LINEAR AND NON-LINEAR DEPENDENCE IN THE STOCK MARKET RETURNS: VALIDITY CHECK OF THE WEAK-FORM EFFICIENT MARKET HYPOTHESIS

Sühan Altay* and C. Coşkun Küçüközmen**

ABSTRACT

This paper investigates the validity of the weak-form-market efficiency by extracting linear and non-linear dependence in major developed capital markets and emerging capital markets. Weak form of market efficiency and its implication, random-walk hypothesis of the stock prices suggest that the stock price changes (returns) are independently and identically distributed random variables with zero mean and finite variance. However, results of this study cannot validate the weak form of market efficiency, since significant linear and non-linear dependence are found in all of the markets that we investigated. Non-linear dependence is explained by certain GARCH-type models, which incorporate the dependence in conditional variance. A special test, BDSL is used to validate the non-linear dependence in the stock returns.

Key words: *Weak-form efficiency, non-linear dependence, stock returns, emerging markets, BDSL.*

* Sühan Altay (altay@fam.tuwien.ac.at) is a PhD candidate at the Vienna University of Technology, Christian Doppler Laboratory for Portfolio Risk Management, Vienna University of Technology, Wiedner Hauptstr. 8/105-1, A-1040 Austria.
Sühan Altay was at the Middle East Technical University, Department of Business Administration when this work was performed.
** C.Coşkun Küçüközmen (kcoskun@metu.edu.tr) is a part-time lecturer in the Department of Financial Mathematics, Institute of Applied Mathematics at the Middle East Technical University. Küçüközmen is also working for the Central Bank of Turkey. The opinions expressed herein are those of the authors.

1. INTRODUCTION

Efficient Market Hypothesis (EMH) and its validity across both in financial markets and real markets have been examined extensively in the finance and economics literature over the last four decades after the milestone articles of Fama (1965, 1970). The essence of the EMH is that efficient market prices *fully reflect* the all-available information (Fama, 1970). Fama (1970) introduced three forms of market efficiency; namely weak, semi-strong and strong forms. The *weak-form* hypothesis asserts that stock prices already reflect all information that can be derived by examining market-trading data such as the history of past prices and trading volume. The *semi-strong form* implies that not just past stock prices but any information, which is publicly available, has been reflected fully in the prices. And *strong form efficiency* implies that the stock prices reflect all information relevant to the firm, even information that is available to insiders.

According to Fama (1970), the statement that the current price of a security *fully reflects* available information implies that successive price changes (returns) are *independent and identically distributed (iid)*. The independence and the identical distribution assumption constitute the logarithmic random walk model of the prices. Random walk model for weak-form of efficient market hypothesis, which implies stock prices reflect past stock prices, is:

$$\log(P_t) = \log(P_{t-1}) + u_t \qquad (1)$$

where, P_t is the price of the security at time t and, P_{t-1} is the price of the security at time $t-1$ (preceding period), and u_t is an independent and identically distributed random variable with zero mean and finite variance. In other words u_t is a white noise process. If u_t is white noise, $u_t = \log(P_t) - \log(P_{t-1})$, the price changes (returns), R_t, are unpredictable from the past stock price changes, making the evidence of the weak form of the market efficiency.

To make it more concrete, if the prices follow a random walk, then the returns defined by

$$R_t = \log(P_t) - \log(P_{t-1}) \qquad (2)$$

should not be related with future returns, making them worthless in predicting the future values of R_t. Therefore, to test the weak-form of the efficient market hypothesis, we need to test the independence of the R_t's. If we can find any linear or non-linear dependence between the returns, we can conclude that the weak form of market efficiency is violated.

In the earlier studies of the weak-form market efficiency, tests for serial independence are conducted to investigate the dependence of the stock returns by the help of autocorrelation functions. However, testing for serial correlation to check for dependence is not enough to conclude for weak form market efficiency. Even if autocorrelations coefficients are statistically not different from zero, this does not mean independence of returns, because autocorrelation functions can only detect linear dependence arising from the unconditional mean of the returns. Therefore, we need to test the nonlinear dependence of returns to validate fully the weak form of efficient market hypothesis. In our study, we follow both the traditional approach for detecting the linear dependence by the help of autocorrelation coefficients and univariate time series modeling and more recent models for detecting non-linear dependence. However, we concentrated on more to extract the non-linear dependence of the stock prices of the various world stock markets by the help of BDSL test developed by Brock et al. (1996). Examining the assumptions of random walk behavior of stock markets, hence testing the validity of the weak form of market efficiency by using BDSL statistic, was originally investigated by Al-Loughani and Chappell (1997) for London Stock Exchange. However, although Al-Loughani and Chappell's work tested serial independence by application of Lagrange Multiplier (LM) test to residuals, they did not take into account this while fitting the GARCH-M model. In order to tackle this problem, which may create possible complications for the BDSL testing procedure, we prefer to follow a two stage procedure, which briefly employs fitting an AR(MA) model to the stock returns firstly hence filtering the linear dependence and then uses filtered residuals to model nonlinear dependence. Obviously, BDSL test is used to determine whether residuals are independent and identically distributed at the end of each stage.

In our study, we choose to study the major developed capital markets and leading emerging capital markets. For the developed capital markets, we choose to investigate the US, UK, Japan, France, Germany and Italy stock markets, whereas as emerging markets we prefer to investigate Taiwan, Philippines, Hong Kong, Argentina, China, South Africa and Turkish stock markets. One of the most important reason for examining both emerging markets and developed markets is that to enlighten the differences between those markets (between developed and emerging) in terms of our research interest, which is non-linear and linear dependence of the stock returns, and implications of the dependencies for the weak-form efficient market hypothesis. Another reason to investigate emerging markets is the fact that emerging capital markets (ECM) have different distributional characterization than the developed markets (Bekaert et al., 1998). Emerging markets offer certain opportunities in terms of portfolio diversification and financial risk management. Studies about linear and non-linear dependency and its implication, weak-form-inefficiency, give valuable information for both investors and regulators in ECM. For instance, work done by Harris and Küçüközmen (2001) revealed the linear and non-linear dependence in Turkish stock market returns and showed the implications of these dependencies for the financial risk management and value at risk models for determining capital requirements in case of unexpected price movements. Also financial turmoils that frequently occurred in the last decade in those emerging markets increase the importance of revealing the dynamic behavior of ECM. To reveal the effects of these financial crises upon the weak form efficiency, we choose to use a data set of 10 years covering 1994-2002 for all the stock markets that we analyze.

Although numerous studies had been conducted for the non-linearities in the developed markets (see, e.g., Abhyankar et al., 1995,1997; Scheinkman and LeBaron, 1989, Philippatos et al., 1993; Al-loughani and Chappell, 1997; Omran, 1997; Opong et al., 1999; Hsieh, 1991; Brooks, 1996; Gilmore, 1996, also a list of studies about non-linearities of major stock markets are detailed in Abhyankar et al. (1997)), studies about emerging markets are not as much of developed countries (see, e.g., for Taiwan Chyi, 1997; for Turkey Harris and Kucukozmen, 2001, for major emerging markets Sewell et al., 1993; for Greece Siourounis, 2002; for Hungary and Poland Poshakwale and Murinde,2001). In most of the studies mentioned above both in developed markets and in emerging markets, significant non-linear dependence had been found.

2. DATA

The data used in this study constitutes the national stock market price index of the six developed capital markets, US, UK, Japan, Germany, France, Italy and seven emerging capital markets, Taiwan, Philippines, Hong Kong, Argentina, China, Turkey and South Africa. The period for the stock price indices is between 03.01.1994-31.12.2003, which makes 10 years (2607 days) of observation of stock prices. Raw data are obtained from *DataStream*. We used the log return of stock prices because of the proposed random-walk hypothesis. But also using log return is an appropriate choice if the concern of the research is about time series modeling such as GARCH modeling due to its time additivity (Dornfleitner, 2003). Descriptive statistics are given in Table 1.

3. METHODOLOGY

To test the weak form efficiency and its immediate implication, random-walk hypothesis of prices, we begin by taking into account the two assumptions that constitutes the random-walk behavior. These are

- Successive price changes (R_t) are identically distributed.
- Successive price changes (R_t) are independent.

First assumption requires that the distribution of changes in stock prices must be stationary over time, which implies that $log\ (P_t)$ should be $I(1)$, have a unit root, and its first difference $R_t = log\ (P_t) - log\ (P_{t-1})$ should be $I(0)$. To test the order of integration for prices and R_t, we use Dickey-Fuller (DF) and Augmented Dickey Fuller (ADF) tests (Dickey and Fuller, 1979).

For the hypothesis of the random walk behavior of the stock prices we define a relationship arising from the equation (2).

$$R_t = c + u_t \qquad (3)$$

Estimating the above equation by ordinary least square (OLS) gives us the information about the zero mean assumption of the white noise process of stock returns. If the constant term in equation (3) is not significantly different from zero, we will be able to say that the zero mean assumption of the white noise process is satisfied. Moreover, the residuals should be iid random variables to satisfy the random-walk hypothesis of the prices. Also we use the Jarque-Bera normality test based on the skewness and kurtosis (Bera and Jarque, 1982) for the residuals of the estimated linear regression. Although normality assumption of the stock price changes is not necessary to validate the random-walk hypothesis, deviations from normality is one of the most important stylized facts that characterize the stock returns (Cont, 2001). Actually, leptokurtic distribution is far more likely to characterize financial time series and to characterize the residuals from financial time series (Brooks, 2002).

In order to detect the linear and non-linear (in)dependence of the stock prices, which is the second assumption that is required for random-walk hypothesis, and also for weak-form efficiency, we follow a method which consists of two stages.

First stage is simply to explore the possibility of whether there is any simple linear dependence in the stock prices. This can be done by straightforward method, which is fitting a linear model, generally an AR or ARMA. To fit an appropriate AR or ARMA model, as suggested by the Box-Jenkins (1976) approach, firstly we investigate the first 12 autocorrelation coefficients for the stock return data series to determine the order of the model. The choice of autoregressive lag length can be made by various ways; some of the mostly used ways are minimizing information criteria such as Akaike's Information (Akaike, 1974) or Schwarz's Bayesian Information (Schwarz, 1978) or using Ljung- Box Q statistics (Ljung and Box, 1978). In our study, we employ both Schwarz's Bayesian Information Criteria (SBIC), and Q-stat offered by Ljung-Box. However, if one of these methods contradicts each other about the lag-length, we generally choose the most parsimonious model since in this study our primary aim is to capture linear dependence rather than to build a full-blown statistically adequate model that captures all relevant characterization of the stock return series.

Second stage of identification of the dependence requires the test for whether there is a non-linear dependence in the return series. The frequently used tests for detecting non-linearity in the return series are Engle's test (Engle, 1982), Tsay's test (Tsay, 1986), Hinich Bispectrum test (Hinich, 1982; Hinich and Patterson, 1985; Ashley, Patterson and Hinich, 1986; Barnet et al., 1996) and BDSL test developed by Brock et al., (1996). We used BDSL test for determining non-linearity of stock markets. We apply the BDSL test to both the residuals of the linear ARMA models and non linear in variance AR–GARCH models (a detailed description of the ARMA and GARCH models for finance can be found in Brooks (2002)).

4. BDSL TEST

The Brock-Dechert-Scheinkman-LeBaron (BDSL) statistic is a non-parametric test to test the null hypothesis that a univariate time series $\{x_t, t=1\ldots n)$ is independently and identically distributed against an unspecified alternative Brock et al., (1991). Generally the alternative hypothesis includes both deterministic chaos and linear and nonlinear stochastic behavior. This test is performed by examining the underlying probability structure of $\{x_t\}$ in order to search for any kind of dependence. The test is based on the correlation integral of a time series, which is proposed by Grassberger and Procaccia (1983).

We can define the correlation integral, by equation (4), as a measure of the fraction of pairs of points $(x_t(m), x_t(s))$ in the series that are within a distance(Euclidean) of ε from each other.

$$C_m(\varepsilon,T) = \frac{2}{(T-m+1)(T-m)} \sum_{t=1}^{T-m} \sum_{s=1}^{T-m} I(x_t(m), x_s(m))$$

where

(4)

$$I(x_t(m), x_s(m)) = \begin{cases} 1, & if \left| x_t(m), x_s(m) \right| \leq \varepsilon \\ 0, & otherwise \end{cases}$$

and T= number of observations,
m = embedding dimension.

Embedding dimension is generally referred to the m-tuples (or histories of) $\{x_t\}$ and generally denoted as $x_t = (x_{t,}\ x_{t+1\ldots}\ x_{t+m-1})$.

Brock, Dechert, Scheinkman, Le Baron (1996) show that if $\{x_t\}$ is *iid* then we have,

$$C_m(\varepsilon,T) = C_1(\varepsilon, T)^m \tag{5}$$

then BDSL statistic is given by

$$W_m(\varepsilon,T) = \frac{\sqrt{T}\left[C_m(\varepsilon,T) - C_1(\varepsilon,T)^m\ \right]}{\sigma_m(\varepsilon,T)}$$

(6)

where, $\sigma_m(\varepsilon)$ is the estimate of the standard deviation of $C_m(\varepsilon, T)$. $W_m(\varepsilon, T)$ converges to the standard normal distribution $N(0,1)$ as T approaches infinity.

Although, BDSL statistic has a standard normal distribution asymptotically, its asymptotic distribution is not suitable when it is applied to the standardized residuals from GARCH model. (Brock et al.1991). In order to tackle this problem, we may either simulate the needed critical values for each GARCH model we considered or we may use the alternative way provided by deLima (1996) and used in Harris and Kucukozmen (2001) study about linear and non-linear dependence of Turkish equity market. This alternative way is to use the natural logarithms of the squared standardized GARCH residuals instead of standardized residuals from GARCH model. We follow the alternative way, taking natural logarithm of the standardized residuals from GARCH model, in our study, since the simulating critical value for every GARCH model we are interested in is computationally very cumbersome.

To compute the BDSL statistic Brock et al., (1991) recommend using ε between one half to two-times the standard deviation of the data, while suggesting that embedding dimension, m, of between 2 to 8. This range of embedding dimension m and ε typically is enough to extract the low order of the dependence in the data. As it is mentioned previously, we apply the BDSL test to the residuals both after filtering the data with ARMA models and with various GARCH type models.

5. MODELING VOLATILITY

In order to capture the source of non-linear dependence present in the stock returns, we employ basically three types of GARCH models, since GARCH models are viewed as capable of explaining both non-linear dependence and leptokurtosis (Bollersev, 1986; Akgiray, 1989). These GARCH models are, GARCH (1,1), GARCH–M (1,1) (Garch-in-Mean) and EGARCH-M (1,1) (exponential Garch-in-Mean). GARCH (1,1) developed by Bollersev (1986) is the most widely used model for modeling the conditional variance and in the studies for capturing non-linearity in stock returns. Besides the traditional GARCH (1,1) model, we also use the GARCH-in-mean model suggested by Engle, et al., (1987). Actually what is suggested by Engle et al., is an ARCH-in mean model but since GARCH models are more widespread, we estimate GARCH-M model. Main advantage of the GARCH-M model is its ability to capture the relationship between expected returns and volatility by allowing for feedback from the conditional variance to the conditional mean equation. The last model that we consider for modeling the conditional variance of returns is EGARCH proposed by Nelson (1991). EGARCH models have certain advantages over the classical GARCH models such as ability to capture the asymmetries in the variance and the lack of non-negativity constraint. Moreover, in our study, we allow EGARCH model to capture the relationship between return and volatility by estimating it as EGARCH-M model.

Since our primary aim is to detect whether there is a non-linear dependence in the stock return and to relate this nonlinear dependence with non-linear dependence in conditional variance, our final preferred models are AR (p)-GARCH models for the stock returns. As mentioned before we decide the appropriate lag length for the autoregressive component by the help of SBIC and Ljung-Box Q statistic. Also it should be noted that if linear dependence involves any moving average (MA) component we do not allow this component to take part in the estimation of conditional variance, since as noted by Brooks (1996) and Granger et al. (1989) MA filtering on the null distribution of the non-linearity test statistics is not well documented as it is with pure autoregressive models.

Lastly, to keep volatility models parsimonious, we limit ourselves the lag length of GARCH components as (p, q) = (1, 1), and for all models we specify normal distribution for the errors. Other possible distributions for errors are Generalized Error Distribution (GED) and student-t distribution. Actually student-t distribution is more likely to characterize the fat-tailed, leptokurtic financial time series. Maximum likelihood estimation of the all models is done by using BHHH algorithm (Berndt et al., 1974)[1].

6. EMPIRICAL RESULTS

Preliminary Statistics

Our preliminary findings (first four moments and normality test statistic of the series), which are tabulated in the Table 1, suggest that in all stock markets that we searched, there is a significant excess kurtosis and deviation from the normality, which can be evidenced by large value of normality test statistics of Jarque-Bera. This stylized fact is consistent with the characterization of the financial markets, namely leptokurtic, fat tailed distribution mentioned in the financial literature. However, one important remark that should be done here is that normality is rejected more strongly in the emerging capital markets (ECM) than the developed capital markets. In ECM's like Philippines, S. Africa, Hong Kong, Argentina, the Jarque–

1 Most of the estimation and statistical tests except computing the BDSL test statistic is done by RATS. BDSL test statistics are computed by the program developed by William Dechert, BDS STATS, version 8.21 (additionally there are two computer programs to compute BDSL test statistic which is written by LeBaron in C programming code and in Matlab available). Also to prevent the possible manual computational error, BDSL statistics are recomputed by Eviews. No significant difference was found between the BDSL statistics computed by Eviews and BDS STATS. The BDSL stats presented in this paper are the results of the BDS STAT version 8.21 by Dechert.

TABLE 1: PRELIMINARY STATISTICS

	UK	US	Japan	Germany	France	Italy
Mean	0.000122	0.000351	-0.00008	0.00015	0.00022	0.00023
Median	0.000229	0.000243	0.00000	0.00013	0.00003	0.00000
Maximum	0.050790	0.053666	0.06458	0.05476	0.06167	0.06902
Minimum	-0.053676	-0.07026	-0.06524	-0.07211	-0.07358	-0.07787
Std. Dev.	0.010192	0.011271	0.01208	0.01249	0.01278	0.01366
Skewness	-0.234148	-0.124834	-0.02399	-0.33220	-0.12647	-0.12463
Kurtosis	5.72539	6.50803	5.60163	5.59111	5.49364	5.30396
Jarque-Bera[a]	830.66200	1343.53700	735.47350	777.24190	682.40770	583.35610

	Taiwan	Philippines	HongKong	Argentina	China	Turkey	S. Africa
Mean	0.00006	-0.00019	0.00000	0.00021	0.00002	0.00176	0.00039
Median	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00008
Maximum	0.08182	0.14808	0.15538	0.16792	0.10710	0.17026	0.07848
Minimum	-0.10300	-0.08564	-0.13601	-0.13394	-0.14288	-0.19460	-0.13676
Std. Dev.	0.01756	0.01398	0.01698	0.01890	0.01961	0.03200	0.01176
Skewness	-0.00151	0.80259	0.00768	0.33916	0.03659	-0.03969	-0.98225
Kurtosis	5.08939	15.15291	12.07238	11.10108	7.88024	6.10906	15.34362
Jarque-Bera[a]	474.21080	16323.06000	8940.74500	7178.76000	2587.67300	1050.68200	16969.86000

[a] All test statistics are significant at 1%

Bera statistics are extremely large relative to those of developed capital markets. The same remark can also be extended to the excess kurtosis of these above-mentioned ECM's; they have larger excess kurtosis.

In order to verify the zero mean requirements that are necessary for random-walk behavior of the stock prices, equivalently white noise process of stock price changes, we estimate the equation (3) by an OLS technique and the results are depicted in Table 2. As it is seen from the

TABLE 2: ESTIMATION OF EQUATION (3) $R_t=c+u_t$

	Constant	t-Statistic		Constant	t-Statistic
UK	0.000122	0.608967	**Taiwan**	5.66E-05	0.164594
US	0.000351	1.588493	**Philippines**	-0.00019	-0.695546
Japan	-8.49E-05	-0.358854	**Hong Kong**	9.97E-07	0.002997
Germany	0.000147	0.602590	**Argentina**	0.000205	0.555138
France	0.000222	0.884827	**China**	2.21E-05	0.057607
Italy	0.000233	0.871902	**Turkey**	0.001763	2.813149
			S.Africa	0.000388	1.684988

Table 2, except for Turkey and S.Africa, the constant terms are not significantly different from zero. For the return series of Turkey, null hypothesis that the mean of the stock price changes (returns) is zero rejected at the 1% significance level and for the S. Africa it is rejected at the 10% significance level.

Another requirement that should be satisfied for the random walk hypothesis is that stationarity of the return series. Table 3 reports the results of the Dickey- Fuller (DF) and augmented Dickey–Fuller (ADF) unit roots on the levels (price) and first differences (returns) of the stock markets' daily series. All of the series are non-stationary in levels, *I(1),* and are stationary in the first differences, *I(0),* which is consistent finding with the random walk behavior of the stock prices and equivalently the white noise process of stock returns.

TABLE 3: TESTING FOR STATIONARITY

	Prices		Returns	
	DF	ADF[a]	DF	ADF[a]
US	-1.51746	-1.46975	-50.60276*	-22.52233*
UK	-1.45361	-1.36284	-49.5759*	-23.12902*
Japan	-1.5408	-1.45321	-48.31399*	-23.47545*
Germany	-1.27988	-1.3306	-48.40949*	-21.87682*
France	-1.17315	-1.11471	-49.29961*	-22.53125*
Italy	-1.31682	-1.40084	-49.99373*	-20.3533*
Taiwan	-1.82421	-1.85545	-50.77869*	-21.15376*
Philippines	-1.23768	-1.40124	-42.5121*	-20.35611*
Hong Kong	-2.12861	-2.2574	-48.8701*	-21.32193*
Argentina	-0.20024	-0.74936	-43.94696*	-20.84204*
China	-1.34073	-1.59898	-42.76743*	-20.539*
Turkey	-0.33751	-0.2849	-48.28814*	-21.16653*
S.Africa	-0.71508	-0.89591	-44.03534*	-20.55408*

* significant at the 1% level.
[a] lag length of 5.

Linear Dependence

We identify the linear dependence existing in the stock return series by the help of autocorrelation coefficients and Ljung-Box Q-stats. Table 4 reports the first 12-autocorrelation coefficients for the stock return series for the 13 world stock markets. Also Table 4 reports the Ljung-Box Q-statistics for the lag length of 4, 8 and 12. As it is evident from the Table 4, most of the stock market return's autocorrelation coefficients are significantly different from zero. The only exception about this finding is the return of the U.S stock market. US stock market autocorrelation coefficients are significantly not different from zero. This fact can also seen by the Ljung-Box Portmanteau statistics for 4 and 8 lags. These test statistics are insignificant at the 1 % level. These two facts conclude that linear dependence of US stock market is not identified. A noticeable result that can be extracted from the results of the autocorrelation coefficients is that generally the significance of the autocorrelation coefficients of the emerging capital market is more apparent and clear. For example, Argentina, Philippines, China and South Africa have very significant first order autocorrelations with value of 0.148, 0.181, 0.175, and 0.149 respectively. As a result, their linear dependence can be identified much earlier in terms of lag length relative to the other stock markets.

By taking autocorrelation coefficients and Ljung-Box statistics into consideration, we estimated various AR or ARMA models for the stock return series. To determine the final model, we used Schwartz Bayesian Information Criterion (SBIC) by minimizing it. Therefore, to remove the linear dependence of the stock returns, we filtered the series with an appropriate AR or ARMA model. The

TABLE 4: LINEAR DEPENDENCE

i.Autocorrelation Coefficients (unfiltered)

Lag	UK	US	Japan	Germany	France	Italy	Taiwan	Philippines	HongKong	Argentina	China	Turkey	S.Africa
1	0.029	0.008	0.055	0.053	0.034	0.021	0.005	0.181	0.043	0.148	0.175	0.055	0.149
2	-0.03	-0.02	-0.024	-0.018	-0.016	0.033	0.049	0.016	-0.033	-0.007	0.015	0.045	0.073
3	-0.069	-0.034	-0.025	-0.008	-0.049	-0.013	0.032	-0.004	0.081	-0.011	0.03	-0.012	-0.005
4	0.023	-0.007	-0.019	0.039	0.005	0.06	-0.072	0.017	-0.026	0.005	0.008	0.035	-0.016
5	-0.047	-0.031	-0.046	-0.022	-0.039	-0.032	0.026	-0.01	-0.026	0.004	-0.023	-0.037	-0.02
6	-0.042	-0.027	-0.064	-0.058	-0.028	0.004	-0.028	-0.007	-0.017	-0.022	-0.019	-0.021	-0.009
7	0.006	-0.032	0.016	-0.006	-0.024	-0.026	-0.019	0.01	-0.035	-0.018	-0.032	-0.014	-0.024
8	0.064	0.014	0.019	0.048	0.035	0.033	0.036	0.016	-0.001	-0.018	-0.001	0.024	0.035
9	0.029	0.001	0.036	-0.004	0.012	0.007	-0.009	0.045	0.021	0.069	-0.025	0.005	0.051
10	-0.041	0.018	-0.012	-0.005	-0.014	0.028	0.022	0.039	0.031	0.093	0.033	0.031	0.004
11	0.011	-0.033	-0.014	0.015	0	-0.011	-0.02	0.033	0.022	0.017	0.037	-0.031	0.018
12	-0.017	0.031	0.015	-0.009	0.004	0.001	0.029	0.067	0.017	0.018	0.07	0.022	-0.001
Q(4)	18.41	4.308	11.94	12.245	9.99	13.9	22.6	86.661	26.462	57.868	83.1	16.8	72.28
Q(8)	39.5	11.92	28.89	28.651	20.7	21.3	30.6	88.042	32.133	60.962	88.1	23.7	78.2
Q(12)	47.29	18.15	34.73	29.553	21.6	23.8	35.4	111.99	37.805	97.478	109	30.2	86

ii.Autocorrelation Coefficients (filtered with AR or ARMA)

	UK	US	Japan	Germany	France	Italy	Taiwan	Philippines	HongKong	Argentina	China	Turkey	S.Africa
Lag	AR(6)	AR(0)	AR(6)	ARMA(2,2)	AR(3)	AR(4)	AR(4)	AR(1)	AR(3)	ARMA(2,3)	AR(1)	AR(4)	AR(2)
1	0	0.008	0.001	0.012	0	0.002	0.002	0.003	0	-0.001	0.004	0.001	0.001
2	0.003	-0.02	0.001	-0.008	-0.002	0	-0.003	-0.016	0.003	-0.004	-0.022	-0.001	0.005
3	0.004	-0.034	0.003	0.024	-0.002	0.002	-0.003	-0.01	0.002	0.002	0.027	0.001	-0.02
4	-0.001	-0.007	0	0.008	0.009	-0.001	-0.001	0.021	-0.036	0.006	0.008	0	-0.016
5	0.002	-0.031	-0.001	-0.033	-0.039	-0.033	0.023	-0.013	-0.024	-0.006	-0.023	-0.038	-0.014
6	0.004	-0.027	0	-0.02	-0.028	-0.001	-0.011	-0.007	-0.019	-0.026	-0.011	-0.024	-0.006
7	0.005	-0.032	0.019	-0.019	-0.025	-0.023	-0.019	0.01	-0.034	0.001	-0.032	-0.009	-0.026
8	0.055	0.014	0.009	0.021	0.033	0.029	0.029	0.007	0.002	-0.018	0.011	0.022	0.032
9	0.025	0.001	0.03	0.023	0.01	0.008	-0.001	0.038	0.021	0.05	-0.032	0.004	0.049
10	-0.036	0.018	-0.014	0.002	-0.012	0.024	0.017	0.027	0.028	0.074	0.033	0.033	-0.007
11	0.014	-0.033	-0.017	-0.016	0.004	-0.012	-0.021	0.015	0.023	0.009	0.02	-0.033	0.015
12	-0.021	0.031	0.016	0.003	0.006	-0.002	0.027	0.054	0.013	0.027	0.055	0.02	-0.013
Q(4)	-	4.308	-	2.2817	0.22	-	-	2.1317	3.3545	0.133	3.39	-	1.829
Q(8)	7.986	11.92	1.175	8.151	10.6	6.51	4.99	3.0696	8.8268	2.7966	8.11	6.77	6.813
Q(12)	14.73	18.15	5.467	10.204	11.4	8.66	8.72	16.881	13.853	25.967	22.7	13.5	14.23

models for the stock returns of various stock market and the autocorrelation coefficients and Ljung-Box Q-stats for the residuals of these models are shown in second part of Table 4. As it is shown in the second part of (ii) table most of the autocorrelation coefficients and Q-stats of filtered series are insignificant at 5% level.

TABLE 5: BDSL STATISTICS FOR AR(MA) FILTERED RETURNS

	UK					US					Japan			
m,σ	**0.50**	**1**	**1.5**	**2**	**m,σ**	**0.50**	**1**	**1.5**	**2**	**m, σ**	**0.50**	**1**	**1.5**	**2**
2	9.59	10.82	11.76	12.15	**2**	7.32	7.08	8.01	8.96	**2**	3.78	4.38	4.39	4.23
3	12.46	14.12	15.42	16.23	**3**	11.93	11.53	12.08	12.61	**3**	6.51	6.84	7.02	6.77
4	15.67	17.27	18.24	18.85	**4**	15.11	15.82	14.35	14.43	**4**	8.38	8.73	8.87	8.28
5	19.56	20.49	20.56	20.69	**5**	18.77	21.50	16.73	16.20	**5**	10.20	10.18	10.08	9.27
6	22.82	23.39	22.48	22.09	**6**	22.92	28.85	18.96	17.68	**6**	11.71	11.53	11.24	10.14
7	27.66	26.99	24.55	23.31	**7**	27.64	38.37	21.05	18.86	**7**	13.98	12.91	12.39	11.01
8	33.76	31.16	26.63	24.39	**8**	33.51	52.61	23.26	20.01	**8**	17.70	14.86	13.66	11.86
	Germany					**France**					**Italy**			
m,σ	**0.50**	**1**	**1.5**	**2**	**m,σ**	**0.50**	**1**	**1.5**	**2**	**m,σ**	**0.50**	**1**	**1.5**	**2**
2	9.51	10.30	9.97	9.20	**2**	5.95	6.77	8.18	9.23	**2**	6.17	7.12	8.26	8.95
3	14.89	15.69	14.87	13.28	**3**	8.71	9.52	11.64	12.99	**3**	9.88	11.09	12.12	12.73
4	19.78	19.93	18.16	15.97	**4**	10.72	12.40	14.41	15.65	**4**	12.83	13.78	14.44	14.66
5	25.52	24.05	20.90	18.09	**5**	12.44	14.29	16.23	17.60	**5**	15.13	15.99	16.22	15.99
6	33.69	28.85	23.38	19.74	**6**	14.09	15.90	17.64	18.86	**6**	18.70	18.56	18.05	17.23
7	45.34	34.20	25.68	21.02	**7**	16.68	17.85	19.04	19.98	**7**	22.40	21.43	19.98	18.40
8	61.79	40.94	28.34	22.37	**8**	18.70	19.97	20.34	20.94	**8**	26.80	24.56	21.83	19.43
	Taiwan					**Philippines**					**HongKong**			
m,σ	**0.50**	**1**	**1.5**	**2**	**m,σ**	**0.50**	**1**	**1.5**	**2**	**m,σ**	**0.50**	**1**	**1.5**	**2**
2	1.76	2.83	3.32	4.14	**2**	9.79	11.23	11.74	11.87	**2**	5.66	7.28	9.49	12.30
3	4.62	5.55	6.14	6.90	**3**	13.19	14.26	14.15	13.68	**3**	7.64	10.11	11.95	14.02
4	7.34	7.25	7.55	8.12	**4**	16.31	16.76	16.14	15.41	**4**	9.27	12.09	13.74	15.18
5	9.67	8.81	8.97	9.31	**5**	19.25	18.95	17.62	16.55	**5**	11.11	13.88	15.31	16.20
6	11.78	10.02	10.03	10.04	**6**	23.25	21.47	19.15	17.56	**6**	12.90	15.57	16.66	17.07
7	14.68	11.22	10.96	10.72	**7**	27.86	24.35	20.74	18.45	**7**	14.87	17.32	17.93	17.69
8	17.30	12.56	11.74	11.23	**8**	32.82	27.34	22.21	19.12	**8**	17.53	19.45	19.40	18.46
	Argentina					**China**					**Turkey**			
m,σ	**0.50**	**1**	**1.5**	**2**	**m,σ**	**0.50**	**1**	**1.5**	**2**	**m,σ**	**0.50**	**1**	**1.5**	**2**
2	10.05	11.61	13.00	13.93	**2**	14.83	13.86	13.09	12.44	**2**	8.26	9.71	10.70	11.40
3	12.15	13.84	14.76	15.49	**3**	18.66	16.87	15.86	14.96	**3**	11.58	12.90	13.26	13.39
4	14.51	15.87	16.16	16.40	**4**	22.59	19.77	17.95	16.50	**4**	13.51	14.81	14.49	14.27
5	16.15	17.31	17.03	16.72	**5**	28.16	22.87	19.62	17.39	**5**	14.50	16.08	15.39	14.58
6	18.06	18.71	17.92	17.19	**6**	35.70	26.21	21.02	18.13	**6**	16.01	17.48	16.33	15.05
7	20.33	20.23	18.78	17.62	**7**	46.03	30.14	22.42	18.71	**7**	17.33	19.04	17.29	15.50
8	22.96	21.95	19.73	18.08	**8**	58.93	34.79	23.91	19.31	**8**	19.37	20.88	18.29	15.96
	S.Africa													
m,σ	**0.50**	**1**	**1.5**	**2**										
2	10.06	10.94	12.09	12.80										
3	12.53	13.21	14.30	14.85										
4	14.78	15.24	16.04	16.45										
5	17.64	17.55	17.57	17.61										
6	20.90	20.01	18.95	18.55										
7	24.97	22.39	20.11	19.25										
8	31.02	25.03	21.21	19.78										

Non-Linear Dependence

In order to identify any non-linear dependence in the stock returns, Table 5 reports the results of the BDSL test statistics which are applied to the residual of the AR(MA) filtered stock return series for each stock market. As it is mentioned in the methodology part, we choose to report the *m* (embedding dimension) from 2 to 8 for values of $\varepsilon=0.5\sigma$, $\varepsilon=\sigma$, $\varepsilon=1.5\sigma$ and $\varepsilon=2\sigma$.

As it is seen from the Table 5, for all values of *m* and ε, the null hypothesis that the AR (MA) filtered stock return series *iid* is strongly rejected. This is clear evidence of significant non-linear dependence besides the linear dependence identified by autocorrelation coefficients. Therefore, we can easily say that weak form of market efficiency is violated for all the markets considered so far, even for US market that we could not identify any linear dependence.

Modeling Volatility

In order to verify the source of the non-linear dependence in stock returns, we estimated basically three types of GARCH models, GARCH (1,1), GARCH-M (1,1) ad EGARCH-M (1,1). And for each model we applied the BDSL test to the natural logarithm of the squared standardized residuals by following deLima (1996). Standardized residuals were obtained by dividing the residual series by the square roots of the estimated conditional variances. The results are given in Table 6,7, and 8 respectively for each model. Table 6 reveals the fact that GARCH (1,1) model incorporates much of the non-linear dependence of the most stock market prices since all the BDSL statistics is substantially reduced for this simple GARCH model for all values of embedding dimension *m* and ε. Actually, besides the reduction of the BDSL statistics, GARCH-type models' residuals turned out to be *iid*, i.e., we could not reject the null hypothesis of *iid*. Residuals from UK, Germany, Italy, Philippines, Argentina, China and S. Africa stock market returns in almost all cases turned out to be *iid* after AR (p)-GARCH (1,1) filtering.

An important implication of the results given in Table 6 and 7 is that further improvements in BDSL test statistics can be achieved by estimating the GARCH-M model. Especially for the stock markets of US, France, Hong-Kong and Turkey, BDSL tests statistics are significantly improved relative to the GARCH (1,1) model. However, there are still significant rejection of null hypothesis of *iid* in the stock market return such as in Japan, France and Turkey.

Our last GARCH model is EGARCH-M (1,1) that has an ability to capture asymmetries in return series. Again, as it is expected, EGARCH-M (1,1) model captures much of the linearity of the return of the stock markets that we are interested in. Although EGARCH-M model brings some improvement in the BDSL statistics relative to the GARCH-M model for almost all cases, it did not bring substantial improvement in some stock return such as in France and Japan as it is reported in previous studies (Harris and Küçüközmen, 2001).This is possibly because of the fact that we use normal distribution instead of GED or Student-t distribution for error distribution. Another possible explanation of this occurrence can be that we restricted our study only to the EGARCH-M with (p,q) of (1,1). However, substantial improvements may be provided with various lag lengths of EGARCH model. For instance, Harris and Küçüközmen (2001) reports substantial improvement in Turkey's stock return series by estimating EGARCH-M (2,2) with student- t distribution.

TABLE 6: BDSL STATISTICS FOR AR(P) -GARCH(1,1) FILTERED RETURNS

	UK					US					Japan			
m,σ	**0.50**	**1**	**1.5**	**2**	**m,σ**	**0.50**	**1**	**1.5**	**2**	**m, σ**	**0.50**	**1**	**1.5**	**2**
2	2.99	3.96	4.93	4.99	**2**	4.26	3.88	3.15	2.53	**2**	2.89	3.94	4.41	3.73
3	2.00	3.02	3.93	4.04	**3**	5.53	4.68	3.84	3.06	**3**	2.67	3.76	4.20	3.46
4	1.32	2.33	3.37	3.62	**4**	5.88	5.19	4.30	3.48	**4**	2.38	3.38	3.85	3.18
5	0.80	1.86	2.99	3.36	**5**	6.73	5.65	4.69	3.66	**5**	2.22	3.15	3.58	3.04
6	0.39	1.38	2.76	3.34	**6**	7.45	6.01	4.90	3.71	**6**	1.99	2.84	3.33	2.87
7	0.39	1.27	2.76	3.41	**7**	7.96	6.37	5.11	3.77	**7**	2.22	2.85	3.20	2.63
8	0.19	1.03	2.62	3.41	**8**	7.95	6.57	5.24	3.82	**8**	2.33	2.84	3.07	2.44

	Germany					France					Italy			
m,σ	**0.50**	**1**	**1.5**	**2**	**m,σ**	**0.50**	**1**	**1.5**	**2**	**m,σ**	**0.50**	**1**	**1.5**	**2**
2	2.79	3.77	4.61	4.19	**2**	3.77	4.01	3.99	3.00	**2**	1.50	3.03	4.45	4.90
3	2.42	3.00	3.71	3.58	**3**	3.76	3.91	3.80	2.70	**3**	1.39	2.88	4.25	4.47
4	1.88	2.23	2.87	2.96	**4**	3.46	3.56	3.60	2.53	**4**	0.67	2.17	3.57	3.94
5	1.77	2.00	2.59	2.73	**5**	3.08	3.15	3.37	2.54	**5**	0.34	1.99	3.41	3.76
6	1.90	1.99	2.58	2.76	**6**	2.93	2.84	3.24	2.51	**6**	0.49	1.88	3.30	3.59
7	1.73	1.95	2.43	2.62	**7**	2.90	2.75	3.09	2.38	**7**	0.01	1.78	3.10	3.34
8	1.63	1.79	2.26	2.43	**8**	3.11	2.84	3.04	2.31	**8**	0.32	2.00	3.09	3.15

	Taiwan					Philippines					HongKong			
m,σ	**0.50**	**1**	**1.5**	**2**	**m,σ**	**0.50**	**1**	**1.5**	**2**	**m,σ**	**0.50**	**1**	**1.5**	**2**
2	5.70	7.17	7.43	5.94	**2**	0.18	0.71	1.20	1.20	**2**	3.10	3.34	3.30	2.82
3	4.60	6.16	6.91	5.96	**3**	0.10	0.90	1.36	1.26	**3**	2.56	2.89	2.98	2.43
4	5.10	6.30	6.94	5.91	**4**	0.72	1.40	1.68	1.49	**4**	2.21	2.73	2.76	2.19
5	4.78	5.95	6.61	5.59	**5**	1.05	1.76	1.78	1.41	**5**	2.34	2.86	2.77	2.15
6	3.76	5.51	6.14	5.13	**6**	1.15	1.74	1.67	1.20	**6**	1.88	2.68	2.55	1.99
7	2.80	4.99	5.51	4.58	**7**	1.35	1.85	1.54	0.96	**7**	1.33	2.50	2.33	1.85
8	1.85	4.52	4.96	4.13	**8**	1.60	2.01	1.50	0.82	**8**	1.46	2.32	2.11	1.72

	Argentina					China					Turkey			
m,σ	**0.50**	**1**	**1.5**	**2**	**m,σ**	**0.50**	**1**	**1.5**	**2**	**m,σ**	**0.50**	**1**	**1.5**	**2**
2	2.87	3.81	4.41	3.75	**2**	1.21	1.92	3.21	4.58	**2**	3.91	5.22	6.32	5.52
3	2.95	3.66	4.01	3.32	**3**	0.50	0.95	1.96	3.05	**3**	2.92	4.41	5.68	5.23
4	2.57	3.20	3.42	2.68	**4**	0.22	0.78	1.42	2.37	**4**	2.60	4.22	5.75	5.50
5	2.16	2.85	2.84	2.11	**5**	0.31	1.00	1.27	2.01	**5**	2.42	3.90	5.49	5.34
6	1.95	2.64	2.49	1.80	**6**	0.22	1.12	1.23	1.95	**6**	2.87	3.87	5.37	5.30
7	2.13	2.38	2.13	1.50	**7**	0.49	1.24	1.23	1.90	**7**	3.58	3.94	5.27	5.15
8	2.04	2.01	1.77	1.30	**8**	0.64	1.36	1.21	1.78	**8**	4.41	3.76	4.95	4.82

	S.Africa			
m,σ	**0.50**	**1**	**1.5**	**2**
2	3.35	2.84	2.19	1.26
3	2.55	1.89	1.47	1.08
4	2.07	1.29	1.07	0.95
5	1.81	0.89	0.96	1.13
6	1.81	0.99	1.08	1.32
7	1.78	1.06	1.20	1.53
8	2.31	1.19	1.31	1.69

TABLE 7: BDSL STATISTICS FOR AR(P)-GARCH-M(1,1) FILTERED RETURNS

	UK					US					Japan			
m,σ	**0.50**	**1**	**1.5**	**2**	**m,σ**	**0.50**	**1**	**1.5**	**2**	**m, σ**	**0.50**	**1**	**1.5**	**2**
2	2.93	3.87	4.83	4.80	**2**	2.43	2.42	1.79	0.94	**2**	2.51	3.36	3.99	3.39
3	1.93	2.93	3.83	3.84	**3**	2.34	2.48	2.05	1.35	**3**	2.58	3.45	4.17	3.44
4	1.28	2.26	3.31	3.50	**4**	1.95	2.29	2.04	1.67	**4**	2.55	3.36	4.12	3.36
5	0.76	1.80	2.93	3.26	**5**	1.80	2.35	2.12	1.86	**5**	2.62	3.15	4.01	3.29
6	0.36	1.29	2.67	3.22	**6**	1.77	2.36	2.15	1.91	**6**	2.93	2.85	3.82	3.11
7	0.14	1.13	2.64	3.26	**7**	1.86	2.35	2.08	1.83	**7**	2.85	2.87	3.83	3.00
8	0.44	0.84	2.47	3.23	**8**	1.48	2.27	1.93	1.67	**8**	2.84	2.92	3.78	2.86

	Germany					France					Italy			
m,σ	**0.50**	**1**	**1.5**	**2**	**m,σ**	**0.50**	**1**	**1.5**	**2**	**m,σ**	**0.50**	**1**	**1.5**	**2**
2	2.46	3.45	4.00	3.37	**2**	3.80	4.08	4.10	3.09	**2**	1.66	2.84	1.54	3.55
3	2.18	2.73	3.07	2.65	**3**	3.68	4.06	4.09	2.88	**3**	1.56	2.56	0.83	2.91
4	1.62	1.93	2.15	1.93	**4**	3.29	3.68	3.86	2.78	**4**	0.67	1.79	0.54	2.63
5	1.68	1.69	1.88	1.71	**5**	2.73	3.25	3.57	2.71	**5**	0.44	1.71	0.24	2.68
6	1.87	1.66	1.93	1.84	**6**	2.46	2.96	3.43	2.71	**6**	0.56	1.65	0.19	2.64
7	1.66	1.60	1.81	1.77	**7**	2.40	2.87	3.32	2.67	**7**	0.35	1.55	0.08	2.55
8	1.81	1.39	1.63	1.61	**8**	2.88	3.02	3.33	2.68	**8**	0.08	1.81	0.02	2.56

	Taiwan					Philippines					HongKong			
m,σ	**0.50**	**1**	**1.5**	**2**	**m,σ**	**0.50**	**1**	**1.5**	**2**	**m,σ**	**0.50**	**1**	**1.5**	**2**
2	5.57	7.37	8.26	7.27	**2**	0.28	1.16	2.55	3.80	**2**	2.88	2.90	2.66	2.20
3	4.66	6.32	7.58	7.11	**3**	0.57	1.35	2.49	3.51	**3**	2.47	2.60	2.51	1.96
4	5.27	6.46	7.60	7.15	**4**	0.99	1.67	2.52	3.33	**4**	2.10	2.59	2.39	1.87
5	5.12	6.12	7.34	6.98	**5**	1.32	1.94	2.56	3.18	**5**	2.29	2.73	2.41	1.85
6	4.57	5.73	6.96	6.63	**6**	1.07	1.93	2.49	3.05	**6**	2.27	2.60	2.23	1.80
7	4.51	5.27	6.41	6.15	**7**	0.76	1.91	2.33	2.79	**7**	1.90	2.43	2.05	1.75
8	3.72	4.75	5.86	5.64	**8**	0.17	1.97	2.29	2.70	**8**	1.59	2.32	1.83	1.68

	Argentina					China					Turkey			
m,σ	**0.50**	**1**	**1.5**	**2**	**m,σ**	**0.50**	**1**	**1.5**	**2**	**m,σ**	**0.50**	**1**	**1.5**	**2**
2	2.44	3.29	3.34	1.76	**2**	0.85	1.07	1.76	2.32	**2**	3.18	3.90	4.09	2.46
3	2.63	3.30	3.16	1.55	**3**	0.33	0.31	0.89	1.43	**3**	2.46	3.30	3.65	2.18
4	2.26	2.94	2.67	1.03	**4**	0.23	0.21	0.39	0.78	**4**	2.18	3.17	3.81	2.42
5	1.91	2.64	2.14	0.49	**5**	0.71	0.57	0.33	0.56	**5**	2.03	2.96	3.68	2.41
6	1.74	2.44	1.77	0.15	**6**	1.12	0.74	0.24	0.47	**6**	2.67	3.02	3.68	2.50
7	1.87	2.21	1.44	0.11	**7**	1.91	0.85	0.23	0.42	**7**	3.55	3.26	3.75	2.52
8	1.91	1.85	1.07	0.30	**8**	2.07	0.98	0.24	0.42	**8**	3.80	3.13	3.48	2.29

	S.Africa			
m,σ	**0.50**	**1**	**1.5**	**2**
2	3.42	2.88	2.18	1.26
3	2.56	1.89	1.47	1.10
4	2.04	1.33	1.08	0.99
5	1.78	0.95	0.96	1.18
6	1.94	1.07	1.07	1.38
7	1.88	1.17	1.19	1.58
8	2.40	1.31	1.30	1.75

TABLE 8: BDSL STATISTICS FOR AR(P)-EGARCH-M(1,1) FILTERED RETURNS

	UK					US					Japan			
m,σ	**0.50**	**1**	**1.5**	**2**	**m,σ**	**0.50**	**1**	**1.5**	**2**	**m, σ**	**0.50**	**1**	**1.5**	**2**
2	2.74	3.97	5.04	5.09	**2**	2.02	1.86	1.16	0.39	**2**	2.46	3.31	4.03	4.54
3	1.80	3.15	4.27	4.52	**3**	1.99	1.74	1.02	0.27	**3**	2.12	3.06	3.80	4.37
4	1.23	2.49	3.73	4.05	**4**	2.00	1.51	0.86	0.30	**4**	1.66	2.38	3.33	4.15
5	0.93	2.04	3.30	3.61	**5**	2.05	1.51	0.76	0.23	**5**	1.34	1.84	2.94	3.94
6	0.30	1.50	2.94	3.43	**6**	2.48	1.78	0.83	0.22	**6**	1.39	1.62	2.80	3.77
7	0.03	1.32	2.87	3.43	**7**	2.78	1.80	0.76	0.10	**7**	1.39	1.67	2.98	3.97
8	0.17	1.10	2.70	3.28	**8**	2.12	1.79	0.71	0.14	**8**	1.27	1.58	3.05	4.06
	Germany					**France**					**Italy**			
m,σ	**0.50**	**1**	**1.5**	**2**	**m,σ**	**0.50**	**1**	**1.5**	**2**	**m,σ**	**0.50**	**1**	**1.5**	**2**
2	3.53	4.62	5.51	5.28	**2**	3.76	4.29	4.49	3.79	**2**	2.32	1.75	2.28	2.20
3	3.05	3.70	4.26	4.09	**3**	3.67	4.24	4.41	3.65	**3**	3.34	2.69	2.83	2.47
4	2.18	2.65	3.08	3.05	**4**	3.33	3.89	4.17	3.45	**4**	2.98	2.20	2.28	2.18
5	1.95	2.31	2.69	2.68	**5**	3.07	3.72	4.14	3.56	**5**	2.88	2.15	2.34	2.46
6	2.23	2.28	2.70	2.76	**6**	2.54	3.46	4.07	3.53	**6**	3.42	2.27	2.44	2.68
7	2.40	2.24	2.54	2.65	**7**	2.29	3.42	4.06	3.52	**7**	3.33	2.41	2.47	2.74
8	2.50	2.05	2.35	2.50	**8**	2.67	3.56	4.07	3.51	**8**	3.16	2.73	2.69	2.87
	Taiwan					**Philippines**					**HongKong**			
m,σ	**0.50**	**1**	**1.5**	**2**	**m,σ**	**0.50**	**1**	**1.5**	**2**	**m,σ**	**0.50**	**1**	**1.5**	**2**
2	5.19	6.64	7.13	5.96	**2**	-0.46	-0.23	0.06	-0.34	**2**	4.00	4.71	4.86	5.22
3	4.34	5.82	6.64	5.80	**3**	-0.16	0.21	0.69	0.46	**3**	3.39	3.98	4.25	4.96
4	4.84	5.80	6.64	5.81	**4**	0.10	0.61	0.96	0.65	**4**	3.42	3.74	3.92	4.42
5	4.78	5.50	6.48	5.73	**5**	0.07	0.94	1.19	0.78	**5**	3.81	3.96	4.19	4.70
6	4.36	5.19	6.19	5.50	**6**	-0.13	1.02	1.20	0.73	**6**	3.81	3.76	4.06	4.68
7	4.18	4.83	5.80	5.14	**7**	-0.17	1.13	1.26	0.87	**7**	3.19	3.43	3.80	4.45
8	4.27	4.30	5.24	4.60	**8**	-0.24	1.11	1.28	0.97	**8**	3.40	3.14	3.54	4.20
	Argentina					**China**					**Turkey**			
m,σ	**0.50**	**1**	**1.5**	**2**	**m,σ**	**0.50**	**1**	**1.5**	**2**	**m,σ**	**0.50**	**1**	**1.5**	**2**
2	2.72	3.68	4.09	3.09	**2**	0.48	0.56	1.17	1.97	**2**	3.39	4.68	5.62	5.39
3	2.49	3.55	3.94	3.15	**3**	-0.09	-0.19	0.41	1.19	**3**	2.70	4.26	5.43	5.40
4	2.46	3.49	3.72	2.90	**4**	-0.04	-0.31	-0.09	0.53	**4**	1.97	3.72	5.15	5.31
5	2.79	3.60	3.70	2.92	**5**	0.39	0.15	-0.06	0.28	**5**	1.29	3.24	4.70	4.85
6	3.41	3.74	3.58	2.80	**6**	0.59	0.37	-0.17	0.09	**6**	1.26	3.17	4.58	4.65
7	4.52	3.77	3.49	2.72	**7**	0.96	0.49	-0.20	-0.05	**7**	1.39	3.29	4.62	4.56
8	5.16	3.66	3.33	2.60	**8**	1.49	0.63	-0.23	-0.15	**8**	1.99	3.12	4.41	4.30
	S.Africa													
m,σ	**0.50**	**1**	**1.5**	**2**										
2	3.85	3.13	2.56	1.99										
3	2.56	1.94	1.78	1.69										
4	1.97	1.33	1.40	1.37										
5	1.53	0.92	1.16	1.10										
6	1.60	1.08	1.26	1.23										
7	1.27	1.18	1.28	1.29										
8	1.59	1.30	1.33	1.41										

7. CONCLUSIONS

This study provides empirical evidence on the linear and nonlinear characteristic of stock markets in the developed and emerging capital markets. Based on our findings, we can say that there is significant linear and non-linear dependence in the selected world stock markets; however their characterization changes from country to country. Both dependencies violate the weak form of efficient market hypothesis and its immediate implication of random-walk behavior of stock prices, meaning unpredictability of stock prices with market trading data. This allows us to conclude that the stock markets that we are considered are inefficient markets in terms of informational efficiency as proposed by Fama (1970).

Also, empirical results identify the certain characteristic of the volatility structure of selected stock markets. Much of the non-linear dependence can be explained by dependence of conditional variance since various GARCH-type models reduce the effect of the non-linear dependence, which is measured by BDSL statistics. Although we found non-linear dependence and its explanation in stock return series, we could not capture whether there is any clear distinction between emerging countries and developed countries in terms of degree of non-linearity. Nevertheless, the finding that there is a tendency for detecting linearity in earlier lags and extracting non-linearity in simpler models for developing countries provides us a strong possibility of detecting the distinction between two group of countries. We hope that it will be revealed by incorporating all possible GARCH-type models to the return series of both emerging and developed markets. Another further research topic can be testing of the other financial markets such as futures, foreign exchange, and commodity in those countries for linear and non-linear dependence by the same methodology used here. By doing that, verification of the weak form market inefficiency in those capital markets can be confirmed.

REFERENCES

Abhyankar, A.; L.S. Copeland; and W. Wong. 1995. "Nonlinear Dynamics in Real Time Equity Market Indices: Evidence from the United Kingdom." *The Economic Journal* 105, no.431 (May): 864-880.

Abhyankar, A.; L.S. Copeland; and W. Wong. 1997. "Uncovering Non-linear Structure in Real–Time Stock Market Indexes: The S&P500, the Dax, the Nikkei 225, and the FTSE-100." *Journal of Business and Economic Statistics* 15, no.1 (January): 1-14.

Akaike, H. 1974. "A New Look at the Statistical Model Identification." *IEEE Transactions on Automatic Control* AC-19, no.6 (December): 716-723.

Akgiray,V. 1989. "Conditional Heteroscedasticity in Time Series of Stock Returns: Evidence and Forecasts." *Journal of Business* 62, no.1 (January): 55-80.

Al-loughani, N., and D. Chappell. 1997. "On the Validity of the Weak Form Efficient Markets Hypothesis Applied to the London Stock Exchange." *Applied Financial Economics* 7, no.2 (April): 173-176.

Ashley, R.A.; D.M. Patterson; and M.J. Hinich. 1986. "A Diagnostic Test for Nonlinear Serial Dependence in Time Series Fitting Errors." *Journal of Time Series Analysis* 7, no.3 :165-178.

Barnet, W.A.; A.R. Gallant; M.J. Hinich; J. Jungeilges; and D.T. Kaplan. 1996. "An Experimental Design to Compare Tests of Nonlinearity and Chaos" in *Nonlinear Dynamics and Economics,* Cambridge, Cambridge University Press.

Bekaert, G.; C.B Erb; C.R. Harvey; and T.E. Viskanta. 1998. "Distributional Characteristics of Emerging Market Returns and Asset Allocation." *Journal of Portfolio Management* 24, no.2 (Winter): 102 –116.

Bera, A.K, and C.M. Jarque. 1982. "An Efficient Large Sample Test for Normality of Observations and Regression Residuals" *Australian National University, Working Papers in Econometrics,* no.40.

Berndt, E.; B. Hall; R. Hall; and J.Hausman. 1974. "Estimation and Inference in Nonlinear Structural Models." Annals of Economic and Social Measurement 3, 653-665.

Bollerslev, T. 1986. "Generalized Autoregressive Conditional Heteroskedasticity." *Journal of Econometrics* 31, no. 3 (April): 307–327.

Box, G.E.P., and G.M. Jenkins. 1976. *Time Series Analysis: Forecasting and Control.* San Francisco: Holden-Day.

Brock, W.A.; W.D. Dechert; J.A. Scheinkman; and B. LeBaron. 1996. "A Test for Independence Based on the Correlation Dimension." *Econometric Reviews* 15, no.3, 197-235.

Brock, W.A; D.A. Hsieh; and B. LeBaron. 1991. *Nonlinear Dynamics, Chaos, and Instability: Statistical Theory and Economic Evidence*. Cambridge, MA, MIT Press.

Brooks, C. 1996. "Testing for Non-linearity in Daily Sterling Exchange Rates." *Applied Financial Economics* 6, no.4 (August): 307-317.

Brooks, C. 2002. *Introductory Econometrics for Finance*. Cambridge, Cambridge University Press.

Chyi, Y.L. 1997. "Nonlinear Dynamics and Daily Stock Returns on the Taiwan Stock Exchange." *Applied Financial Economics* 7, no.6 (December): 619-634.

Cont, R. 2001. "Empirical Properties of Asset Returns: Stylized Facts and Statistical Issues." *Quantitative Finance* 1, no.2 (March): 223-236.

deLima, P.J.F. 1996. "Nuisance Parameter Free Properties of Correlation Integral Based Statistics." *Econometric Reviews* 15, no.3, 237-259.

Dickey, D.A., and W.A. Fuller. 1979. "Distribution of the Estimators for Autoregressive Time Series with a Unit Root." *Journal of American Statistical Association* 74, no.366 (June): 427-431.

Dornfleitner, G. 2003. "Why the Return Notion Matters?" *International Journal of Theoretical and Applied Finance* 6, no.1 (February): 73-86.

Engle, R.F. 1982. "Autoregressive Conditional Heteroscedasticity with Estimates of the Variance of UK Inflation." *Econometrica* 50, no.4 (July): 987-1007.

Engle, R.F.; D.M. Lilien; and R.P. Robins. 1987. "Estimating Time Varying Risk-Premia in the Term Structure: The ARCH-M Model." *Econometrica* 55, no.2 (March) 391-407.

Fama, E.F. 1965. "The Behavior of Stock Market Prices." *Journal of Business* 38, no.1 (January): 34-105.

Fama, E.F. 1970. "Efficient Capital Markets: A Review of Theory and Empirical Work." *Journal of Finance* 25, no.2 (May): 383-417.

Gilmore, C.G. 1996. "Detecting Linear and Non-linear Dependence in Stock Returns: New Methods Derived from Chaos Theory." *Journal of Business Finance and Accounting* 23, no.9-10 (November-December): 1358-1377.

Granger, C.W.J.; H. White; and M. Kamstra. 1989. "Interval Forecasting: An Analysis Based upon ARCH-quantile Estimators." *Journal of Econometrics* 40, no.1 (January): 87-96.

Grassberger, P. and I. Procaccia. 1983. "Measuring the Strangeness of Strange Attractors." *Physica D Nonlinear Phonemena* 90, no.1-2 (October): 189-208.

Harris R.D.F, C.C. Küçüközmen. 2001. "Linear and Non-linear Dependence in Turkish Equity Markets and its Consequences for Financial Risk Management." *European Journal of Operational Research* 134, no.3 (November): 481-492.

Hinich, M.J. 1982. "Testing for Gaussanity and Linearity in a Stationary Time Series" *Journal of Time Series Analysis* 3, no.3 (May):169-176.

Hinich, M.J., and D.M. Patterson. 1985. "Evidence of Nonlinearity in Daily Stock Returns." *Journal of Business and Economic Statistics* 3, no.1 (January): 69-77

Hsieh, D.A. 1991. "Chaos and Non-linear Dynamics: Application to Financial Markets." *Journal of Finance* 46, no.5 (December): 1839-1877.

Ljung, G.M., and G.E.P. Box.1978. "On a Measure of Lack of Fit in Time Series Models." *Biometrika* 65, no.2 (August): 297-303.

Nelson, D.B. 1991. "Conditional Heteroscedasticity in Asset Returns: A New Approach." *Econometrica* 59, no.2 (March): 347-370.

Omran, M.F. 1997. "Non-linear Dependence and Conditional Heteroscedasticity in Stock Returns: UK Evidence." *Applied Economic Letters* 4, no.10 (October): 647-650.

Opong K.K.; G. Mulholland; A.F. Fox; and K. Farahmand. 1999. The Behavior of Some Equity Indices: An Application of Hurst and BDS Tests." *Journal of Empirical Finance* 6, no.3 (September): 267-282.

Philippatos, G.C.; E. Pilarinu; and A.G. Mallirais. 1993. "Chaotic Behavior in Prices of European Equity Markets: A Comparative Analysis of Major Economic Regions." *Journal of Multinational Financial Management* 3, no.3-4, 5-24

Poshakwale, S., and V. Murinde. 2001. "Modelling the East European Emerging Markets: Evidence on Hungary and Poland." *Applied Financial Economics*, 11, no.4 (August): 445-456.

Scheinkman J.A., and B. LeBaron. 1989. "Nonlinear Dynamics and Stock Returns." *Journal of Business* 62, no.3 (July): 311-337.

Schwarz, G. 1978. "Estimating the Dimension of a Model." *Annals of Statistics* 6, no.2 (March): 461-464.

Sewell, S.P.; S.R. Stansell; I. Lee; and M.S Pan. 1993. "Nonlinearities in Emerging Foreign Capital Markets." *Journal of Business Finance and Accounting* 20, no.2 (January): 237-248.

Siourounis, G.D. 2002. "Modeling Volatility and Testing for Efficiency in Emerging Capital Markets: The Case of Athens Stock Exchange." *Applied Financial Economics* 12, no.1 (January): 47-55.

Tsay, R.S. 1986. "Nonlinearity Tests for Time Series" Biometrika 73, no.2 (August): 461-466.