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Full Length Research Paper

Chaotic processes of common stock index returns: An empirical examination on Istanbul Stock Exchange (ISE) market

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The nonlinearity and accompanying concept, namely the chaos receive great attention from researchers. This study employs nonlinearity and chaos theories to examine the behavior of the Istanbul Stock Exchange (ISE) all share equity indices. The main purpose was to explore the existence or nonexistence of nonlinearity and chaotic behavior in the ISE market. Therefore, the efficient markets' characteristics, which are the random behavior of asset prices and nonlinear chaotic dynamics, were contrasted and the probabilistic and deterministic behaviors of the asset prices were compared. Our results based on BDS, Hinich Bispectral, Lyapunov Exponent and NEGM tests reject the efficient market hypothesis that the index series examined in this study is not random, independent and identically distributed (i.i.d).

Key words: Efficient market hypothesis, nonlinearity, chaotic dynamics.

INTRODUCTION

Most of the studies on the behavior of the Istanbul Stock Exchange (ISE) market prices support the weak form market efficiency against the existence of chaos. The detection of nonlinearity and chaos versus efficient market hypothesis (EMH) in the ISE market is the main focus of this study. The main results in this study chal-lenge the dominant findings in the literature and imply the existence of nonlinear structure and chaos in the ISE market. The finance and economics literature on the non-linearity and chaos increases in quantity as well in quality in recent years. Studies try to find out the (non-) existence of the chaos in financial time series. The importance of this research topic comes from the fact that chaos and efficient market hypothesis are mutually exclusive paradigms. This study is motivated from this fact. Nonlinearity and chaos theories were employed to examine the behavior of the ISE all share equity indices.

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Abbreviations: ISE, Istanbul stock exchange (Market/Turkey); **EMH,** efficient market hypothesis; **i.i.d,** independent identically distributed.

Identification of research problem

For the last four decades, the EMH has been the dominant theory in the financial markets. Many studies have been conducted to test the theory. Under the EMH, stock returns processes should be random. Market efficiency idea mentions that prices fully reflect all information and price movements do not follow any patterns or trends. That is, past price movements cannot be used to predict the future price movements but follow what is known as a random walk, an intrinsically unpredictable pattern (Campbell et al., 1997; Fama, 1965). The mathematical expression of EMH is that the financial time series is

independent and identically distributed (i.i.d.), so behave in a random manner.

The deterministic nonlinear equations can generate data which seems as if random. This is the shortest defini-tion of the chaos. Chaos phenomena were first observed in natural sciences and its theoretical fundamentals are founded in these areas such as physics and ecology. Later, these theoretical basics were transferred to many other fields, such as economics and finance (Creedy and Martin, 1994; Gleick, 1987; Mantegna and Stanley, 2000; Lorenz, 1993; McKenzie, 2001; Pesaran and Potter, 1993; Ruelle, 1993; Trippe, 1995; Barnett and William, 2004).

Related research

There are many studies supporting the EMH in the literature (Kendall, 1953; Brealey, 1970; Dryden, 1970; Cunningham, 1973; Brock, 1987). These studies find no evidence of chaos in macroeconomic time series in the US and Canadian markets. The studies on the United Kingdom stock market also detect the weak form market efficiency. These authors base their studies on the assumption that UK stock market price changes are i.i.d. Fama (1965) admit that linear modeling techniques have limitations as they are not sophisticated enough to capture complicated 'patterns' which chartists claim to see in stock prices. Moreover, most of the studies on the behavior of ISE market prices supported the weak form market efficiency against the existence of chaos (Kenkül, 2006; Topçuo lu, 2006; Çıtak, 2003; Adali, 2006).

Barnett et al. (1996) report the successful detection of chaos in the US division monetary aggregates. This conclusion is further confirmed by several authors (e.g. Hinich and Rothman 1998; Barnett and William, 2004). Furthermore, foreign exchange markets are an essential domain in which chaos has been detected (Mantegna and Stanley, 2000; Das and Das, 2007). Many researchers (e.g. Granger and Newbold, 1974; Campbell et al., 1997; Lee et al., 1993; Bonilla et al., 2006) argue that financial market series exhibit non-linearity. The terms of many financial contracts such as options and other derivative securities are also nonlinear (Mantegna and Stanley, 2000). Therefore, a natural frontier for financial econometrics is the modeling of nonlinear phenomena (Barnett and William, 2004; Barnett et al., 1997; Barnett and Hinich, 1992). Findings of Abhyankar et al. (1997) are also consistent with the existence of the nonlinearity. Scheinkman and LeBaron (1989) study U.S.A. weekly returns on the Center for Research in Security Prices (CRSP) value-weighted index, employing the BDS statistic, and find rather strong evidence of nonlinearity and some evidence of chaos. Frank and Stengos (1989) obtain similar results by investigating daily prices for gold and silver, using the correlation dimension and the Kolmogorov entropy. Serletis and Gogas (1997) find the evidence consistent with a chaotic nonlinear generation process in seven East European black market exchange rates. Sewell et al. (1993) report evidence of dependency in the market index series in Japan, Hong Kong, South Korea, Singapore and Taiwan. De Lima (1995) argues that for the US data, non-linear dependence is present in stock returns after the 1987 crash. Some studies on Turkish ISE market (e.g. Bayramoglu, 2007; Ozgen, 2007) demonstrate that the market is not efficient.

Despite the affirmative chaos test results, there are some critiques of the chaos in the literature as well (Lee et al., 1993). Hamill and Opong (1997) report that despite the nonlinear dependence in Irish stock returns, there exist no chaos. Willey (1992) find no evidence of chaos in the Financial Times Industrial Index.

DATA AND RESEARCH METHODOLOGY

The data set is taken from ISE 100 index series. Although it begins on 02 January 1982, daily data for the "All Share Index" are available in Datastream only after 02 February 1997. Thus, the early times of the ISE 100 index were not included in the subsequent analyses considering the immature characteristics period of a new born market that resulted in noisy data sets. Therefore, daily ISE composite price closing index (all share index) was used in analysis for the period between 02 February 1997 and 16 March 2009 comprising 3,036 observations. Descriptive statistics for the observations were shown in Table 1.

The daily returns of the ISE composite index were calculated as the change in logarithm of closing stock market indices of successive days. Taking the first differences may not only ensure that the time series are stationary but also it is a common practice in standard econometric work to whiten the time series.

For testing the stationary of ISE time series the Augmented Dickey-Fuller (ADF) test by Dickey and Fuller (1979) was utilized. The ADF test shows whether a time series is stationary or not, hence the existence of unit root and auto-correlation is tested. For testing the nonlinearity, the BDS test by Brock et al. (1996) and the Hinich Bispectral test by Brockett et al. (1988) were employed. For testing the chaos, the Lyapunov Exponents test by Wolf et al. (1985) and the NEGM test by Nychka et al. (1992) were used.

STATISTICAL TEST RESULTS

Augmented dickey-fuller (ADF) test

Time series data analysis has many applications in many areas. Many analysts use the linear regression models to predict some variables change over time or extrapolate

Table 1. Descriptive Statistics for $rt = ln\left(ISE_t / ISE_{t-1}\right)$.

Parameter	Value
Number of observations in sample	3036
Mean	0,00124
Std. Error of Mean	0,00055
Median	0,00070
Std. deviation	0,03028
Variance	0,00092
Skewness	0,081
Kurtosis	4,066
Range	0,377
Sum	3,411
Minimum	-0,201
Maximum	0,176

from present conditions to future conditions. However, caution is needed during the interpretation of the results of regression models estimated using time series data. Analysts working with time series data uncovered a serious problem with standard analysis techniques applied to time series. For instance, the estimation of parameters of the Ordinary Least Square Regression model produces statistically significant results between time series that contain a trend and are otherwise random. This leads to considerable work on how to determine what properties a time series must possess if econometric techniques are to be used. In this respect Granger and Newbold made one basic conclusion such that "any time series used in econometric applications must be stationary" (Granger and Newbold, 1974). In this study, the ADF test was employed to test the stationary of ISE time series. The value of ADF test statistics (-13.17) is much larger than the MacKinnon critical values at 1, 5 and 10% significant levels (Table 2) . As it can be seen, the ISE time series was found to be stationary for all significance levels.

Table 2. Results for the ADF test statistics for three significance levels (1, 5 and 10%). Note that the ADF test statistic critical value is -13.17.

Significance level (%)	Critical values
1	-3.7979
5	-2.8451
10	-2.4899

Nonlinearity tests

For testing the nonlinearity, the BDS and the Hinich Bispectral tests were employed. The BDS statistic has its origins in the correlation dimension plots of Grassberger and Procaccia (1983). Brock et al. (1996) proposed a non-parametric tool as a test of the null hypothesis of an i.i.d. (that is random) time series.

In the first step of BDS test, the best fitting ARIMA (*p*, *d*,*q*) model is determined and fitted to data. This eliminates the linearity from the data. In the second step of BDS test, the test is applied by running it on the residuals of that ARIMA (*p*, *d*, *q*) model, which by default must be linearly independent, so that any dependence found in the residuals must be nonlinear in nature.

The time series $(X_t : t = 1, 2,.....,T)$ to be analyzed is used to form the so-called *m*-histories $\left(X_t\right)_m = \left(X_{t-m+1},....., X_t\right)$, where *m* is known as the "embedding dimension". These histories can be used to define a correlation integral as below:

$$C^{m}(e) = (1/N^2) \sum_{i,j=1}^{T} Z(e - |X^i - X^j|), \quad i \neq j \qquad (1)$$

$$Z(e) = \begin{cases} 1 & e - |X_i - X_j| > 0 \\ 0 & e - |X_i - X_j| \leq 0 \end{cases}$$

T = the number of observations
e = distance
C_m = correlation integral for dimension *m*
X = index (data) series.

If the X_i in the time series *X* (with *T* observations) are independent and X_i series are lagged into "*m* histories", then the correlation integral $C_m(e,T)$ is calculated as:

$$C_m(e,T) \rightarrow C_1(e)^m \qquad (2)$$

The correlation integral simply fills the space of whatever dimension it is placed in. The BDS statistic, W_N, that follows is normally distributed;

Table 3. ARIMA models for Stock Exchange Indexes daily returns. Note that $_i$ is the parameter for an MA at lags *i*.

Index	Model		Q_1	Q_2	Q_3
ISE Composite	ARIMA(0,1,3)	Coefficient	0.802075	0.137213	0.050019
		T-Statistic	33.97	4.55	2.12

$$W_N(e,T) = \left| C_m(e,T) - C_1(e,T) \right|^N * \left[T / S_N(e,T) \right]^{1/2} \quad (3)$$

Where $S_N(e,T)$ is an estimate of the standard deviation under the null hypothesis.

The null hypothesis under the BDS test is that the increments of the time series are independent and identically distributed. A rejection of the null hypothesis for the BDS test could mean any one or a combination of three major possibilities. First, there can be linear serial dependencies in the data; second, the time series can be non-stationary; and third, there can be a nonlinear serial dependency in the data, either chaotic or stochastic.

Since BDS test is a two- tailed test, we should reject the null hypothesis if the BDS test statistic is greater than the positive critical z-value or less than the negative critical z-value. For example, if = 0.05, the critical z-value = ± 1.96.

Using the Box-Jenkins methodology an ARIMA (autoregressive integrating moving average) process was adjusted for the chosen stock exchange (ISE composite) index log return.

Briefly, an ARIMA (*p*, *d*, *q*) model was fitted to the time series, where *p* denotes the number of autoregressive terms, *d* the number of times the time series has to be differenced before it becomes stationary, and *q* is the number of moving average terms. For the model selection criteria the Akaike Information Criterion (AIC) (Akaike, 1974) was used, and the order of the model was determined by relying on the minimum Akaike Information Criterion estimated as ARIMA (0, 1, 3) . These captured residuals became the whitened returns series subject to the statistical analysis for BDS test.

The ADF test was applied and found that the ISE time series was a stationary process as desired. In fact, the Box-Jenkins methodology applies only to stationary data series, which means that the time series has a mean and a variance essentially constant through time.

Using the lag operator *L*, that is, $LX_t = X_{t-1}$. The ARIMA models assume the form:

Table 4. BDS statistics-residuals from the ARIMA to log returns.

Index	*m*	0.5		1.5	2
ISE Composite	2	15.719	16.292	14.438	13.064
	3	19.322	18.763	15.765	13.933
	4	21.876	20.319	16.644	14.424
	5	25.284	22.014	17.187	14.527

Note: *m*: embedding dimension; : distance between points measured in terms of number of standard deviations of the raw data; : standard deviation. All statistics are significant at the 5% level.

$$(1-L)Y_t = \left(1-\theta_1 L - \theta_2 L^2 - \theta_3 L^3\right)u_t \quad (4)$$

Where *Y* is the first difference of the natural logarithm of the original time series, θ_1 , θ_2 and θ_3 are the moving average coefficients and the random shock u_t is assumed to be an i.i.d. random variable with a mean of zero and a constant variance.

Table 3 presents the main results of the fitted models, which satisfy the stationarity and invertibility conditions. These models are stationary since they have no autoregressive coefficients. The invertibility conditions require $i < 1$ for all *i*. The residuals of the ARIMA models were used to perform the BDS test. To compute the BDS statistic using between one-half to two times the standard deviation of the raw data (0,5 2) while suggesting that *m* = 2 is a general approach. For samples with less than 500 observations, *m* should be set less or equal to 5.

Table 4 presents the results of the BDS test for the ARIMA residuals of log returns. It can be seen that the null hypothesis being i.i.d. was rejected at the 5% level for all ISE composite index. In other words, non-linear dependence was not absent from the series returns. It was thus conclude that the weak form effi- ciency hypothesis was not validated for the Istanbul stock exchange composite index in the data set considered in

this study.

The hypothesis of linearity was rejected by the BDS test. In fact, the results allowed rejecting the null hypothesis of daily returns being i.i.d., non-linear dependence was present on those returns, therefore, contradicting the random walk model supposition. Since the test results indicate that non-linear structure was present in the data, it is possible that exploitable excess profit opportunities may exist in the Istanbul stock market (ISE). However, the main characteristic of chaos, namely the sensitive dependence to the initial conditions, observed in the tests prevents that excess profit opportunities by the use of a chaotic anticipation pattern in ISE.

The null hypothesis may be formulated as;

H_0: pure whiteness, independent data, data generated by an i.i.d. stochastic process, market efficiency, i.e. the error terms of data in time series is independent and identically distributed (i.i.d.).

H_1: The error terms of data in time series are not i.i.d. This implies that time series is non- linearly dependent, since linear dependence has been removed. Hence, there exist non-linear dependence and absence of the market efficiency.

When the BDS test statistic is large (greater than 2), H_0 is rejected. The BDS statistics are computed for the underlying dimension of m = 2, 3, 4, 5, 6, 7, 8, 9 and 10 and for values of 0.50, 1, 1.5 and 2. A level of significance ( ) of 5% is taken and thus the critical value for the test is ±1.96, indicating that the null hypothesis should be rejected if the BDS test statistic is greater than 1.96 or less than -1.96. Table 5 indicated that all test statistics of error terms were greater than the critical value of 1.96 significantly under different embedding dimension and ratio of tolerance to standard deviation. Thus, the null hypothesis of i.i.d. for data should be rejected. The results strongly suggest that the series were non-linearly dependent at the 5% level of significance.

BDS test was applied to these residuals and result showed that residuals were not independently identically distributed. For all embedding dimensions BDS test rejected the null hypothesis of i.i.d.-ness (that is returns are nonlinearly dependent). Running the BDS test is far from straightforward, since the test is extremely computationally intensive and special algorithms are needed to ensure the implementation viable. In this study a MATLAB program was used to apply the BDS test.

Hinich Bispectral test is, on the other hand, a frequency domain approach test. It is used to estimate the bispectrum of a stationary time series and provides a direct test for non-linearity and also a direct test for Gaussianity. If the process generating the data (in this case the rates of return) is linear, then the skewness of the bispectrum will be constant. If the test rejects constant skewness, then a non-linear process is implied (Hinich and Clay, 1968). Linearity and Gaussianity can be tested using a sample estimator of the skewness function.

The null hypothesis of the Hinich “linearity” test is given by

H_0: flat skewness function, absence of third order non-linear dependence;

H_1: non-linear dependence, absence of efficiency,

H_0 is rejected if the standard normal test statistic Z is large (that is over 2 or 3). When the null is Gaussianity, the related test statistic is denoted by H and is also a standard normal random distribution under the null hypothesis (Hinich and Patterson, 1989).

The existence of the third order nonlinear dependence (that is tests the flatness of skewness function or lack of third order nonlinear dependence) was examined, and the null hypothesis of linearity was rejected. Therefore, it is concluded that the series was nonlinear. As reported in Table 6, the test statistic is 3.73, which is larger than the critical value of 2.55. This implies that the null hypothesis of linearity can be rejected. As for the Gaussianity test, normality of daily ISE returns was analyzed. In this case, the test statistic of 8.47 was again much larger than the critical value of 3, implying that the null hypothesis of Gaussianity can be rejected. The rejection of linearity provides support for the conclusion on non-linearity in ISE stock indexes returns and, therefore, for the absence of weak form efficiency.

Chaos tests

For testing the chaos, the Lyapunov Exponents and the NEGM test were used. These tests were applied to the ISE data set to analyze the existence of chaos in the ISE. The distinctive feature of chaotic systems is sensitive dependence on initial conditions, that is, exponential divergence of trajectories with similar initial conditions. The most important tool for diagnosing the presence of sensitive dependence on initial conditions (and thereby of chaoticity) is provided by the dominant Lyapunov Exponent ( ). This exponent measures average exponential divergence or convergence between trajectories that differ only in having an infinitesimally small difference in

Table 5. BDS test results: Daily ISE composite index returns.

/ ratio	Embedding dimension (*m*)	BDS test statistics	/ Ratio	Embedding dimension (*m*)	BDS test statistics
0.5	2	6.9552	1.5	2	9.7703
0.5	3	9.9729	1.5	3	12.4650
0.5	4	12.9582	1.5	4	14.90410
0.5	5	15.9241	1.5	5	15.9980
0.5	6	17.8642	1.5	6	16.8969
0.5	7	20.5240	1.5	7	17.9367
0.5	8	23.6152	1.5	8	18.8290
0.5	9	27.9350	1.5	9	20.9880
0.5	10	30.9720	1.5	10	21.9630
1.0	2	7.7246	2.0	2	11.9860
1.0	3	10.6841	2.0	3	14.9670
1.0	4	12.8480	2.0	4	16.1290
1.0	5	14.8520	2.0	5	16.820
1.0	6	17.4790	2.0	6	17.9380
1.0	7	19.6260	2.0	7	18.0085
1.0	8	21.5650	2.0	8	18.5470
1.0	9	23.8750	2.0	9	19.3130
1.0	10	25.9699	2.0	10	19.9840

their initial conditions and remains well defined for noisy systems (Wolf et al., 1985).

In mathematics the Lyapunov exponent or Lyapunov characteristic exponent of a dynamical system is a quantity that characterizes the rate of separation of infinitesimally close trajectories. Quantitatively, two trajectories in phase space with initial separation " " diverge. The difference between the results is given by;

$$d_n = exp\left(n \cdot \lambda\left(X_0\right)\right) \cdot \varepsilon \qquad (5)$$

Let consider two points, X_0 and X_{0+}, apart from each other by only the infinitesimal difference " " and apply a map function to each of the two points *n* times. Here " " is the Lyapunov exponent. After solving for the convergence (or divergence) rate the maximal Lyapunov exponent can be defined as follows:

$$\lambda = \lim_{n \to \infty} \frac{1}{n} log \left| \frac{d_n}{\varepsilon} \right| \qquad (6)$$

There are three possible values for the Lyapunov exponent where Lyapunov exponent denoted by :

$\lambda < 0$, When Lyapunov exponent is less than zero, system is convergent

$\lambda = 0$, When Lyapunov exponent is equal to zero, the system is in some sort of steady state mode.

$\lambda > 0$, When Lyapunov exponent is greater than zero, it indicates a sensitive dependence on initial conditions (i.e. system is chaotic).

If a system has at least one positive Lyapunov Exponent, the system is chaotic and trajectories, which start at two similar states, will diverge exponentially. The larger the dominant positive exponent is, the more chaotic the system becomes, and the shorter the time span of system predictability. A positive Lyapunov Exponent is, therefore, viewed as "an operational definition of chaotic behavior". Wolf et al. (1985) estimate the Lyapunov Exponent by averaging the observed orbits divergence rates.

Table 7 presents estimates of the maximum Lyapunov Exponents of the daily log returns series using the estimation method of Wolf et al. (1985). The Lyapunov Exponents were estimated with embedding dimensions up to four as in Wolf (1991) . The results (all are positive) appear to point to the above stated operational definition of chaos. It allows us to accept chaos for the financial time series considered.

Table 6. Result of Hinich bispectral test.

Test	Statistic	Critical value	Conclusion
Linearity test statistic (*Z*)	3.73	2.55 (=0.05)	Reject the Linearity
Gaussianity test statistic (*H*)	8.47	3.00 (=0.05)	Reject the Gaussianity

Table 7. Lyapunov exponents for log returns.

ndim	max	(ISE Composite share)
1		0.22368791
2		0.23458914
3		0.35612712
4		0.41236514

Note: *ndim*: embedding dimension, max : maximum estimated value of Lyapunov Exponent.

Since Lyapunov Exponent method is less reasonable when we are dealing with noisy systems, Nychka et al. (1992) developed an alternative approach, namely NEGM test, based on Jacobian methods in order to avoid upward bias when estimating Lyapunov Exponents. They proposed that regression (or Jacobian) method, involving the use of neural network models, to test for positivity of the dominant Lyapunov Exponent. NEGM is a procedure for testing for chaos by estimating the dominant Lyapunov Exponent. Lyapunov Exponent for a bounded system is the operational definition of chaos. Jacobian method is used to calculate Lyapunov Exponent where the neural network method has been used to estimate this exponent.

The hypotheses of the NEGM test are:

H_0 = Lyapunov Exponent is negative or time series is not chaotic or $\lambda \leq 0$.

H_1 = Lypunov Exponent is positive or time series is chaotic or $\lambda \geq 0$.

Since Lyapunov Exponent point estimate is “0.42”, which is a positive number, then the null hypothesis can be rejected, implying that the time series is chaotic.

Conclusions

This paper employs two tests for nonlinearity on the daily ISE composite returns, namely, BDS Test and Hinich Bispectral test. The test results rejected the presence of linearity for ISE returns by the BDS test. In order to test the chaotic behavior, Lyapunov Exponents test and NEGM test were employed.

Both tests showed that chaos existed in ISE composite returns. We conclude that the test results indicate sufficient evidence for non-linearity and chaos in the ISE daily returns. By providing significant evidence against the popular efficient market hypothesis, this study challenges the existing studies on ISE market. In other words, ISE market does not follow the random walk pattern, hence it is not i.i.d.

Compared to the existing literature on Turkish ISE, the results might be different for several reasons. One reason can be the volume of the data sets. Because, as mentioned in Harrison et al. (1999: 501), the accuracy of test results improves with the increase in the number of recording points and the length of the time series. Another reason could be that ISE has been relatively a young financial market. Moreover, Turkey has experienced many economical and financial crises during the last twenty years.

Thus, ISE has some maturity problems. It is possible that the studies conducted with similar ISE data sets can show contradicting results because of the noise in the data, low number of data points and the methods utilized. For further studies, it is recommended that researchers use larger (probably 5.000 or more) data sets with different test methods and make comparisons to clarify the reliability of methods.

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