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Studying Tehran Stock Exchange Index in the Framework of FISTAR Model

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ABSTRACT

The main purpose of this study was to investigate Tehran stock exchange total index considering two characteristics of TEPIX time series: long memory and nonlinearity. The data employed in this study were the monthly data of stock exchange total index over the period of 09-1997 to 01-2012. Also, FISTAR model (fractionally integrated smooth transition autoregressive), proposed for the first time by Van Dijk (2002) was employed.The main reason for using this model was its more accurate and qualitative analysis about the fluctuations of total index, especially when these fluctuations are driven by a steady process. By programming in MATLAB software, the model was extended in a way that the state transition function became exponential which transformed FISTAR model into FIESTAR (fractionally exponential integrated smooth transition autoregressive) model. The statistical results indicated that stock exchange total index had long memory, since the differencing factor was 0.47. Also, it showed a nonlinear trend due to the asymmetry in coping with fluctuations such that the adjustment speed in the nonlinear model was slower than linear model.

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INTRODUCTION

Long term memory, which is also called dependency with long term range, explains the correlation structure of time series values in long intervals. The presence of long term memory in time series means that there is a correlation between its data even with long time intervals. So, previous intervals can be used to forecast future intervals; this issue allows for employing a profitable strategy. Over the last decade, a major part of time series analysis has focused on processes with long memory.

For the first time, long memory models in the form of fractional integration were introduced to econometrics by Granger and Joyeux (1980).

A long memory time series can be specified by autocorrelation function (ACF) which decreases with hyperbolic rate. Hyperbolic decreasing rate is much slower than the decreasing rate of autocorrelation function in the time series with short memory.

Long memory models represent the nonlinear structure of capital markets and, as a result, show that linear models are inefficient in terms of describing the real nature of these markets. The nonlinear structure of capital market makes its forecasting difficult (Jin Xin & Yao Jin).

Moreover, in recent years, the significant extensions of nonlinear models have been employed.

In financial and economic markets, nonlinear threshold models are gaining more and more importance; for instance, the threshold between two states of inflation and recession.

One of the most widely used models in threshold models is STAR (smooth transition autoregressive) model. STAR model is employed to examine the nonlinear characteristics of time series. In this model, the transition function consists of transition parameters, threshold parameter, and transition variable. In most applications, the transition function is an exponential or logistic function which indicates the nonlinear structure of time series. The nonlinearity property in time series can be discussed using asymmetry in variable dynamics; for example, the desired shocks have more important and a more stable effect on the economy than the undesired ones. So, in this paper, both of these two characteristics of economic and financial time series (i.e. long memory and nonlinearity) were discussed. Therefore, with respect to the suggestions presented in this paper, the aim was to find out whether stoke exchange total index had long term memory or followed a nonlinear process. So, FISTAR model, which was introduced for the first time by Van Dijk (2002), was employed

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to investigate Tehran stock exchange total index, where FI denotes fractional integration process and is determined by parameter d .

2) Literature review:

Van Dijk was the first one who investigated FISTAR model. This model can simultaneously analyze both long memory and nonlinearity in time series and also make long term forecasts.

Van Dijk and Hans Franses (2002) studied the U.S. unemployment rate using FISTAR model. The U.S. monthly unemployment rate has two important empirical characteristics: shocks have a relatively stable effect and increase of unemployment rate seems to be more rapid in the crisis than its decreasing speed at the time of thrive, which indicates the asymmetric effects of shocks.

In another study by Small Wood (2004), mixed testing was presented for long term memory and nonlinear model; his work was a case study on the U.S. PPP marker. Two econometric techniques were employed to find unit root, which were long term memory and nonlinear models. While using long term memory and regime change models have been separately widespread but it is clear that these two techniques are interrelated. He employed mixed testing for both characteristics (long term and nonlinear) to determine the importance of each technique in this content. He also found some pieces of evidence for nonlinear behavior (ESTAR) of real exchange rate in many European and developed countries, in contrast to the countries outside the European Union such as Japan and Canada which did not show any nonlinear behavior. Moreover, it should be mentioned that, in the countries with a nonlinear behavior, there were also some significant evidence of long term memory.

In another study by Maria Caporale and Luis Gil (2004), the U.S. unemployment rate was investigated in FISTAR model framework. This model can analyze asymmetry and long memory characteristics of unemployment rate. The empirical results indicated that the U.S. unemployment rate in the form of fractional integration process combined with several nonlinear functions of employment demand variables (oil real price and real interest rate) can have better real results.

In a study by Swanson et al. (2005), long term and short term memory models were compared in relation to the output of the U.S. daily stock. They investigated the effects of trade cycles on the forecast performance of ARFIMA, AR, MR, ARMA, GARCH, and STAR models and concluded that the trade cycles had no effect on the forecast performance of ARFIMA model.

Mohamed Boutahar et al. (2006) investigated FISTAR model based on the primary work done by Dijk, but in FIESTAR model framework and on a monthly basis for the U.S. real effective exchange rate over the period of June 1978 to April 2002. They proposed two approaches for forecasting the real effective exchange rate: simultaneous estimation and step-by-step estimation. Employing FIESTAR model provided better forecasts, especially compared with the linear models and random walk.

In another research by Mohamed Boutahar and Adnen Ben Nasr (2007), inflation was studied in the nonlinear long term memory model framework, but on a seasonal basis. In this paper, three characteristics of long term memory, nonlinearity, and seasonality of the U.S. inflation rate, were discussed. Therefore, SEAFISTAR model, which is the extension of FISTAR model, was employed and it was found that the seasonal ARFI models were executable by FISTAR models.

In another study by Mohamed Boutahar et al. (2008), fractionally integrated models with an emphasis on parameter d were investigated. By supposing that fractional parameter d was random and by introducing a FLSTAR model, they presented an estimation method for this model. The results indicated that this new model provided a framework for describing dynamicity in some financial series.

Benamar et al. (2009) investigated the purchasing power parity in the northern African countries using a FISTAR model. In this study, both nonlinearity and long memory were employed. Using these techniques independently can be desirable in some cases for discussing PPP; but, in most cases, it fails. In fact, the empirical evidence has shown that these two models are technically interrelated. In this paper, Benamar et al. employed FISTAR model, which was introduced by Franses, Van Dijk, and Paap (2002) for investigating PPP. The results indicated that long memory and nonlinearity were not accepted for all the discussed countries (northern Africa) and in relation to the exchange rate. Also, the results demonstrated that equal purchasing power cannot be accepted in a country like Tunesia. There were no pieces of evidence for long term memory in Egypt and Algeria. Moreover, the studies revealed that, when only ESTAR model was employed, the exchange rate behavior could be inaccurately interpreted; this can be the reason why FISTAR model is used to deal with the exchange rate shocks, especially when they are characterized by a long term process.

Simon Yoya and Shittu (2009) investigated forecast performance of ARMA and AFRIMA models. Application of this research was related to the exchange rate (UK pound, U.S. dollar). The classic approach for economic series models is to use Box-Jenkins methodology for ARMA and AFRIMA models which depends on whether time series is static or not. If time series has a long term property, forecasts performance is not reliable based on ARIMA model. Therefore, the main issue is the forecast performance of ARMA (p,d,q) and AFRIMA (p,d,q) for the static type of time series which has a long term property.

They evaluated their time series from 1971 to 2008 and found that, by employing Dickey–Fuller test, non-stationarytime series was rejected at all levels; but, KPSS approved the existence of long term memory considering that the fractional parameter value was d=0.4956. These results approved time series statist and the existence of long term memory. Finally, ARFIMA model was found to be a better indicator of current economic facts in these two countries.

In another study by Simon Yaya and Shittu (2010), inflation was investigated in FILSTAR model framework. In their opinion, long term memory and nonlinearity were two key characteristics of macroeconomic time series which were specified by continuous shocks. It seems that they had a more rapid increase at the time of recession than the decrease at the time of booming. So, this paper was aimed to apply FILSTAR model on the inflation rate such that a better estimation of parameters could be obtained. As a result, interesting ratios were found for the inflation rate in developing and developed countries.

3) Model presentation:

In recent years, there have been many studies on determining stock exchange behavior all around the world. In all of these studies, one of the important results is that the stock exchange index is non-stationary time series and a differencing process is employed to make it stationary.

The starting point for the literature related to the fractionally integrated processes has been the fact that many financial and economic series are neither i(0) nor i(1). They show significant correlations in their very long interruptions which is referred to as (hyperbolic). When this series is differentiated once, it seems that one-time differencing is too much for them (Banerjee &Urga, 2005).

Therefore, ARFIMA(p,d,q) is a useful class of models for the time series with a long term memory behavior. These processes are the extension of integrated moving autoregression processes (ARIMA), where the differencing parameter can take a non-integer number (Man & Tiao, 2006).

So, with respect to the above definitions, partially integrated process in terms of the above relation is a process with long term memory. The process y_t is partially integrated with order d .

$$(1-L)^d Y_t = X_t \qquad \textbf{(1)}$$

In this relation, L is interrupt operator, -0.5<d<0.5 and$x_t$is a stationary process and has a positive evaluation spectrum at all frequencies. Now, if x_t is integrated by the order of zero and also is weak stationary and 0<d<0.5, the process y_t has long term memory in terms of the second definition and all its autocorrelations are positive and with(ازبینمیروند) hyperbolic rate.

For -0.5<d<0 (absolute value), the sum of process autocorrelation values approaches a fixed value; so, the first definition has long term memory. When 0.5<d<1, the process $y_t$is not stationary and non-invertible, because the process variance is not limited. Although the series is non-stationary in this case, it can be observed that, according to Hosking's formula, autocorrelation function still approaches zero. This issue implies that the process memory is limited and the shock on the process is reflected in the mean. Hence, these processes are called (returning to mean). When d>1, the process does not return to the mean and the shock on the process causes the process to deviate from the starting point.

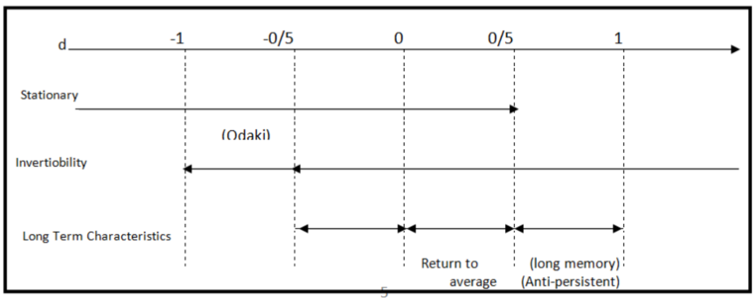

Fig. 1: Characteristics of Different d Values.

3-1) Modified rescaled range analysis:

In this research, it was preferred to employ MRS test which could provide as more accurate and reliable response than other methods for estimating d. Lo (1991) proposed a stronger test than rescaled range analysis which is known as modified rescaled range analysis. MRS statistic is given as:

$$R/S(n) = \frac{\left[\begin{array}{ll} Max\sum_{t=1}^{k}(X_t - \overline{X}_n) - Min\sum_{t=1}^{k}(X_t - \overline{X}_n) \\ o \le k \le n \qquad\qquad o \le k \le n \end{array} \right]}{S(n)} \qquad \textbf{(2)}$$

q is interrupt order and there is no special statistical rule for it. For q=0, the value of MRS statistic is rescaled range statistic.

After calculating R/S (n) for different N's, H statistic is given by estimating Relation (2) using OLS method.

$$LogR/S(n) = LogC + H.Logn \qquad \textbf{(3)}$$

If 0.5≤H≤1, it can be concluded that the studied series has long term memory. Pitters (1999) defined the relationship between H and d as follows:

$$H = 0.5 + d \qquad \textbf{(4)}$$

3-2) ARFI(p)model:

If ARFIMA model is defined as follows:

$$(1-L)^d y_t = Fy_t \qquad \textbf{(5)}$$

And if autoregressive model is given as:

$$y_t = \alpha_0 + \alpha_1 y_{t-1} + ... + \alpha_p y_{t-p} + \varepsilon_t \qquad \textbf{(6)}$$

Then, ARFI model is given by combining the above two models:

$$Fy_t = \alpha_0 + \alpha_1 Fy_{t-1} + ... + \alpha_p Fy_{t-p} + \varepsilon_t \qquad \textbf{(7)}$$

ARFI model is really an autoregressive fractionally integrated model which examines linearity and long memory characteristics in time series. In fact, this model is presented to be compared with FISTAR model and give a better insight into the mentioned model.

In FISTAR model, the characteristic of smooth transition around a threshold point can be referred to, which depending on the given issue, can take exponential or logistic state in a way that could consider the nonlinearity characteristics of time series; but, ARFI models do not have such a capability.

The existence of long term memory in asset outputs has important practical and theoretical aspects. First, since the long term memory is a special form of nonlinear dynamics, it is impossible to model it using linear methods; so, developing and using nonlinear pricing models are encouraged. The existence of long term memory in financial market negates the weak form of market efficiency hypothesis and also challenges the linear models of asset pricing and indicates that nonlinear models should be used in pricing capital assets.

3-3) Smooth transition models:

In recent years, significant extensions of nonlinear models have been employed. In financial and economic markets, the nonlinear threshold models are gaining more and more importance; for instance, the threshold between two states of inflation and recession. So, a model called STAR and its different states are used to investigate this behavior. There are two different types of STAR model which are different from each other in autoregressive delay degrees. Logistic STAR model is an extended from of standard autoregressive model where autoregressive coefficient has a logistic function.

$$y_t = \alpha_0 + \alpha_1 y_{t-1} + ... + \alpha_p y_{t-p} + \theta\left[\beta_0 + \beta_1 y_{t-1} + ... + \beta_p y_{t-p}\right] + \varepsilon_t \qquad \textbf{(8)}$$

$$\theta = \left[1 + \exp(-\gamma(y_{t-1} - c))\right]^{-1}$$

In the above equation, parameter γ is called smoothness parameter and $\boldsymbol{C}$ is threshold parameter I n a limit state if γ comes close to zero or infinite LSTAR model is converted into a AR(P) model, because θ will be constant under this conditions.

بهازایمقادیرγبینصفروبینهایت،درجهٔتأخیراتورگرسیوبستگیبهمقدار (ESTAR) خواهدداشت. درشکلنماییمدل y_{t-1}

STARمقدارθدررابطهبالابامقدارزیرجایگزینمیشود.

$$\theta = 1 - \exp\left[-\gamma(y_{t-1} - c)^2\right] \qquad \gamma > 0$$

Otherwise, the model shows a nonlinear behavior. The interesting point is that ESTAR model coefficients are symmetric around point y_{t-1}=c . Ify_t comes close to c, then θ will come close to zero; so, y_t behavior will change based on relation $\alpha_0 + \alpha_1 y_{t-1} + \cdots + \alpha_p y_{t-p} + \varepsilon_t$. $If\ y_{t-1}$ from c; then, θ is inclined toward 1; so, y_t behavior will be according to the relation $(\alpha_0 + \beta_0) + (\alpha_1 + \beta_1)_{y_{t-1}} + \cdots + \varepsilon_t$.

3-4) Terasvirta test:

One of the tests employed for selecting nonlinear function form is Terasvirta test, based on which the nonlinear pattern is specified as LSTAR or ESTAR. If delay parameter d is supposed to be constant, Equation 10 is obtained using regression no.9 and by forming Taylor extension on this equation and substituting fy_t by y_t.

The null hypothesis is:

$$\mathrm{H}_0: \pi_{2i} = \pi_{3i} = \pi_{4i} = 0 \qquad (i = 1,2,\dots,p) \qquad \textbf{(9)}$$

$$y_t = \pi_0 + \sum_{i=1}^{p} \pi_{1i} y_{t-i} + \sum_{i=1}^{p} \pi_{2i} y_{t-i} y_{t-d} + \sum_{i=1}^{p} \pi_{3i} y_{t-i} y_{t-d}^2 + \varepsilon_t \qquad \textbf{(10)}$$

$$fy_t = \pi_0 + \sum_{i=1}^{p} \pi_{1i} fy_{t-i} + \sum_{i=1}^{p} \pi_{2i} fy_{t-i} fy_{t-d} + \sum_{i=1}^{p} \pi_{3i} fy_{t-i} fy_{t-d}^2 + \sum_{i=1}^{p} \pi_{4i} fy_{t-i} fy_{t-d}^3 + \varepsilon_t \qquad \textbf{(11)}$$

If the null hypothesis (H_0) is rejected, nonlinearity of the model is rejected. If H_1 is rejected, LSTAR model is selected. If H_1 is not rejected, but H_2 is rejected, ESTAR model is selected. Also, if H_1 and H_2 are not rejected, but H_3 is rejected, ESTAR model is selected.

$$H_1: \pi_{4i} = 0 \quad , \quad (i = 1,2,\dots p) \qquad \textbf{(12)}$$

$$H_2: \pi_{3i} = 0\,|\pi_{4i} = 0 \quad , \quad (i = 1,2,\dots p) \qquad \textbf{(13)}$$

$$H_3: \pi_{2i} = 0|\pi_{3i} = \pi_{4i} = 0 \quad , \quad (i = 1,2,\dots p) \qquad \textbf{(14)}$$

3-5) FISTAR model:

If AFRIMA model is given as:

$$(1-L)^d y_t = Fy_t \qquad \textbf{(15)}$$

And if STAR model is given as:

$$y_t = \alpha_0 + \alpha_1 y_{t-1} + ... + \alpha_p y_{t-p} + \theta\left[\beta_0 + \beta_1 y_{t-1} + ... + \beta_p y_{t-p}\right] + \varepsilon_t \qquad \textbf{(16)}$$

Then, FISTAR model is obtained by combining these two models which was introduced for the first time by Van Dijk (2002).

(17)

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3-6) FIESTAR model:

If, in the above model, the exponential form of STAR model is used instead of θ, FIESTAR model is obtained which is as follows:

$$Fy_t = \alpha_0 + \alpha_1 Fy_{t-1} + \alpha_2 D + \alpha_3 Fy_{t-12} + \left(1 - \exp\left[-\gamma (Fy_{t-1} - c)^2\right]\right) \left[\beta_0 + \beta_1 Fy_{t-1}\right] + \varepsilon_t \quad (18)$$

3-7) Methodology:

Since the coefficients of FISTAR model are as products, they cannot be estimated by OLS method. Here, it is necessary to employ the nonlinear least squares (NLS) method to obtain the accurate estimation of coefficients. Unfortunately, values of γ and C cannot be simultaneously determined based on many numerical methods used in estimating parameter values. So, the initial conditions of C and γ should be guessed to use these numerical methods. Therefore, a general method is that the coefficients are estimated simultaneously by reasonable initial guesses and using NLS method. Therefore, what is obtained will be a new estimation for γ. At the second stage, γ is set equal to its estimated value and a new estimation of C is obtained. This process is repeated until the subsequent values of γ and C become consistent; in other words, the interval between their two subsequent values becomes less than a specified limit. When the values of parameters reach the consistency limit, all the model parameters can be simultaneously estimated using final estimated values.

Based on initial reasonable guesses and using the known values adopted for C, a specified and constant number is given for γ and other coefficients of model can be estimated. After estimating the model coefficients, θ, which is the exponential form of STAR model here should be estimated. A programming technique in MATLAB software is employed for this estimation. For each period (month), a θ is obtained and the total mean is θ=0.059 which is positive.

4) Data:

In this paper, Tehran stock exchange total index (Tepix) over the period of 1997-2011 was employed. So, the size of the samples used in this study was 172 observations per monthly index.

Tehran stock exchange total index trend is shown in Figure 2. The related data were collected from Tehran stock exchange website and Tadbir Pardaz software.

4-1) Data persistency:

Identifying a random trend in a time series is easily possible by (generalized) unit root tests. Augmented Dickey–fuller (ADF) is usually employed to examine the data persistency. But, this method gives an accurate estimation of data only when there is no structural break in the studied time series. It should be mentioned here that, due to the selling of the shares of block of telecommunication company and Isfahan Oil Refinery Company and also the notable increase in the selling of governmental institutes to the private sector in the early 2001, it can be guessed that the stock exchange total index has experienced a structural break. Accordingly, using Quandt-Andrews test and also chow test, a structural break was found in the second month of 2009. So, Phillips-Perron test was employed to investigate the persistency of the mentioned time series. Therefore, augmented Dickey–fuller (ADF) test was of no help in terms of examining the persistency of time series.

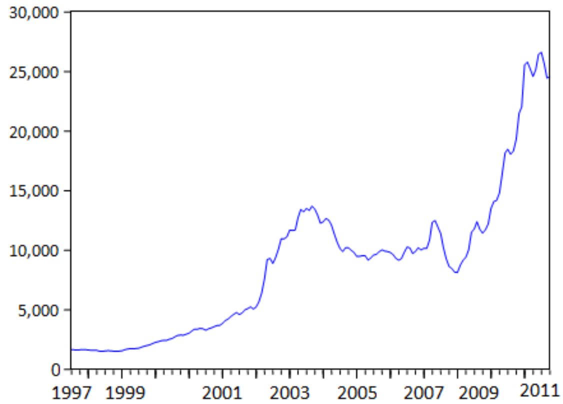

Fig. 2:

In Phillips-Perron test, ρ is given as ρ =1 which indicates the existence of unit root in the given time series. The studied time series becomes persistent by the first differencing and its autocorrelation function rapidly approaches zero.

4-2) Quandt-Andrews test:

In fact, this test is applied to determine whether there is a structural break in the studied time series or

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not. It is based on chow test. Therefore, it is necessary to provide a brief description of this test.

There are three methods for calculating Chow test: 1- F statistic test which is based on the comparison of residuals squared sum in constrained and unconstrained models and is given as follows:

$$F = \frac{(\bar{u}'\bar{u} - (u_1'u_1 + u_2'u_2))/k}{(u_1'u_1 + u_2'u_2)/(T-2k)} \qquad \textbf{(19)}$$

In this equation, $\bar{u}'\bar{u}$ is residuals squared sum in constrained model, $u_i'u_i$ is residuals squared sum in unconstrained model, T is the number of observation, and k is the number of parameters in the equation.

LR (likelihood ratio) test:

It is based onx^2 distribution with (m-1)k degrees of freedom. The null hypothesis indicates that there is no structural break. Moreover, in this test, m is the number of partition mode for data.

Wald test:

This test is based on x^2distribution.

Now, based on these two tests (i.e. Wald test and test LR) with respect to F distribution and in the framework of the following three formulas, Quandt–Andrews can be calculated.

$$MaxF = \max_{T_1 \le T \le T_2} (F(T)) \qquad \textbf{(20)}$$

$$ExpF = in\left(\frac{1}{k}\sum_{T=T_1}^{T_2} \exp\left(\frac{1}{2}F(T)\right)\right) \qquad \textbf{(21)}$$

$$AveF = \frac{1}{k}\sum_{T=T_1}^{T_2} F(T) \qquad \textbf{(22)}$$

Distribution of these test statistics is non-standard. Andrews (1993) and Hansen (1997) have presented a standardized distribution and a suitable estimation of these tests.

Table 1: Results of Quandt-Andrews test.

Statistic	Value	Prob.
Maximum LR F-statistic (1988M02)	10.04413	0.093
Maximum Wald F-statistic (1988M02)	10.04413	0.093
Exp LR F-statistic	2.150707	0.1529
Exp Wald F-statistic	2.150707	0.1529
Ave LR F-statistic	1.601357	0.5195
Ave Wald F-statistic	1.601357	0.5195

Table 2: Results of Chow test.

F-statistic	10.0441	Prob. F(2,167)	0.0001
Log likelihood ratio	19.4233	Prob. Chi-Square(2)	0.0001
Wald Statistic	20.0883	Prob. Chi-Square(2)	0

4-3) Phillips–Perron*test:*

Since the persistency of time series data in Phillips–Perrontest framework was considered, it was necessary to state the desired statistic defined as follows:

$$X_t = \alpha_0 + \alpha_1 DU_t + d(DTB)_t + \gamma DT_t + \beta t + \rho X_{t-1} + \sum_{i=1}^{\rho} \phi_i \Delta X_{t-1} + e_t \qquad \textbf{(23)}$$

In this statistic, DU_t denotes the variation in the intercept, DT denotes variations in the slope of data curves, and therefore DTB examines the desired jump in data. If ρ tends toward 1, it indicates the existence of unit root in the studied time series.

Table 3: Results of Phillips–Perrontest.

Variable	Coefficient	Std. error	t-Statistic	Prob.
C	137.2974	70.56531	1.945679	0.0534
TDT	2.813358	0.857617	3.280434	0.0013
P(-1)	0.983892	0.008491	115.8716	0
D(P(-1))	0.382202	0.07081	5.3976	0
R-squared	0.993922	Mean dependent var		8902.725
Adjusted R-squared	0.993812	S.D. dependent var		6265.876
S.E. of regression	492.9034	Akaike info criterion		15.26175
Sum squared resid	40330325	Schwarz criterion		15.33554
Log likelihood	-1293.249	Hannan-Quinn criter.		15.29169
F-statistic	9048.105	Durbin-Watson stat		1.921483
Prob(F-statistic)	0			

4-4) Results of optimized interrupt determination:

In order to find the optimized degree of vector autoregression, the interrupt length considered by the software was tested. The minimum criterion of all the three criteria of Akaike, Schwarz, and Hannan-Quinn, was indicated by an asterisk. The minimum criterion of the three criteria suggested the interrupt length of 1. The optimized length was 1 based on the results obtained from Eviews software.

Table 4: Results of determining optimized interrupt .

Lag	Log L	LR	FPE	AIC	SC	HQ
0	2215.94	NA	1.62e+09	26.88412	26.92177	26.89941
1	1587.77	1233.508*	841224.4*	19.31836*	19.43130*	19.36421*
2	1584.92	5.521376	853089.0	19.33234	19.52058	19.40875
3	1584.08	1.603669	886484.5	19.37067	19.63421	19.47765
4	1579.54	8.585750	880796.4	19.36412	19.70295	19.50166
5	1577.98	2.904631	907441.8	19.39374	19.80787	19.56185
6	1576.11	3.454083	931362.5	19.41950	19.90893	19.61818

4-5) Estimation and evaluation of the linear model:
ARFI model:

The value obtained for H was 0.97; using the formula H=0.5 +d, the value of d became d=0.47. As d was between 0 and 0.5, the existence of long memory in the studied time series was shown. Having known the parameter d, ARFI model as a fractionally integrated autoregressive model can be estimated using Eviews software and its theoretical form is as follows. Statistical results of this model are estimated in the following table.

$$Fy_t = \alpha_0 + \alpha_1 Fy_{t-1} + ... + \alpha_p Fy_{t-p} + \varepsilon_t \quad \textbf{(24)}$$

Table 5: Results of Arfi model.

Variable	Coefficient	Std. error	t-Statistic	Prob.
C	31.36495	1.270192	24.69307	0
AR(1)	0.476083	0.069319	6.868043	0
AR(12)	0.168448	0.085603	1.96777	0.0509
R-squared	0.259912	Mean dependent var		31.29694
Adjusted R-squared	0.250423	S.D. dependent var		6.571345
S.E. of regression	5.689345	Akaike info criterion		6.333755
Sum squared resid	5049.508	Schwarz criterion		6.391659
Log likelihood	-500.5335	Hannan-Quinn criter.		6.357269
F-statistic	27.39283	Durbin-Watson stat		1.826563
Prob(F-statistic)	0			

4-6) Estimation and evaluationof the nonlinear model
STAR model estimation:

With respect to the above table, F-statistic approved the threshold behavior. Now, it should be specified which pattern was more appropriate. With regard to the conducted estimations and considering T statistics, the statement $fy_{t-i} fy_{t-d}^2$ { $fy\,(-1) * fy\,(-2)^2$ } cannot be omitted from the equation model. So, the presence of ESTAR model was accepted.

Table 6: Results of Terasvirta test.

Variable	Coefficient	Std. error	t-Statistic	Prob.
C	13.97207	2.311897	6.043552	0
FY(-1)	0.633401	0.095101	6.660275	0
FY(-1)*FY(-2)^2	-7.62E-05	3.66E-05	-2.083386	0.0387
R-squared	0.261553	Mean dependent var		31.23629
Adjusted R-squared	0.252656	S.D. dependent var		6.377826
S.E. of regression	5.513571	Akaike info criterion		6.269894
Sum squared resid	5046.312	Schwarz criterion		6.325455
Log likelihood	-526.8061	Hannan-Quinn criter.		6.292442
F-statistic	29.398	Durbin-Watson stat		1.970733
Prob(F-statistic)	0			

Fiestar model:

Based on the reasonable initial guesses and using the specified values considered for C and with several repetition periods and necessary convergences in Eviews software, fixed and certain numbers were obtained for C and γ as 27.94 and 0.0014, respectively. Moreover, other coefficients of the model were obtained simultaneously, as shown in the following table.

As indicated before, the model was FIESTAR as follows:

$$Fy_t = C(1) + C(2)Fy_{t-1} + C(3)D + C(4)Fy_{t-12} + \left(1 - \exp\left[-\gamma(Fy_{t-1} - c)^2\right]\right)\left[C(5) + C(6)Fy_{t-1}\right] + \varepsilon_t \quad \textbf{(25)}$$

Table 7: Results of Fiestar model.

Variable	Coefficient	Std. error	t-Statistic	Prob.
C(1)	-0.02941	6.269417	-0.00469	0.9963
C(3)	-1.03537	1.612298	-0.64217	0.5217
C(4)	0.195772	0.085979	2.276979	0.0242
C(2)	0.826015	0.188339	4.385786	0
c	27.94425	13.761	2.030685	0.044
C(5)	24.10027	23.99844	1.004243	0.3169
C(6)	-0.95304	0.328538	-2.90085	0.0043
R-squared	0.320664	Mean dependent var		31.2969
Adjusted R-squared	0.293848	S.D. dependent var		6.57135
S.E. of regression	5.522086	Akaike info criterion		6.29842
Sum squared resid	4635.003	Schwarz criterion		6.43352
Log likelihood	-493.724	Hannan-Quinn criter.		6.35328
F-statistic	11.958	Durbin-Watson stat		1.75176
Prob(F-statistic)	0			

Finally, using programming technique in MATLAB, the total mean for θ was given as 0.059 (it should be mentioned that θ was the exponential state of the present model and caused FISTAR to be converted into FIESTAR).

4-7) Interpretation of the results:

Arfi model:

In Table 5 (shown above), which provides the estimation results of ARFI model, c denotes intercept. AR(1) is the coefficient of one period ago (on month ago) and indicates that 0.47 of fluctuation effects remains in the next month. AR(12) is the coefficient of one year ago in the model and indicates that 0.16 of fluctuation effects remains in the next year.

Fiestar model:

In Table 7 presented above, the estimation results of FIESTAR model are demonstrated. As is known, this model can be divided into two linear and nonlinear parts.

Linear part of the model:

In the mentioned table, c(1) denotes intercept of the linear part, c(3) shows the January effect in the model and is known as dummy variable coefficient in the model, c(4) is the coefficient of one year ago (12 periods ago) in the model which indicates that 0.19 of fluctuation effects remains in the next year, and c(2) is the coefficient of one period ago in the model (a month ago) which indicates that 0.82 of fluctuation effects remains in the next month.

Nonlinear part of the model:

c is the (local) threshold parameter in the model which was converged into 27 .94, c(5) denotes the intercept, and c(6)=-0.95 is the coefficient of one period ago in the model (one month ago); since the total mean of θ was 0.059, it can be stated that by taking into account the nonlinear part of the model, the fluctuation effect became stationary more rapidly.

Because:

By supposing the linear effect of the model:

$$Fy_t = C(2)Fy_{t-1} \quad \textbf{(26)}$$

$$Fy_t = 0.82\,Fy_{t-1} \quad \textbf{(27)}$$

By supposing the linear and nonlinear effect of the model:

$$Fy_t = (C(2) + \theta C(6))Fy_{t-1} \quad \textbf{(28)}$$

$$Fy_t = (0.82 + 0.059 - 0.95)Fy_{t-1} \quad \textbf{(29)}$$

Also, it can be concluded that the closer θ is to 1 (provided that c(6) becomes negative), the more rapid the fluctuation effect in the stock exchange would be stationary. Also, the closer θ is to 0 (by supposing negative c(6)), the later the fluctuation effect on the stock exchange would diminishe and the old information would be more valuable. It can be generally concluded that the fluctuation adjustment speed in ARFI linear model is more rapid than FIESTAR linear model in terms of model estimations. Also, if FIESTAR model is divided into two linear and nonlinear parts, the fluctuations adjustment speed would be higher than the situation where there is only the linear part of FIESTAR model.

4-8) Lagrange coefficient test (LM):

After estimating the appropriate model, in order to ensure that ARCH effect exists in the selected time series, Lagrange coefficient test was employed. The null hypothesis indicated the absence of ARCH effect in the mentioned data. Rejection of this hypothesis means the acceptation of the opposite hypothesis and presence of ARCH effect in the data related to time series. The following table shows Lagrange coefficient test to identify ARCH effects.

Table 8: Breusch-Godfrey serial correlation LM test.

F-statistic	6.88339	Prob. F(1,151)	0.0096
Obs*R-squared	6.93207	Prob. Chi-Square(1)	0.0085

With respect to the probabilities related to F-statistics in this table, the null hypothesis indicating the absence of ARCH effect was rejected and the opposite hypothesis was accepted. It is clear that accepting H_1 implies the existence of ARCH effect. After ensuring the existence of conditional variance unlikelihood phenomenon or ARCH effect in the considered time series, the standard model GARCH (1,1) was estimated using the given interval for the time series.

4-9) Results of Garch test:

Table 9: GARCH = C(1) + C(2)*RESID(-1)^2 + C(3)*GARCH(-1).

Variable	Coefficient	Std. error	z-Statistic	Prob.
C(1)	0.00355	0.023937	0.14841	0.882
C(2)	0.33839	0.116734	2.89885	0.0037
C(3)	0.76978	0.075592	10.1834	0
R-squared	0.28007	Mean dependent var		31.297
Adjusted R-squared	0.23658	S.D. dependent var		6.5714
S.E. of regression	5.74163	Akaike info criterion		5.1445
Sum squared resid	4911.99	Schwarz criterion		5.3375
Log likelihood	-398.99	Hannan-Quinn criter.		5.2229
F-statistic	6.44044	Durbin-Watson stat		1.7932
Prob(F-statistic)	0			

As shown in Table 9,GARCH numerical coefficient used in this model was 0.76. It should be noted that the bigger the GARCH numerical coefficient than 1, the later the effect of response to shocks and fluctuations would diminish. In other words, by introducing new shocks to the market, the total index would be affected for a longer time. In this market, the older information is more important than the recent information and the effect of such information diminishes more lately (Magnus & Fusu, 2006).

5*)Conclusion:*

The general conclusions obtained from this paper can be stated in the form of answers to the model hypothesis as follows:

Stock exchange total index has long term memory:

As observed in Hurst statistical estimation by EXCEL software, H is given as H=0.97; hence, d=0.47. It was found earlier that, if 0<d<0.5,then there is long memory in time series; i.e. Tehran stock exchange total index has long memory. Also, if some fluctuations increase in the index, its effect will remain for a longer time.

The existence of long term memory in financial and economic markets negates the weak form of market efficiency hypothesis. Also, the linear models challenge the assets pricing and indicate that nonlinear models should be used in capital assets pricing.

Stock exchange total index follows a nonlinear process:

As stated before, smooth transition models, especially ESTAR, are more effective in converging model parameters, especially γ and C, and better fit the data.

This point indicates that Tehran stock exchange total index has a nonlinear structure. Moreover, this characteristic has an important role in qualitative description and more accurate forecasting of time series. In general, it can be concluded that the fluctuation adjustment speed in ARFI linear model is more rapid than FIESTAR nonlinear model in terms of model estimations. Also, if FIESTAR model is divided into two linear and nonlinear parts, the fluctuation adjustment speed is more rapid than the situation where there is only the linear part of FIESTAR model.

5-*1)Applied results:*

This research showed how to investigate the stock exchange total index in FISTAR model framework with an emphasis on considering both nonlinearity and long term memory characteristics of stock exchange index. With respect to this characteristic of stock exchange total index, some qualitative analyses were performed that can be the basis of more accurate planning, especially long term forecasts for more complicated models (nonlinear time series). Also, the positive and negative policies can be implemented to cope with the effects of shocks and fluctuations on the index over the relatively long periods. Moreover, the analysis of this model can be a basis for investigating different issues in the time series area.

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