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Emerging Stock market Efficiency: Nonlinearity and Episodic Dependences Evidence from Iran stock market

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ABSTRACT

Motivated by the institutional features of emerging stock markets, the present paper examines the weak form efficiency of Iran stock market as an emerging market based on stock returns data generating process. Through a synthesis of the nonlinear structure in stock price series and the stylized facts of stock return series, we adopted a methodology to detect both linear and nonlinear dependencies in the stock return series. The results show that the stock returns data generating process is fitted by the ARMA- GARCH_ M model .Therefore, the future stock returns based on the past pattern of stock price changes would be predictable. Another interesting finding is that the common assumptions of constant variance and Gaussian stock returns are invalid for this emerging stock market.

KEYWORDS: market efficiency, nonlinearity, ARIMA model, GARCH model

1. INTRODUCTION

Doubtless the stock market efficiency has been the dominating concept in the theoretical and empirical literature of finance. Due to scarcity of the financial resources, an efficient stock market is critically important in mobilizing national saving and financing of new investment projects. Furthermore, stock market efficiency plays a crucial role in decision making of companies concerning diversification of their sources of investment capital and spread investment risk. In an efficient stock market, stock prices reflect all available information which is relevant for the evaluation of a company's future performance, and therefore the market share price is equal to its inherent value. Any new information, which is expected to change a company's future profitability, is immediately reflected in share prices. In an informationally efficient market, stock is appropriately priced at equilibrium level and there is no distortion in the pricing of capital and risk.

Stock market efficiency depending on the type of relevant information appears at three levels. Firstly, the weak form efficiency which claims that current stock prices reflect all relevant and available (historical) information. Secondly, the semi-strong form of efficiency which indicates that present stock prices reflect historical and all relevant public information. Finally, if the stock prices reflect the public and private (insider) information, the stock market would be efficient in strong form. In a stock market which is efficient in weak form, the subject of this paper, stock prices changes only in response to new information which by definition must be unpredictable. Under these circumstances, the prices of stock behave randomly, or without any identifiable pattern. Therefore, in the weak form of efficient stock market the prediction of future pattern of the stock price movements based on past prices is impossible.

In view of the well known properties of financial time series such as stylised fact, volatility clustering and no normality, absence of linear dependence does not necessarily mean unpredictability of the stock price movements. In this view, a methodology in testing stock market efficiency should apply which is capable to detect both linear and nonlinear dependences.

In this study, using data from the Iran stock market, we seek to examine the concept of weak form efficiency in the light of specific institutional features of the market under investigation. Additionally, the stylised facts of stock return time series are taken into account in the model-building process. Specifically, we adopt a testing methodology in accordance with underlying dynamic in data which enables us to identify the possible existence of non-linear behaviour and episodic dependences in stock prices process.

The remainder of the paper is divided into four main areas. The theoretical background is discussed in section 2.Section 3 outlines and explains research methodology which is used. A description of the data employed in the analysis and empirical results is presented in section 3. The paper ends with summarising the main conclusions.

Theoretical issues

The conventional stock market efficiency tests such as variance ratio test, serial correlation test, runs test and unit root test assume linearity in the stock return (stock price changes) generation process and are not able to capture possible non-linear behaviour in time series. The assumption of linearity implies that the means and

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standard deviations of stock returns are constant through time. In the light of structural changes, high amplitude shocks, technological innovation, changes in regulations, the characteristics of market microstructure, the unreliable and unqualified information, the existence of bid-ask spread, the existence of market imperfections (market frictions e.g. transaction cost, tax, government interventions), the occurrence of unexpected events and the complex dynamics of the environments in which economies operate, this assumption is not likely to be reasonable. This means that the existence of above features lead to the appearance of nonlinear structure in the stock returns generation process.

Furthermore, stock market efficiency hypothesis implicitly assumes that investors are rational where rationality implies risk aversion, unbiased forecasts and instantaneous responses to new information. Such rationality leads to stock prices responding linearly to new information. These attributes especially in emerging stock market with uninformed participants (traders) are not realistic. Therefore, the behavioural biases of investors may result in stock prices responding to new information in a non-linear manner. In addition, given the informational asymmetries and lack of reliable information, noise traders may also lean towards delaying their responses to new information in order to assess informed traders' reaction, and then respond accordingly.On the other hand, emerging stock markets are typically characterised by low liquidity, thin trading and considerable market volatility which may lead to delay in investors to new information and therefore stock prices change as non- linear style. Additionally, the price limits which are introduced especially in emerging markets to control market volatility may result in non-linear behaviour in stock prices.

Another explanation for the existence of non-linear structure in distribution of stock return series is the special features of the financial data as "stylized facts". The empirical distribution of stock returns appears as stylized facts like fat tails, high peakness (excess kurtosis) and skewness. Furthermore, volatility clustering, long memory (volatility is highly persistent) and leverage effects are other features of empirical behavioural of stock returns distribution. Accordingly, time series of stock returns (stock price changes) is generally volatile and nonlinear in nature.

Failure to take into account the special properties of financial data and the institutional features of stock market specific to developing countries may lead to incorrect identification of data generating process or statistical illusions regarding stock market efficiency or inefficiency. In this sense, the special features of stock return time series should be taken into account in model-building process and analysis of stock market behaviour.

As mentioned earlier, the empirical literature of stock market efficiency has been mainly focused on testing the stock market efficient hypothesis in weak form using the traditional random walk test. Technically, these tests are conducted to investigate the linear serial independence in stock price movements, but cannot detect any nonlinear structure in the data. If independence is concluded by those tests, it will only reject the linear predictability of stock prices, but does not rule out the possibility of nonlinearity dependences in the underlying structure of stock price series. In other words, the lack of correlation (linearly uncorrelated) between stock prices or stock returns does not guarantee the independence of them. Accordingly, recent studies use more sophisticated tests of independence and focus on higher-order moments. The theoretical distribution of stock return series displays higher-order dependence which is known as nonlinear behaviour in financial economics.

In recent years, especially in emerging stock market the examination of stock returns behaviour with regarding to nonlinear dynamic has been considered. [23] using the nonlinearity tests and FIGARCH model show the evidence that the Tunisia stock market does not follow random walk theory. [13] re-examine the weak form efficiency of 10 Asian emerging stock markets using a battery of nonlinearity tests (the McLeod-Li test, Engle LM test, Brock–Dechert–Scheinkman test, Tsay test, Hinich bicorrelation test and Hinich bispectrum test). They conclude that that all the stock returns series still contain predictable nonlinearities even after removing linear serial correlation (using AR(P) model) from the data. [12] applying the previous procedure, signifies the same results for the Middle East and Africa stock markets. [17] using a battery of nonlinearity test and GARCH (1, 1) documents that the Ghana stock market is not efficient in weak form. The efficiency of the Chinese stock market is examined by [11] using the nonlinearity toolkit which is introduced by [21]. They provide the evidence of nonlinear serial dependence in the underlying China stock returns generating process. Through the detection of a non-linear dynamic with potential for predictability of stock return, [4] show that the Mexican market fails to satisfy the weak form of the efficient capital market hypothesis. [6] investigates the existence of nonlinearities in the dynamics of the returns of stock markets indices from CEE (Central and Eastern Europe) economies. Applying the Brock–Dechert–Scheinkman (BDS) test on autoregression (AR)-filtered returns in rolling estimation windows, [10] find brief time periods with non-linear predictability in all markets, contradicting the weak-form efficient markets hypothesis.

METHODOLOGY

Given the nature of the financial data, we apply the following process to identify the data generating process for time series of stock price changes or stock returns in Iran stock market:

-The random walk hypothesis is applied and then the **I.I.D** hypothesis is examined through the battery of tests: the Jarque-Bera (JB) test for normality; the Ljung-Box (LB) test statistic for autocorrelation [7] test for ARCH effects, [17] and [5] BDS test for randomness and non-linearity. All these tests share a common principle: once any linear serial dependence is removed from the data, any remaining dependence must be due to nonlinearities in the data generating process. In addition, we investigate whether the data generating process of stock price changes could be explained by an ARIMA model.
- If both the RW model and the ARIMA model fail to clarify the behaviour of the Iran stock prices and there is strong evidence against the null hypothesis of **I.I.D**, then we will employ nonlinear model specifically the GARCH model.

As stated above, weak-form stock market efficiency implies that stock prices follow a random walk process without drift such as:

$$p_t = p_{t-1} + \varepsilon_t \qquad (1)$$

Where p_t is the natural logarithm of stock price index at time t, p_{t-1} is the natural logarithm of stock price index at time t-1 and ε_t are residuals (stochastic error term) with **E** $(\varepsilon_t) = 0$, **V** $(\varepsilon_t) = \sigma^2$ and **Cov** $(\varepsilon_t, \varepsilon_s) = 0$ $\forall$ t≠ s . The random walk hypothesis implies two concepts: (a) successive price changes (returns) are independent; (b) successive price changes are identically distributed. Then $\varepsilon_t = p_t - p_{t-1} = \boldsymbol{r}$, which, being white noise, is unpredictable from previous stock price changes. Under these circumstances, the I.I.D assumption implies that not only the increments of stock price changes are linearly uncorrelated, but any non-linear functions of the increments are also uncorrelated .To test the assumptions indicated by the random walk hypothesis, the following equation is estimated by least squares procedure:

$$\Delta p_t = r = \mu + \varepsilon_t \qquad \textbf{(2)}$$

Under the random walk theory, p_t should be **I (1)** and therefore $\Delta p_t = r$ **~ I (0),** the estimate of the constant term (μ) should be insignificantly different from zero and the resultant residuals should b **I.I.D**. If the null of **I.I.D** is rejected, the implication is that the residuals contain some hidden, possibly non-linear behaviour.

At the same time, regarding to stylized features of financial data such as volatility clustering, leptokurtosis and leverage effect, the mean equation of stock price changes (stock returns) process could be described as:

$$\Delta p_t = \mu + \sum \phi_i \Delta p_{t-i} + \varepsilon_t \ , \quad \varepsilon_t / \Omega_{t-1} \approx NID(0, h_t) \qquad (3)$$

The error term ε_t is conditionally heteroscedastic $\varepsilon_t = z_t \sqrt{h_t}$

where Z_t is **I.I.D** with zero mean and unit variance. The conditional variance equation according to the standard GARCH model is represented as:

$$h_t = \omega + \sum_{i=1}^{p} \alpha_i \varepsilon_{t-i}^2 + \sum_{j=1}^{q} \beta_j h_{t-j} \qquad (4)$$

The restrictions of **ω**>0, $\alpha_i > 0$ and $\beta_i \geqslant 0$ are imposed to ensure $h_t \geqslant 0$ **.**

The $\emptyset_i$ parameter in (3) is included in the mean equation to take into account the autocorrelation induced by non-synchronous trading in the stock prices or returns [15,24]. It is obvious that the implication of significant $\emptyset_i$ is that the previous stock price changes are useful in predicting the future of stock price movements. This consequence is inconsistent with efficient market hypothesis.

In order to choose an appropriate nonlinear model describing the returns generating process, it is crucial to consider the source of nonlinearity in the data. Nonlinearity can enter through the mean of a return generating process, or appear in the variance of stock returns. GARCH model is applied to capture the nonlinearity through the variance, at the same time the GARCH-M (GARCH in mean) model can be employed to take into account the nonlinearity through the stock returns mean.

Given the probability of the existence of nonlinearity through the mean, we apply the GARCH-M which accounts for the risk premium effect by introducing a volatility term into the mean equation:

$$\Delta p_t = \mu + \sum \phi_i \Delta p_{t-i} + \delta h_t + \varepsilon_t \qquad (5)$$

The GARCH-M measures the relationship between risk and stock returns (risk premium effect). An insignificant δ implies that risk does not affect the stock returns process.

EMPIRICAL RESULTS

Data and Preliminary Analysis

Empirical research in nonlinear dynamics needs large sample data set. In addition, long time interval data series can be non-stationary, especially in emerging markets where financial liberalization and deregulation have led to multiple structural breaks in stock market data series. To handle this problem, we use the daily closing price of the Iran stock market index, from January 2, 1999 December 30, 2009, with a total of 2632 observations. The data is obtained from Iran Stock market. Market prices index are transformed to daily returns $r = \ln(p_t / p_{t-1})$ *100 where p_t and p_{t-1} are stock prices index prices at date t and $t-1$ respectively.

Table 1 provides the descriptive statistics for Iran stock returns. The high standard deviation with respect to the mean is an indication of the high volatility in the Iran stock market and the risky nature of the market. A visual analysis of the market volatility can be seen in Figure 1. The large stock price changes tend to follow large changes, and small changes tend to follow small changes. This is a property of stock prices, called volatility clustering (a type of heteroscedasticity) that Iran stock prices index seems to exhibit. Positive skewness means that the Iran stock returns distribution has a long right tail. At the same time, the kurtosis or degree of excess, in the Iran stock returns series is bigger than the normal value of 3. As a result, the Iran stock return series has peaked–leptokurtic distribution. It is worth highlighting that with regarding to the skewness and the kurtosis of Iran stock returns it can be concluded that the distribution of stock returns departs from normal distribution. Furthermore, according to the calculated Jarque-Bera statistics and corresponding p-value in table 1, the stock return series is not well approximated by the normal distribution. The theoretical graph and ***QQ***-plot shown in Fig.2 and Fig.3 also confirm that the daily Iran stock returns are not normally distributed. Generally speaking, the same as findings of other empirical studies in emerging stock markets, Iran stock return time series are characterized by some "stylized fact" and does not appear to be a sequence of i.i.d random variable.

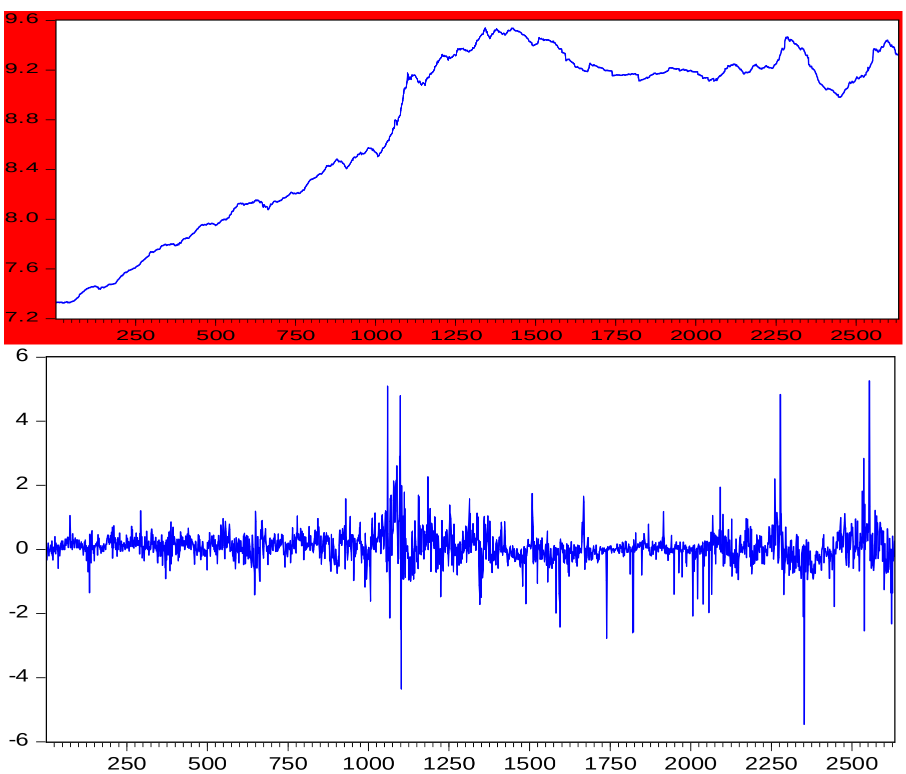


Fig1. The time plot of daily Iran stock prices index and returns

Table1. Descriptive statistics for Iran stock returns

Mean (%)	**0.0756**
Median (%)	**0.0592**
Minimum (%)	**-5.4330**
Maximum (%)	**5.2581**
Standard Deviation (%)	**0.5169**
Skewness (*s*)	**0.5595**
Kurtusis (k)	**25.9423**
Jarque-Bera Statistic	**57838.40**
P-value	**(0.0000)**
Observations	**2631**

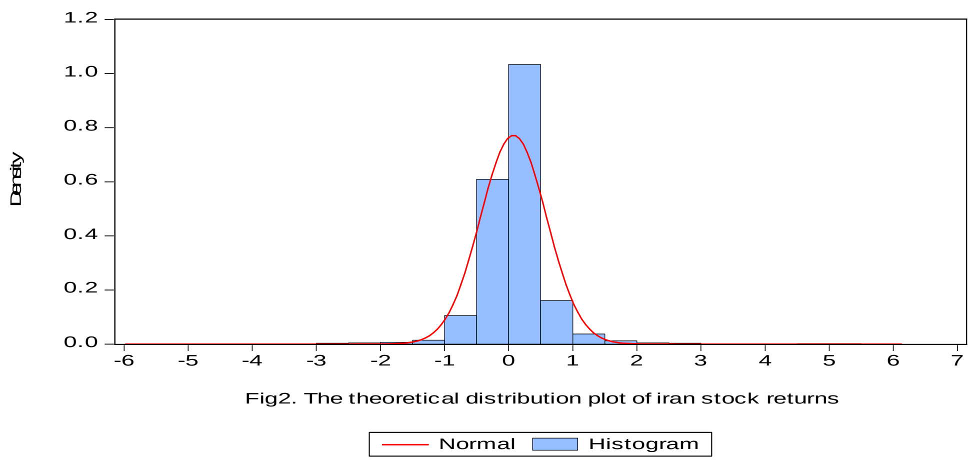


Fig2. The theoretical distribution plot of iran stock returns

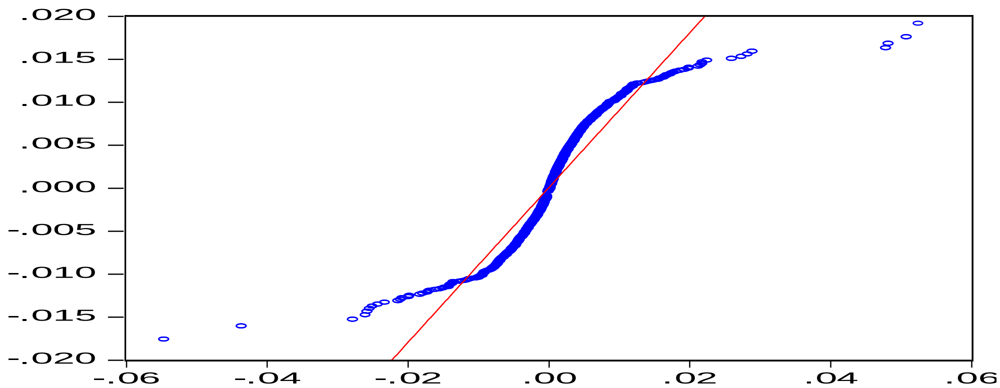


Fig3.The QQ-plot for the daily Iran stock returns

Table 2 below represents the OLS estimate of the constant (or drift) by estimating Eq. 2. The results indicate that the mean of the return series is significantly different from zero, which is inconsistent with the random walk hypothesis. As a consequence, the Iran stock returns data generating process is not fitted by the random walk model. Note that *JB* test statistic supports the same conclusion as with the descriptive statistic in Table 1, signifying a departure from normality in stock return series, a common feature of financial asset returns.

Table2. Results of the regression of the random walk with drift

Estimated Constant	**t-Statistic**	***JB****
0.07564	7.5058	57838

Note: *significance at the 5% level, *JB* is the Jarque–Bera test for normality

As mentioned earlier, under the random walk hypothesis, the distribution of stock returns should be stationary over time. Furthermore, since structural changes can lead to rejection of the **I.I.D** process, it is important to detect the possible nonstationarity in data series. In searching for unit roots, we employ conventional **ADF** and **PP** unit root tests. The findings in table 3 imply that the stock price series is non-stationary in levels and stationary in first differences (stock returns) at 5% level of significance.

Table3. The results of Unit Root Tests

	LnP_t		r_t	
	Intercept	**Trend and intercept**	**Intercept**	**Trend and intercept**
ADF	-2.2737	-1.0549	-9.6238	-9.8385
PP	-2.3992	-0.8462	-45.7102	-45.4640

To examine the linear dependence of the returns series, we use the modified *Q*-statistic of Ljung and Box. Table 4 represents the autocorrelations coefficients up to lag 36. The results imply the existence of significant serial autocorrelation at all lags. It is important to note that the serial correlation of the stock returns should not necessarily imply that the Iran stock market is inefficient. Spurious autocorrelation may exist due to institutional factors such as non-synchronous trading which may induce price-adjustment delays into the trading process.

In order to investigate the I.I.D assumption for stock return series we apply the **BDS** test. It is a powerful test frequently used to detect several nonlinear structures and to examine the adequacy of a variety of models. Table 5 provides the **BDS** statistic for embedding dimension 2 to 8 and for epsilon values starting from 0.5 to 2 times the standard deviation of the returns series. The outcomes strongly reject the null hypothesis of independently and identically distributed stock prices index changes at 1% significance level.

Table4. Test for serial correlation of the daily returns: Modified *Q*-statistic

MQ (5)	*MQ* (10)	*MQ* (15)	*MQ* (20)	*MQ* (25)	*MQ* (30)	*MQ* (36)
735.72*	1135.7*	1350.7*	1515.9*	1585.5*	1659.4*	1680.8*

Note: *MQ* (*k*) is the modified *Q*-statistic at lag *k*, *significance at the 5% level.

Table5. The BDS test statistic for Iran stock returns data

m	ε/σ		ε/σ		ε/σ		ε/σ	
2	0.5	34.52472	1	30.30870	1.5	26.87644	2	23.34982
3	0.5	42.13359	1	32.01117	1.5	27.19334	2	23.83401
4	0.5	50.29843	1	32.98223	1.5	26.55742	2	23.07210
5	0.5	61.83773	1	34.32615	1.5	26.13596	2	22.26737
6	0.5	78.10177	1	36.24301	1.5	25.94956	2	21.58381
7	0.5	102.3649	1	39.03821	1.5	26.09759	2	21.13172
8	0.5	137.6415	1	42.25773	1.5	26.30727	2	20.77283

Note: *m* is embedding dimension, ε is the bound, all statistics are significant at the 1% level. The critical values for *BDS* test are 1.96 for 5% and 2.58 for 1%.

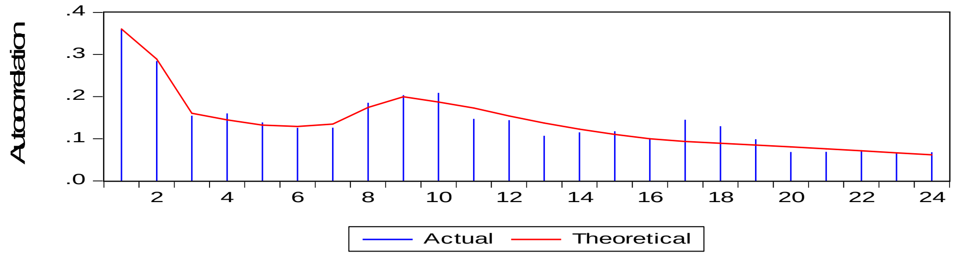
Now we focus on uncovering the structure of dependency in the stock returns series. Since the **BDS** test has a good power against linear as well as nonlinear systems, firstly we use a filter to remove the serial dependence in the stock return series and the resulting residuals series are re-tested for possible nonlinear hidden structures. An ARIMA model is applied to take out all the linearity in the series. Empirical studies indicate that thin trading and non-synchronous trading introduce negative first-order autocorrelation in the observed time series of stock returns [1, 2, 3, 8, 14,22]. An advantage of using the residuals of ARMA(p, q) model is that it adjusts the effect of infrequent trading, which is appears more in stock prices index of thinly traded stock markets (emerging stock market) [19]. The identification of the ARMA (p, q) bases on the autocorrelation and partial correlation of the residual of estimation of Eq.2 as well as the lowest AIC criteria. Accordingly, the ARIMA (9, 1, 8) model is adopted for linearity modelling of Iran stock return series. Table 7 represents the serial correlation test for the residuals and the squared residuals of estimated ARIMA (9, 1, 8) model. According to outcomes from table 6 and figure 4, it can be noted that the residuals of the ARIMA (9, 1, 8) model are white noise, implying that the model is adequate for all the linearity dependence in the Iran stock return series.

It is necessary to point out that the nonexistence of evidence concerning autocorrelation in the residuals of the ARIMA model does not mean that the residuals of the whitened data follow a pure random process. A the same time, the significant values of McLeod-Li (ML) test statistics in table 6 imply that the squared residuals of ARIMA model display significant autocorrelation, indicating evidence of nonlinear dependencies in the Iran stock returns series. In other words, the strong degree of nonlinear dependence in the residuals of the ARIMA model indicates the inadequacy of the model to explain the behaviour of Iran stock returns. To verify the presence of nonlinear dependence, we employ the BDS test to the residuals of the whitened residuals series. The BDS statistics displayed in Table 7 strongly reject the I.I.D assumption, which introduces an obvious indication of the existence of nonlinear dependencies in stock returns series. [9] argues that the rejection of the I.I.D assumption after removing linear dependence may be due to either non-stationarity or non-linearity in the stock returns series. Previously in table 3 we have demonstrated the stationarity of the stock returns according ADF and PP unit root tests. The presence of nonlinearities in the stock returns series could imply evidence of return predictability. In this sense, [20] indicates that technical trading rules to create excess stock returns need some form of nonlinearity in stock prices and [18] argues that the existence of nonlinearity is a crucial condition for trading rules to have potential predictive power.

Table6. Test for serial correlation of the residuals of ARIMA (9, 1, 8) model

LB(5)	**LB(10)**	**LB(15)**	**LB(20)**	**LB(25)**	**LB(30)**	**LB(36)**
-	5.56	11.67	25.13	26.90	32.47	41.86
McL(5)	McL(10)	McL(15)	McL(20)	McL(25)	McL(30)	McL(36)
-	325.52*	350.37*	376.34*	382.59*	384.95*	396.62*

Note: * denotes significance at the 1% level, *MQ* (*k*) is the modified *Q*-statistic at; *ML* (*k*) is the McLeod-Li test



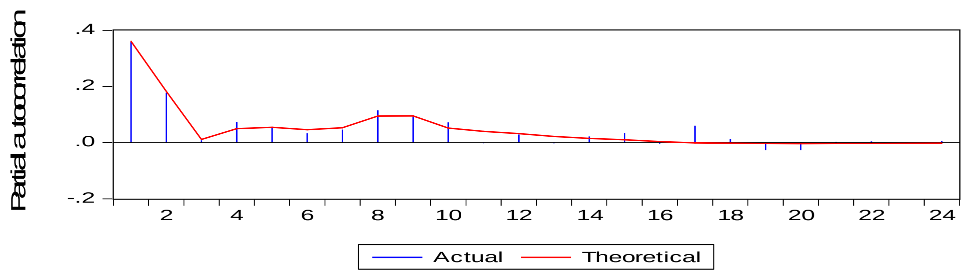


Fig4. ACF and PCF for the residuals of ARIMA(9,1,8)

Table7. The *BDS* test statistic for the residuals of pre-whitening ARIMA model

m	ε/σ		ε/σ		ε/σ		ε/σ	
2	0.5	23.8030	1	20.9495	1.5	19.9949	2	17.4831
3	0.5	29.1741	1	22.9067	1.5	21.3397	2	19.1900
4	0.5	34.8051	1	24.3329	1.5	21.4987	2	19.2989
5	0.5	42.0064	1	25.4999	1.5	21.5550	2	19.0266
6	0.5	51.3633	1	26.9768	1.5	21.7823	2	18.8026
7	0.5	63.7197	1	28.7280	1.5	21.9243	2	18.4533
8	0.5	80.3183	1	30.5012	1.5	22.0124	2	18.1165

Note: *m* is embedding dimension, ε is the bound, all statistics are significant at the 1% level. The critical values for *BDS* test are 1.96 for 5% and 2.58 for 1%.

Table8. ARCH-LM test for the residuals of ARIMA (9, 1, 8) model

ARCH (1)	*ARCH* (2)	*ARCH* (3)	*ARCH*(4)	*ARCH* (5)
112.67*	167.75*	206.55*	210.07.52*	209.97*

Note: * denotes significance at the 1% level, χ^2 -test.

Since the squared residuals measure the second moments of the series, significant autocorrelations of the squared residuals are evidence of time varying conditional heteroskedasticity in the daily stock returns as well as in the residuals of the ARIMA model. In order to test of the existence ARCH effect in the residuals of ARIMA model we apply ARCH-LM test. According to the results in table 8, the existence of ARCH effect is strongly confirmed. After the identification of non-stationarity and removal of linearity as causes of the rejection of the I.I.D assumption, we have documented the inherent nonlinearity in the Iran stock returns data generating process.

In spite of the existence of inherent nonlinearity in stock returns series based on the results from the BDS test, it is not clear whether nonlinearity appears through the mean or the variance of the returns series. In order to uncover the source of nonlinear behaviour, we apply the GARCH-M model which allows the appearance of nonlinear behaviour in the mean and the variance of time series. We have examined several GARCH-M model and according to the results of diagnostic tests (residual test) on mean and variance equations as well as AIC and BIC criteria we conclude that the ARMA (9, 8)-GARCH (1, 1) -M model is most likely to succeed in describing the Iran stock return generating process.

Table 9 provides the estimation results of ARIMA and GARCH models. To consider the special characterises of stock returns distribution particularly fat tails (given the evidence from Table 1), the student's t-distribution was employed for the GARCH estimates (assuming that the conditional distribution of the error term is student's t). The AR (1) and AR (9) coefficients (lagged returns) are highly significant across GARCH models. These findings imply that past information is useful in predicting the future path of stock prices (stock returns) and trading strategies could be designed to create abnormal returns. Therefore the implication of these results is inconsistent with the weak form efficiency. The MA error coefficients may capture the effect of non-synchronous trading [stock prices are often recorded at regular intervals (e.g. daily closing price) but not all stock trade at the same time] and is highly significant.

The coefficients of the conditional variance equation, $\boldsymbol{\alpha}$ and $\boldsymbol{\beta}$, are significant at 1% level implying a strong support for the ARCH and GARCH effects in stock returns data generating process. In addition, the sum of the parameters estimated by the conditional variance equation is close to one. A sum of $\boldsymbol{\alpha}$ and $\boldsymbol{\beta}$ close to one is an indication of a covariance stationary (weakly stationary) model with a high degree of persistence; and long memory in the conditional variance. $\boldsymbol{\alpha} + \boldsymbol{\beta} = 0.96$ is also an estimation of the rate at which the response function decays on daily basis. Since the rate is high, the response function to shocks is likely to die slowly. On the other hand, the risk premium parameter $\boldsymbol{\delta}$ as a measure of the risk-return trade-off is positive and statistically significant (at %1). This means that in Iran stock market the investors are compensated for assuming higher levels of risk. In other words, in this market higher risk specified by the conditional variance will lead to higher stock returns. A possible explanation for the existence of risk premium is the presence of the supposed risk (e.g. political risk and economic policy) of investing in emerging stock market. It is necessary to point out that the low liquidity as a common feature of emerging stock market plays a significant role in explaining the existence of risk premium in these markets.

Diagnostics analysis

According to the Ljung-Box (MQ) statistics on the standardized residuals and the McLeod-Li (ML) statistics on the standardized squared residuals of ARMA (8, 1) – GARCH (1, 1) _M model in table 10, it can be seen that there is no evidence of serial correlations and nonlinear dependencies in the Iran stock returns series. Furthermore, in table 11 from the findings of ARCH-LM test it can be concluded that there is no evidence of conditional heteroscedasticity in the data. This implies that the fitted volatility model is adequate and it has counted for all the volatility clustering in the stock return series. The *JB* test in table 10 rejects the null hypothesis that the standardized residuals are normally distributed. To get more comprehensive conclusion about the normality assumption, we look at the *QQ*-plot given in Fig. 5 deviation in both tails from the normal *QQ*-line is significant, thus the normality for the residuals of the fitted volatility model may not be suitable. It can be highlighted that the non- normal distribution of the standardized residuals is not really a problem because if the equations for the mean and variance are correctly specified, the parameter estimates will still be consistent. Of course the non- normal distribution of the standardized residuals may due to outliers that cannot be explained by the GARCH model.

To assess whether the ARMA (9, 8) – GARCH (1, 1) _M model has succeeded in capturing all the nonlinear structure in the stock return series; we employ the BDS test to its standardized residuals. As mentioned above, based on represented statistics in table 10, the autocorrelation coefficient for both the standardized residuals and squared standardized residuals show that the fitted model captures all the linear as well nonlinear dependencies in the Iran stock return series. Table 12 demonstrates the BDS statistics on the standardized residuals from the ARMA (8, 1) – GARCH (1, 1) _M model. In line with the findings from table 11, the BDS test except $\boldsymbol{\varepsilon/\sigma = 0.5}$ fails to reject the null hypothesis that the standardized residuals are I.I.D random variables at 5% and 1% degree of significance.This confirms that the ARMA (9, 8) – GARCH (1, 1) _M process captures all the nonlinearity in the series, and therefore it can be noted that the conditional heteroscedasticity is the cause of the nonlinearity structure revealed in the stock returns series. In other words, based on the outcomes from BDS test on the standardized residuals of fitted model, it can be remarked that the conditional heteroskedasticity is responsible for all the nonlinearity in Iran stock return series.

Finally, Fig. 6 represents the conditional volatility obtained from the fitted model. It is apparent from the graph that the conditional standard deviation varies over time. This is inconsistent with the common assumptions of constant variance or standard deviation and Gaussian returns underlying the theory and practice of option pricing, portfolio optimization and value-at-risk (*VaR*) calculations. In other words, it can be noted that based on the stock returns data generating process, the assumptions of constant variance is invalid for this emerging stock market.

Conclusions

Motivated by theoretical background and empirical literature, this paper investigates the weak-form stock market efficiency hypothesis based on underlying data generating process of Iran stock return series. In order to verify the stock price changes process, firstly we apply the RW hypothesis and ARIMA model. After removing the linear dependence in stock return series, using the nonlinearity tests we recognise the episodic nonlinearity dependences in the stock return series. Finally, by undertaking the nonlinearity structure and stylized fact of stock return series, it is concluded that the ARMA- GARCH_ M model is adequate for Iran stock return data generating process. On the other hand, the findings imply that the risk premium parameter in the line with other emerging stock market exist in Iran stock market. The stock returns with lags are significant in mean equation, inconsistent with the weak form efficiency of Iran stock market. Another interesting finding is that the common assumptions of constant variance and Gaussian stock return series are invalid for Iran stock market as an emerging stock market.

Table9.The estimation results of ARIMA (9, 1, 8) and ARMA (9, 1, 8)-GARCH (1, 1) _M models

Coefficient	**ARIMA (9, 1, 8)**		**ARIMA (9, 1,8)-GARCH**		**ARIMA (9, 1,8)-GARCH-M**	
		P-value		P-value		P-value
μ	0.0008	0.0153	0.0007	0.0000	0.0008	0.0000
ϕ_1	0.8423	0.0000	0.7375	0.0000	0.6910	0.0000
ϕ_9	0.0528	0.0074	0.0429	0.0000	0.0486	0.0000
MA (1)	-0.5813	0.0000	-0.2864	0.0000	-0.2093	0.0000
MA (3)	-0.1131	0.0000	-0.0555	0.0000	-0.0442	0.0080
MA (8)	-0.6890	0.0000	0.0210	0.0314	0.0267	0.0037
ω			2.30E-06	0.0000	1.71E-06	0.0000
$\boldsymbol{\alpha}$			0.4863	0.0000	0.5232	0.0000
$\boldsymbol{\beta}$			0.4909	0.0000	0.4410	0.0000
$\boldsymbol{\delta}$					12.0317	0.0000
$\boldsymbol{\alpha+\beta}$			0.98		0.96	
Log likelihood	10353.65		11357.99		11365.61	
AIC	-7.8929		-8.6559		-8.6610	
BIC	-7.8795		-8.6335		-8.6364	
JB	97440.33	0.0000	46104.19	0.0000	47292.97	0.0000

Note: ϕ, $\boldsymbol{\alpha}$, $\boldsymbol{\beta}$, $\boldsymbol{\delta}$ are the AR, ARCH, GARCH and risk premium parameters respectively. JB is the Jarque–Bera test for normality of the standardized residuals series.

Table10. Test for serial correlation of the residuals of ARIMA (9, 1, 8) - GARCH (1, 1)-M model

LB(5)	**LB(10)**	**LB(15)**	**LB(20)**	**LB(25)**	**LB(30)**	**LB(36)**
5.80	16.81	34.56	49.01	56.37	63.52	72.00
McL(5)	McL(10)	McL(15)	McL(20)	McL(25)	McL(30)	McL(36)
6.23	9.84	13.59	19.11	25.11	28.98	44.02

Note: MQ (k) is the modified Q-statistic at; ML (k) is the McLeod-Li test.

Table11. ARCH LM test for the residuals of ARIMA (9, 1, 8)-GARCH (1, 1) _M model

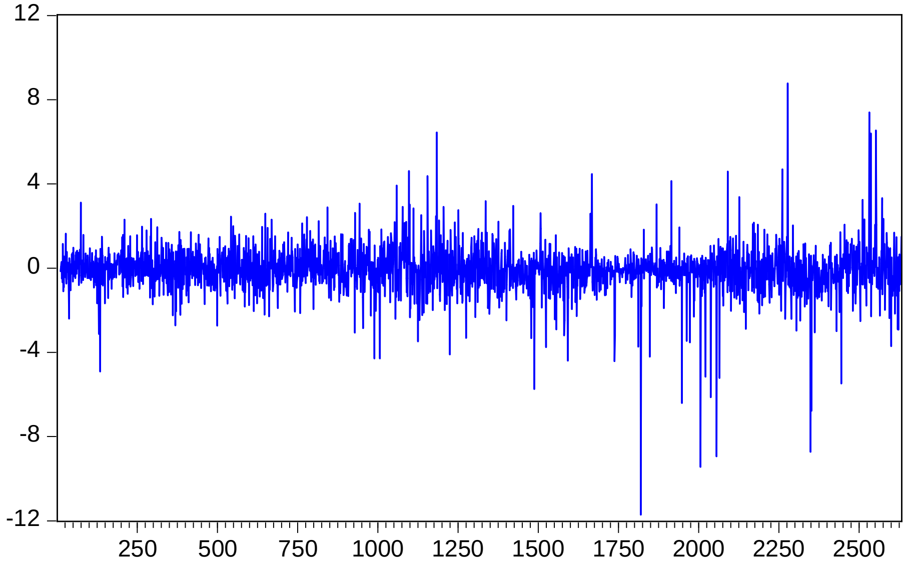
ARCH (1)	*ARCH* (2)	*ARCH* (3)	*ARCH* (4)	*ARCH* (5)
0.3467	1.2727	5.0060	5.6420	6.1807

Note: χ^2 -test.

Table12.The *BDS* test statistic for the standardized residuals of ARMA (9, 1, 8) - GARCH (1, 1) _M model

m	ε/σ		ε/σ		ε/σ		ε/σ	
2	0.5	3.2804	1	0.5999	1.5	-0.7730	2	-0.6011
3	0.5	3.3287	1	0.1609	1.5	-1.4794	2	-1.2937
4	0.5	4.0408	1	0.6641	1.5	-1.2505	2	-1.3043
5	0.5	4.5294	1	0.5960	1.5	-1.3332	2	-1.3293
6	0.5	5.5304	1	1.0741	1.5	-1.0389	2	-1.1939
7	0.5	5.9958	1	1.4816	1.5	-0.8914	2	-1.2640
8	0.5	6.4481	1	1.6309	1.5	-0.8658	2	-1.3676

Note: *m* is embedding dimension, ε is the bound, and the critical values for *BDS* test are 1.96 for 5% and 2.58 for 1%.



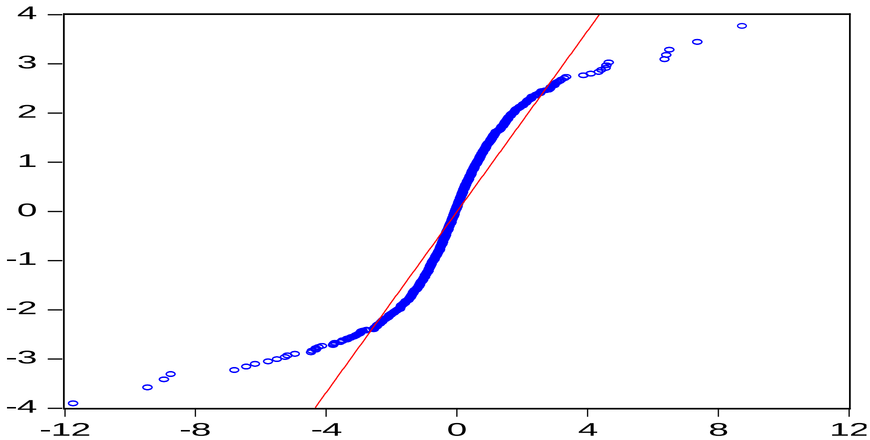


Fig5. ARMA(9,8)-GARCH(1,1)-M standardized residuals

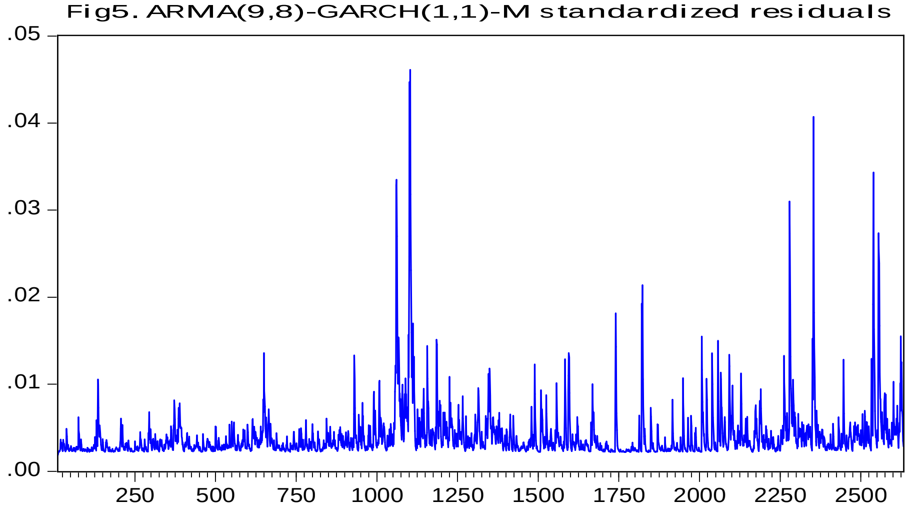


Fig6. Time varing volatility (conditional standard deviation) of Iran stock return series

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