoon (2007) investigated long memory patterns in returns and volatility of the Korean stock market. They reported that long memory dynamics in the returns and volatility can be adequately estimated by the joint ARFIMA-FIGARCH model.

For emerging markets, research on long memory has been equally impressive. Barkoulas, Baum and Travlos (2000) investigated long memory in the Greek stock market using fractional differencing parameters. They reported significant and robust evidence of positive long-term persistence in the Greek stock market. Cajueiro and Tabak (2006) investigated long-range dependence in asset returns in the Chinese stock market using Hurst's exponent. They reported that while type B shares presented strong evidence of long- range dependence, type A shares presented only weak evidence of such dependence. Assaf and Cavalcante (2005) investigated long-range dependence in the returns and volatility of the Brazilian stock market. They reported that significant long memory is conclusively demonstrated in the volatility measures, while there was a little evidence of long memory in the returns themselves. Tan, Chong and Yeap (2010) examined long memory in the Malaysian stock market during the 1985- 2009 period. Their results showed persistent long memory in the sub-period up to the 1997 Asian crisis.

For research that included the Egyptian market, Assaf (2007) investigated long memory properties of stock market returns and volatility for countries in the Middle East and North Africa (MENA) region using non-parametric fractional integration procedures. He found evidence of long memory in the stock returns for Egypt and Morocco. For Jordan and Turkey, he found evidence of anti-persistence. All countries examined showed evidence of long memory in the volatility series. Anoruo and Gil-Alana (2011) examined the behavior of stock market returns and volatility in several African countries using fractionally integrated techniques. They found evidence of long memory in the markets of Egypt and Nigeria and to a lesser extent in the markets of Tunisia, Morocco and Kenya. For squared returns, they found evidence of long memory in Nigeria and Egypt. Sourial (2002) investigated market returns volatility using ARFIMA and FIGARCH models on IFC-Global weekly returns for the Egyptian market. He concluded that both models provided evidence that returns volatility exhibited fractional dynamics with long memory features.

Research on the impact of structural breaks on long memory has increased in recent years as testing methods have been included in many econometric software applications. Structural breaks can be exogenously identified if the break dates are known. Exogenously identified break periods include the crash of 1929, the oil shocks of 1973-1974, the Asian financial crisis in 1997, the World Trade Center disaster in 2001, the world financial crisis in 2008-2009 among others. Structural breaks are endogenously detected when the break dates are identified from the changing statistical properties of the time series using a structural breaks test. Only research on endogenously identified structural breaks is covered. Kormaz, Cevik, and Ozatac (2009) apply the ICSS test on the Istanbul Stock Exchange. They identified four break points between January 1988 and January 2008. Babikir, Gupta, Mwabutwa, and Owusu-Sekyere (2010) found evidence of structural breaks in the unconditional variance of the stock returns series of the Johannesburg Stock Exchange (JSE) All Share Index. They reported high levels of persistence and variability in the parameter estimates of the GARCH (1,1) model during the break periods. Arouri, Hammoudeh, Lahiani, and Nguyen (2012), identify several structural break points in the returns of precious metals using the modified ICSS algorithm. Kim, Leo, and Leatham (2010) identified structural breaks in the markets of Korea, Japan, Hong Kong, and Singapore using the Sup-LM test. Structural breaks are common among the time series of various assets, if ignored could lead to inaccurate or false model specifications.

3. The Data Set

Data for all the indices were obtained from the Egyptian Exchange. The indices used were the EGX 30 benchmark, EGX 70, EGX 100, and the EGX 20. All indices had the same start and end dates covering the period from 3/1/2008 to 31/12/2012.

The EGX 30 index was initially the Cairo and Alexandria Stock Exchange (CASE) 30 index. The inception date of the index is January 2nd 1998. The index includes the top 30 companies in terms of liquidity and activity. The index value is calculated in Egyptian Pounds and denominated in US dollars since 1998. The EGX 30 index is weighted by market capitalization and adjusted by the free float of each constituent company.

The EGX 70 index was introduced on March 1st 2009 and is retroactively computed as of January 1st 2008. The index tracks the performance of the 70 active companies after excluding the 30 most active constituent companies of EGX 30 and is not market capitalization weighted.

The EGX 100 index was introduced on August 2nd 2009 and is retroactively computed as of January 1st 2006. The index tracks the performance of the 100 active companies, including both the 30 constituent companies of EGX 30 and the 70 constituent companies of EGX 70 and is not market capitalization weighted.

The EGX 20 capped is computed as of January 30th 2003. The index is designed to capture the performance of the most active 20 companies in terms of market capitalization and liquidity, capping the weight of any constituent to a maximum of 10%.

Index daily returns are computed as the logarithmic continuously compounded percentage rate of return at time t where:

$$R_t = \ln (Pt/P\ t\text{-}1)*100 \qquad (1)$$

R_t is the rate of return and P_t is the daily closing price of the index.

Volatility is defined as the absolute value of returns.

4. Methodology

Structural breaks are common in financial time series and are triggered by regime changing events that impact the dynamics of returns and volatilty in financial markets. Statistical properties that may be apparent for a given period are considerably different once structural breaks are considered. The presence of structural breaks in a times series causes volatility to increase more than expected (Korkmaz, Cevik, and Ozatac 2009). Therefore, it is not easy to distinguish between the long memory property from the occasional-break process and the one from the I(d) process (Granger and Hyung 2004). Evidence of long memory may therefore be a result of structural breaks in the time series and not the presence of long-term dependence. In order to identify break points in the time series, the Bai-Perron (2003) test was used. This test allows testing for a fixed number of breaks where the break dates are unknown. Using a dynamic programming algorithm, the test produces an efficient computation of the break points as a global minimizer of the sum of squared residuals. In this research, structural break points were first identified, then long memory was investigated for the full sample period and then for the individual break periods. The presence of up to three break points was investigated.

A stationary stochastic process is defined as a long memory process if the autocorrelation coefficients are positive and decay monotonically and hyperbolically to zero. More formally, a time-series y_t, exhibits long memory, if the quantity:

$$\lim_{T\to\infty} \sum_{k=-T}^{T} |\rho_k| \tag{2}$$

is non-finite, where ρ_k is the autocorrelation function of y_t.

One method used for capturing the effect of long memory is the fractionally integrated times series model introduced by Granger and Joyeux (1980) and Hosking (1981). In this model, the autocorrelation coefficients decline at a hyperbolic rate displaying persistence over long lags. The form of the fractionally integrated model is as follows:

$$\Phi(L)(1-L)^d(y_t-\mu)=\Theta(L)u_t \text{ where } u_t \sim i.i.d.(0,\sigma_u^2) \tag{3}$$

where d is the fractional integration parameter, L is lag operator, u_t is white noise residual, and the roots of Φ(L) and θ (L) lie outside the unit circle.

The fractional differencing lag operator $(1-L)^d$ can be represented as follows:

$$(1-L)^d=\sum_{k=0}^{\infty}\frac{\Gamma(k-d)L^k}{\Gamma(-d)\Gamma(k+1)}, \tag{4}$$

where Γ is the gamma function.

For d=0, the process is stationary and exhibits short memory; for d=1 the process is non-stationary and follows a unit root process; for 0<d<0.5 the process has positive dependence between distant observations exhibiting long memory; and for -0.5<d<0 the process has negative dependence between distant observations exhibiting anti-persistence. Also referred to as pink noise or 1/f noise, anti-persistence is a phenomenon describing a time series that reverses itself more frequently than a random series. In order to determine the differencing operator, several non-parametric and semi-parametric methods can be used including the GPH log-periodogram regression, local Whittle estimator, Phillips-Kim modified GPH estimator, and the Andrews-Guggenberger biased corrected GPH estimator (mGPH) among many others. In this research both the GPH and the mGPH tests were used.

The GPH test is one of the most widely used estimating procedures for the differencing parameter. In this test, the ordinates of the log spectral density are regressed on a trigonometric function. The GPH test is easy to apply and is robust to non-normality and short-range dependence but suffers from small sample bias. If the number of observations is small, estimates of the differencing parameter may be upwardly biased. As the sample size becomes larger, the power of the GPH test becomes higher. In order to overcome this shortcoming, the modified GPH test by Andrews and Guggenberger (2003) is also used. The mGPH includes additional regressors in the estimation equation in order to reduce the small sample bias of the original GPH test. In this research both GPH and mGPH tests were used since small samples were generated when the break periods were indentified. Elder and Villupuram (2012) applied the same approach in order to investigate persistence in the returns and volatility of home price indices in the United States.

Presence of a structural break indicates a change in the statistical properties of the break period. Consequently, model parameters for a GARCH process would also change during the break periods identified. Kim, Leo, and Leatham (2010) reported changes in GARCH parameters during structural breaks for Asian markets where the ARCH coefficient tends to decrease while the GARCH coefficient tends to increase, indicating higher persistence of volatility. Babikir, Gupta, Mwabutwa, and Owusu-Sekyere (2010) reported that structural breaks in the stock market of South Africa lead to variability in the parameter estimates of the GARCH (1,1) model across the sub-samples defined by the structural breaks. Such conclusions are natural since break periods signify changes in statistical properties that would require different parameters for accurate model specification. In this research we investigated how structural changes impact EGARCH parameters for the different break periods. An EGARCH (1,1) is estimated for the full sample for each index, and then estimated for each break period and the generated parameters are compared.

5. Empirical Findings

Descriptive statistics for all indices are provided in Table 1. For all indices, returns exhibit a small negative mean and a large standard deviation compared to the mean. All indices are negatively skewed indicating a longer left tail. All indices exhibit excess kurtosis with fat tails and a high peak around the mean. Values for the skewness and kurtosis indicate a significant deviation from the normal distribution which is confirmed by the Jarque-Bera (JB) statistic for all indices.

Table 1: Descriptive statistics for daily returns of the Egyptian Exchange indices

	EGX 30	**EGX 70**	**EGX 100**	**EGX 20 Capped**
Mean	-0.056381	-0.062125	-0.055857	-0.056480
Median	0.098145	0.000000	0.110681	0.109111
Maximum	7.311303	8.187253	6.891087	7.430365
Minimum	-17.98597	-16.76269	-16.20638	-17.40228
Standard Deviation	2.023514	2.085412	1.940144	2.008181
Skewness	-1.159151	-1.397609	-1.534819	-1.136323
Kurtosis	10.65218	10.89490	12.03491	10.28279
Jarque-Bera	3172.548 (0.00000)	3480.834 (0.00000)	4518.466 (0.00000)	2888.369 (0.00000)

P- values are given in parenthesis

Table 2 displays the indentified break dates by the Bai-Perron test for each index. For the EGX 30, EGX 70, and the EGX 100 the identified breaks are related only to the subprime crisis and the world financial crisis of 2008 and 2009. For the EGX 20, the test accurately identified break periods related to the Egyptian revolution. One in January, at the beginning of the revolution and one in March when the Egyptian market was re-opened.

Table 2: Break dates for each index

Break Point	EGX 30	EGX70	EGX 100	EGX 20
1	8/9/2008	14/9/2008	14/9/2008	5/2/2009
2	24/11/2008	26/10/2008	26/10/2008	6/1/2011
3	4/11/2009	1/10/2009	1/10/2009	24/3/2011

Table 3 displays the results for the GPH test and the mGPH test according to Andrews and Guggenberger who adjusted for small sample biases. The tests were applied to returns and absolute returns as a proxy for volatility. The tests were applied on the full sample (2/1/2008-31/12/2012) and on each identified break period for each index. For the returns of the full sample, both GPH and the mGPH presented weak evidence of long memory. For the break periods of the EGX 30, EGX 70 and the EGX 100, we have stronger evidence of anti-persistence indicated by negative values of the differencing parameter followed by a period of long memory. It seems that there are alternating periods of anti-persistence and long memory. For the break periods of the EGX 20, we have one period of anti-persistence followed by three periods of clearly indicated long memory. Therefore, for the returns of the EGX 30, EGX 70, and the EGX

100 long memory is considered spurious while for the EGX 20 long memory is considered to be more apparent.

For volatility as represented by the absolute value of returns, strong evidence of long memory was present in the full sample period for all indices. For the EGX 30, long memory was also indicated in the break periods except for one period from November 2008 to January 2009 where the time series seem to be non-stationary. For the break periods of the EGX 70, long memory was indicated except for one short period from September 2008 to October 2008 where weak anti-persistence was indicated. For the EGX 100 we have break periods of alternating strong long memory and strong anti-persistence. For the EGX 20, strong evidence of long memory was present except for the last break period where weak anti-persistence was indicated. Overall, it can be surmised that for volatility, real long memory was present in the EGX 30, the EGX 70, and the EGX 20, while spurious long memory is present in the EGX 100 because of the presence of periods exhibiting strong ant-persistence.

Table 3: Output for differencing parameter (d)

	Returns		**Absolute returns**	
	GPH	**mGPH**	**GPH**	**mGPH**
EGX 30				
Full sample period	0.17819	0.16644	0.38597	0.37929
3/1/2008-7/9/2008	-0.23117	-0.20846	0.07033	0.19376
8/9/2008-23/11/2008	0.60997	0.41010	0.13720	0.08222
24/11/2008-3/1/2009	-0.61489	-0.08862	0.68816	0.64208
4/1/2009-31/12/2012	-0.00558	0.00837	0.24083	0.23934
EGX 70				
Full sample period	0.01659	0.01934	0.29959	0.29254
3/1/2008-13/9/2008	0.32821	0.31464	0.18350	0.29145
14/9/2008-25/10/2008	-0.26392	-0.13796	-0.13854	-0.02751
26/10/2008-30/9/2009	0.22956	0.32043	0.19191	0.33711
1/10/2009-31/12/2012	-0.57841	-0.59818	0.07896	0.07759
EGX 100				
Full sample period	0.02283	0.02657	0.33448	0.33010
3/1/2008-13/9/2008	0.23274	0.25738	0.18654	0.27568
14/9/2008-25/10/2008	-0.48864	-0.29050	-0.51992	-0.38306
26/10/2008-30/9/2009	0.16741	0.21976	0.30509	0.54748
1/10/2009-31/12/2012	-0.24380	-0.25695	-0.13190	-0.16192
EGX 20 Capped				
Full sample period	0.11633	0.11260	0.39591	0.38691
3/1/2008-4/2/2009	-0.14225	-0.15332	0.63472	0.62724
5/2/2009-5/1/2011	0.50984	0.47540	0.40676	0.41657
6/1/2011-23/3/2011	0.13236	0.35067	0.19863	0.36191
24/3/2011-31/12/2012	0.21175	0.19688	-0.03092	-0.02959

mGPH are results of the modified GPH according to Andrews and Guggenberger (2003)

Table 4 displays EGARCH (1,1) specifications for the indices. For the full sample, all indices were well specified with high values of β demonstrating high persistence in the presence of long memory as indicated by the GPH and mGPH tests. Also, the leverage effect was apparent and significant. For the break periods of the EGX 30, failure to improve likelihood was encountered in three periods. This could be due to the small sample sizes of the break periods. According to Ng and Lam (2006), if the sample size is too small the estimated conditional variances may be noise only. They also reported if the sample size is less than 700, two or more optimal solutions may be found by the maximum likelihood estimation method. For the EGX 70 failure to improve likelihood was encountered for a break period with only 24 observations, which is an expected result. Also, for the last break period, the unusual result of a negative β beta was reported in the presence of weak long memory as indicated by the GPH and mGPH tests. For the EGX 100 all break periods were well specified, including periods with small sample sizes. For the two periods where anti-persistence was reported, one period was specified with a negative α and a small β. The second period where anti-persistence was reported, a highly negative and statistically significant β was reported. This finding demonstrates the success of the EGARCH model in specifying volatility during periods of anti-persistence. In the EGARCH model the non-negativity constraints for the parameters ω, α and β can be relaxed because of the log value of the volatility that guarantees a positive value of the variance. For the EGX 20, the expected result of failure to improve likelihood was encountered where the sample size was 14. For break periods where strong long memory was indicated by the GPH and the mGPH tests, β values were high indicating high persistence.

It is significant to report that for the full period, the parameters α, β, and γ are all close in value for the indices. However, for each index, the parameters for the full sample were considerably different from the parameters for the break periods. Therefore, testing for structural breaks is important in order to obtain specification parameters that are more precise for each break period.

Table 4: EGARCH parameters for the different break periods

		Mean Equation	**Variance Equation**			
Index	**Sample Size**	**C**	**ω (Constant)**	**α (Arch Effect)**	**β (Garch Effect)**	**γ (Leverage Effect)**
EGX 30						
Full sample period	1191	0.000185	-0.631275	0.282543	0.948586	-0.117287
		(0.7003)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
3/1/2008-7/9/2008	169	*-0.000460*	*-1.851023*	*0.111025*	*0.791728*	*-0.198391*
		(0.7091)	*(0.0225)*	*(0.4674)*	*(0.0000)*	*(0.0143)*
8/9/2008-23/11/2008	49	*-0.013737*	*-0.507552*	*-0.251567*	*0.889026*	*-0.257671*
		(0.0000)	*(0.0000)*	*(0.0000)*	*(0.0000)*	*(0.0000)*
24/11/2008-3/1/2009	23	*0.010536*	*-11.51455*	*2.407601*	*-0.266818*	*-0.144654*
		(0.0000)	*(0.0000)*	*(0.0078)*	*(0.2070)*	*(0.8362)*
4/1/2009-31/12/2012	947	0.000388	-0.982906	0.341770	0.911657	-0.116381
		(0.4553)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
EGX 70						
Full sample period	1191	0.000597	-0.962303	0.278927	0.906374	-0.138783
		(0.2507)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
3/1/2008-13/9/2008	173	-0.000304	-2.175232	0.326267	0.764759	-0.119975
		(0.8260)	(0.1077)	(0.0099)	(0.0000)	(0.1443)
14/9/2008-25/10/2008	24	*-0.016404*	*-13.59556*	*0.923770*	*-0.913982*	*0.012988*
		(0.0000)	*(0.0000)*	*(0.1593)*	*(0.0005)*	*(0.9841)*
26/10/2008-30/9/2009	230	0.003747	-8.716859	0.402678	-0.063375	-0.225509
		(0.0041)	(0.0000)	(0.0139)	(0.8123)	(0.0673)
1/10/2009-31/12/2012	761	-0.001056	-14.29868	0.329473	-0.773563	0.054703
		(0.1187)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
EGX 100						
Full sample period	1191	0.000433	-0.703758	0.248873	0.936939	-0.134350
		(0.3708)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
3/1/2008-13/9/2008	173	0.000112	-1.659295	0.242737	0.825626	-0.133116
		(0.9314)	(0.0464)	(0.0277)	(0.0000)	(0.0816)
14/9/2008-25/10/2008	24	-0.013049	-2.829525	-2.000886	0.351960	-0.910991
		(0.0000)	(0.0000)	(0.0000)	(0.0007)	(0.0118)
26/10/2008-30/9/2009	230	0.004810	-1.994208	0.370531	0.786048	-0.161981
		(0.0001)	(0.0045)	(0.0051)	(0.0000)	(0.0260)
1/10/2009-31/12/2012	761	-0.000663	-14.85379	0.338562	-0.796202	0.087383
		(0.2106)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
EGX 20 Capped						
Full sample period	1191	9.96E-05	-0.659282	0.285119	0.945300	-0.113545
		(0.8366)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
3/1/2008-4/2/2009	266	-0.002519	-0.465059	0.128235	0.953343	-0.188159
		(0.0273)	(0.0000)	(0.1124)	(0.0000	(0.0000)
5/2/2009-5/1/2011	476	0.000941	-0.254053	0.188099	0.987544	-0.047487
		(0.1355)	(0.0207)	(0.0000)	(0.0000)	(0.0049)
6/1/2011-23/3/2011	14	*-0.012630*	*-11.77939*	*2.083331*	*-0.325891*	*-0.622254*
		(0.0000)	*(0.0037)*	*(0.1368)*	*(0.5653)*	*(0.1592)*
24/3/2011-31/12/2012	432	0.000424	-1.471874	0.303755	0.846447	-0.090646
		(0.6513)	(0.0026)	(0.0000)	(0.0000)	(0.0136)

Italics indicate failure to improve likelihood

6. Summary and Conclusion

In this research, memory characteristics were investigated in the presence of structural breaks for daily returns and volatility for indices of the Egyptian equity market. A maximum of three structural breaks were indentified using the Bai-Perron test. The GPH test and the mGPH test by Andrews and Guggenbeger that corrects for small sample bias were used to investigate memory dynamics for the full period and the break periods for each index. Also the EGARCH model was estimated for the full period and each break period for the indices in order to investigate how model parameters change in response to the structural breaks.

For the EGX 30, EGX70, and the EGX 100 the break periods identified were all related to the subprime crisis and the world financial crisis that followed in 2008 and 2009. The Bai-Perron test accurately identified two break periods directly associated with the Egyptian revolution for the EGX 20. One in January, at the beginning of the revolution and one in March when the Egyptian market was re-opened after being closed for almost two months.

Results of the GPH and the mGPH tests for daily returns for the full period indicated the presence of weak long memory. However, for the EGX 30, the EGX 70, and the EGX 100 strong anti-persistence was present in the break periods indicating that the long memory in returns is spurious. As for the EGX 20, long memory in the returns were apparent for most of the break periods indicating that long memory is less spurious for the index. For volatility, real long memory was indicated for the EGX 30, EGX 70, and the EGX 20. While spurious long memory was indicated for the volatility of the EGX 100 because of the presence of clear anti-persistence in two of the break periods. The findings of spurious long memory in daily returns and real long memory in daily volatility in the Egyptian stock market is similar to that in empirical research on emerging and developed markets where long memory is apparent and persistent in volatilty and not in returns. Assaf (2012) reported evidence of long memory in Egypt for returns and volatility. Sourial (2002) reported evidence of fractional dynamics with long memory features in IFCG-Egypt weekly data. Anoruo and Gil-Alana (2011) reported evidence of long memory in the returns and the volatility for Egypt, Morocco, Tunisia and Nigeria. These findings provide strong evidence of market inefficiencies for the Egyptian stock market leading to the rejection of the weak-form efficient market hypothesis in the case of Egypt. Therefore, investors and portfolio managers who adopt random walk models should reconsider their methodology and implement models that utilize long memory and long range dependence. On the other hand, this finding supports the use of technical analysis where information extracted from past price changes is used to predict future price changes.

The EGARCH parameters for the indices were similar for the full period but were very different for the break periods for each index. This is an indication that not testing for structural breaks carries significant risk. Apparently accurate model specifications for the full period can be misleading, inaccurate, or incorrect. Therefore, it is necessary to take the presence of structural breaks into considertaion in order to estimate the correct model parameters that reflect the statistical properties of the time series being investigated.

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