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Statistical tests for linear and nonlinear dependence and long-memory in Romanian stocks market

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ABSTRACT.
In this paper various statistical tests are used to identify certain linear and/or nonlinear dependencies, respectively a long memory behavior in Romanian stocks returns.

1. INTRODUCTION

The concept of efficient financial market has an important place in finance. Testing of the financial markets efficiency is an important issue for investors and policymakers. An efficient capital market is necessary and useful for a competitive market economy; inducing an efficient assignation of capital within the economy. The efficient market hypothesis (EMH) asserts that financial markets are efficient in what concerns information. By defining efficient market as a market where prices fully reflect all available information, Fama [4] points three sufficient conditions for the efficiency of the market: the absence of transaction costs, the availability of all relevant information to traders without cost, the integration of current information in the current price.

The information channels are efficient as long as the information is spreading rapidly and new information becomes public quickly. This new information will lead to purchasing and selling, so that price should correspond to the new value of the company. Therefore, the given information is quickly assimilated within the next stock price. In this paper we examine the weak form of market efficiency. Testing of this efficiency form is made through tests concerning the predictability of stock returns. The weak-form of market efficiency requires that successive price changes are independent and identically distributed, which corresponds to the random walk process.

There is extended reference literature regarding the weak-form of market efficiency. The EPH hypothesis is examined by using different statistical methods. A number of recent studies focused on European emerging equity markets. Of these, we mention here some recent studies: Gilmore and McManus [6], Worthington and Higgs [22]. Worthington and Higgs [22] have studied the weak-form of market efficiency of twenty-seven emerging markets from different regions. The authors conclude that most emerging markets are weak-form inefficient. In general, empirical studies show mixt results about efficiency of emerging markets.

Empirical studies tend to identify some characteristics specific to emerging markets: stock returns are more predictable than in developed markets, the efficiency of capital markets in emerging economies increases over time, as a result of gradual liberalization, respectively stock returns exhibit nonlinearity and time-varying volatility.

Regarding possible long-memory behavior, empirical studies indicate that it is likely for the long memory to be found in emerging or small markets. Wright [23], on testing for long memory in returns for a wide large of emerging markets, finds some evidence for positive long dependence in 7 of 17 time series of returns. Tolvi [21] investigates the presence of long memory in Finnish stock market return, for daily returns on six indices and forty companies. Depending upon the tests used, statistically significant long memory is identified in 24% to 67% of the series.

In this paper we make use of different statistical tests in order to identify certain linear and/or nonlinear dependencies, respectively a long-memory behavior in Romanian stock returns. A first purpose of the study is to investigate information efficiency of the capital market from Romania, starting with 2000. It is known that the results of empirical studies strongly depend not only upon the market characteristics, but also upon the methodology used. Three groups of statistical tests will be used consequently.

Efficiency testing of the Romanian capital market has been already approached in several articles; the conclusions vary from one study to another, according to the methodology used, respectively the period of time taken into account. Harrison and Paton [8], using a GARCH model, find evidence of inefficiency in the Bucharest Stock Exchange for the period mid-1997 to September 2002, but after January 2000 the efficiency of the market was improved.

By using classical tests in order to identify correlations within stock returns, Todea [19] points out the existence of positive autocorrelations in the series of rentabilities observed, which disappear however in the case of adjusted rentabilities. There are taken into consideration 10 stocks. Todea and Zoicac-Ienciu [18], use the Hinich and Patterson windowed-test procedure to reach the conclusion that relatively long sub-periods of random walk periods are interrupted by short and intense linear and/or nonlinear correlations; time series of BET index cover the period between September 1997 and May 2006. Similar results were obtained for other five Central-East European stock market indices. On using the modified version of this procedure, proposed by the authors, results prove to be diverging.

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Pele and Voineagu [15] use, to test EHM in its weak form, an approach based on decomposing stock returns into a stochastic trend and a white noise component. By applying this model for the time series of daily returns of BET Index, for the period between September 1997 and January 2007, the conclusion shows that one could not reject the hypothesis of market efficiency.

The second objective is to highlight the type of dependencies in stock returns. It thus becomes easier to chose proper stochastic models to improve return forecasts. Three groups of statistical procedures will be used here: tests to detect linearly correlations, tests to identify nonlinear dependencies respectively procedures meant to identify a possible long-memory behavior. There are taken into account BET returns as well as fifteen time series returns of individual stocks.

2. Statistical Tests for dependence and long memory

We are considering the continuously compounded returns (or logarithmic return) R_t

$$R_t = \ln(c_t/c_{t-1}) = C_t - C_{t-1},$$

where $C_t = \ln(c_t)$ is the logarithm of the BET index price respectively the logarithm of the individual closing prices stock, observed at time t. The equation of the random walk with drift process is the following

$$C_t = \mu + C_{t-1} + \varepsilon_t \quad \text{or} \quad R_t = \Delta C_t = \mu + \varepsilon_t,$$

where μ is the drift parameter and ε_t the random error term. Upon random walk hypothesis the variables ε_t are independently and identically distributed.

In general, emerging markets are characterized by thin trading. Miller, Muthuswamy, and Whaley [14] suggest correcting data for thin trading. The purpose of the method thus proposed is to eliminate serially artificially induced correlations in the time series of returns. Thin trading adjustment remove the effect of thin trading, reduces the negative correlation among returns. An AR(1) model is estimated for series returns

$$R_t = a + bR_{t-1} + e_t.$$

Residuals from this model are used to adjust returns, the adjusted returns being estimated as follows: $RA_t = \widehat{e}_t/(1 - \widehat{b})$, where RA_t is the return at time t adjusted for thin trading. Todea (2005) also applies this type of adjustment.

2.1. **Testing for linear correlations in stock returns.** The common test used to detect the serial linear correlation in stock returns R_t is the Ljung-Box Q-statistics, based on autocorrelation coefficients. The Q-statistics at lag m is a test for the null hypothesis that there is no autocorrelation up to order m

$$Q = T(T+2)\sum_{k=1}^{m}(T-k)^{-1}\widehat{\rho}_k^2$$

where T is the number of observations, and $\widehat{\rho}_k$ is the sample autocorrelation between R_t and R_{t-k}. Under null hypothesis, of first m autocorrelation coefficients ρ_k equal to zero, Q is asymptotically χ^2 distributed with m degrees of freedom. Tests based on autocorrelation coefficients detect only linear correlation. If the stock returns are linearly correlated, a linear autoregressive moving average models ARMA can be specified and used to generate forecasts.

2.2. **Nonlinear Behavior Tests.** In order to identify a possible nonlinear incorporation of information within the price of assets we apply nonlinearity tests. Empirical studies show that stock returns display nonlinearity and time-varying volatility, especially on emerging markets. Among the causes of this behavior, we can mention: low liquidity, law changes, incomplete information, specific behavior of investors (Todea [19]).

There are several tests useful to detect the nonlinear behavior of stock returns. The McLeod-Li and Li [13] provide a test for non linear dependence. The test points out the existence of autocorrelations in squared residuals, the expression being similar to that of the Ljung-Box test

$$LM(m) = T(T+2)\sum_{k=1}^{m}(T-k)^{-1}r_{ee}^2(k),$$

where $r_{ee}(k)$ represents the sample autocorrelation function of squared residuals. This test is asymptotically χ^2 distributed with m degrees of freedom. The identification of significant autocorrelations in squared residuals time series proves the necessity of nonlinear modeling framework. The test detects rather multiplicative nonlinearity. A stronger test, which distinguishes between additive and multiplicative nonlinearity is the Hsieh test (Koller and Fischer [10]).

Another test commonly used to identify nonlinear dependencies is the BDS test, proposed by authors Brock, Dechert, Scheinkman and LeBaron [2]. Under the BDS test, the null hypothesis is that Y_t are independently and identically distributed, where the alternative hypothesis assumes a variety of possible deviations from independence including nonlinear dependence. To define the test, it is used the concept of correlation integral $C_{m,T}(\varepsilon)$ at embedding dimension m, from chaos theory. The test statistics

$$B(m,\varepsilon) = \frac{C_{m,T}(\varepsilon) - C_1(\varepsilon)^m}{\sigma_{m,T}(\varepsilon)/\sqrt{T}} \to N(0,1)$$

follows asymptotically the standard normal distribution. The embedding dimension m is the number of consecutive data used in the set to define the points. Correlation integral $C_{m,T}(\varepsilon)$ is an indicator of the probability that the distance between two randomly points is smaller than ε. Under the null hypothesis

$$C_{m,T}(\varepsilon) \to C_1(\varepsilon)^m \text{ as } T \to \infty.$$

The expression for the standard deviation can be found in Brock, Dechert, Scheinkman and LeBaron [2]. The application of the test requires the use of adequate values for m and ε.

Both tests detect indirectly a nonlinear behavior. In case of linear correlations in the series, it is recommended to estimate previously an ARMA model and apply tests upon estimated residuals; linear correlations from stocks returns are also previously filtered (Koller and Fischer [10]). The grounds for this procedure resorts to the fact that once linear dependencies were extracted out of the data, the serial dependence possibly left from estimated residuals must be due to a nonlinear generating process. This approach is also used in empirical study of authors Kosfeld and Robe [11].

If tests highlight nonlinear dependencies in stock returns, the best procedure resorts to nonlinear time series models, such as TAR models in case of additive nonlinearity respectively GARCH models for multiplicative nonlinearity, to improve the forecasts.

2.3. **Testing for long memory in the stock returns.** The presence of long-term memory in stock returns is not consistent with weak-form efficiency hypothesis. In a long-memory process, autocorrelations remain persistently high at large lags, the time series seem to manifest dependence between distant observations. A long memory indicates slow assimilation of information in the price of financial assets. The existence of such behavior suggests the possibility to obtain speculative profits.

Among common test of unit roots, the Kwiatkowski, Phillips, Schmidt, and Shin (KPSS) seems to be consistent against stationary long memory alternatives (Lee and Schmidt [12]); it is used together with other tests to investigate the rejection of short memory hypothesis in a time series. The KPSS test is applied here under the null hypothesis of stationary level. The statistic is based on the residuals from the OLS regression of Y_t on a constant $e_t = Y_t - \overline{Y}$ and has the following formula

$$LM = \frac{1}{T^2}\sum_{t=1}^{T} S_t^2/f_0$$

where $S_t = \sum_{j=1}^{t} e_j$ is a cumulative residual function, and f_0 is an estimator of the residual spectrum at frequency zero.

Fractional integration models are stronger techniques for the identification of some forms of long-memory in a time series. The introduction of the concept of fractional integration by Hosking [9], Granger and Joyeux [7], has enabled the study of the presence of long-term memory or long time dependence in a time series. In order to define the concept of fractional integration it is used the fractional differencing operator determined by binomial series expansion, for any real $d > -1$

$$\Delta^d = (1-L)^d = \sum_{k=0}^{\infty} \frac{\Gamma(k-d)}{\Gamma(-d)\Gamma(k+1)}$$
$$= 1 - dL + \frac{d(d-1)}{2!}L^2 - \frac{d(d-1)(d-2)}{3!}L^3 + \dots$$

where $\Gamma(\cdot)$ is the gamma function; L is the lag operator $LY_t = Y_{t-1}$ for all $t > 1$.

The class of processes which can incorporate long-memory behavior is represented by the fractional autoregressive integrated moving average $ARFIMA(p,d,q)$, where the integration parameter d may assume non-integral values. In the context of detecting long-memory or long-term dependence in the returns one should take into consideration $ARFIMA(p,d,q)$ models with $d \in (-0.5, 0.5)$

$$\phi(L)(1-L)^d Y_t = \theta(L)\varepsilon_t; \quad d \in (-0.5, 0.5),$$

where $\phi(L)$ and $\theta(L)$ are the autoregressive and moving average polynomials of order p and q in L. When d takes values in this interval the process is stationary and invertible.

From d in the range $0 < d < 0.5$ the returns display long-range positive dependence (or persistence). In such case Hosking [9] showed that the autocorrelation function declines hyperbolically to zero, while speed depends upon d. For a stationary ARMA process the parameter $d = 0$, and the autocorrelation function decreases faster to zero (exponential decay), and the process displays short memory. For $-0.5 < d < 0$ returns display long-range negative dependence or anti-persistence.

TABLE 1. Descriptive statistics of daily stock returns

Stock	T	Mean	Standard Deviation	Skewness	Kurtosis	JB Prob
BET Index	2034	0.0013	0.016	−0.32	8.96	0.00
ART	1138	0.0049	0.054	−0.037	4.59	0.00
ALR	1503	0.0025	0.094	10.18	558.25	0.00
ATB	1915	0.0024	0.046	16.09	512.96	0.00
BCC	863	0.0006	0.021	0.22	7.04	0.00
BRD	1648	0.0015	0.029	2.14	92.17	0.00
IMP	1826	0.0023	0.035	1.56	35.74	0.00
RRC	910	0.0006	0.029	0.44	6.66	0.00
SIF1	1976	0.0021	0.029	−0.32	8.93	0.00
SIF2	1980	0.0023	0.031	−0.28	8.46	0.00
SIF3	1923	0.0021	0.028	0.01	7.92	0.00
SIF4	1960	0.0018	0.029	−0.26	8.47	0.00
SIF5	1968	0.0022	0.029	−0.17	8.63	0.00
SNP	1490	0.0011	0.026	−0.09	9.50	0.00
TEL	411	0.0011	0.023	0.15	4.59	0.00
TLV	1926	0.0025	0.029	4.88	92.47	0.00

The fractional difference parameter d indicates the degree of long memory in the stock returns. In this study the memory parameter d is estimated through the Geweke and Porter-Hudak (GPH) [5] method, and also through the Reisen method [16]. These procedures are based upon the estimation of the spectral density function, given by

$$f_Y(\omega) = (4\sin^2(\omega/2))^{-d} f_w(\omega),$$

where $f_w(\omega)$ is the spectral density of $w_t = (1-L)^d Y_t$. Therefore

$$\log(f_Y(\omega)) = \log(f_w(\omega)) - d\log(4\sin^2(\omega/2)).$$

The spectral density function is estimated through the periodogram function. The GPH estimator of d is (minus) the slope estimator in regression for the logarithm of the periodogram function on $\log(4\sin^2(\omega/2))$ and a constant. Given the time series Y_t, $t = 1, 2, \dots, T$, in order to set the number of frequencies $\omega_j = 2\pi j/T$, $j = 1, \dots, T^\alpha$, are suggested the values for α between 0.5 and 0.6. Reisen [16] proposed the use of the smoothed periodogram function on the regression equation, as an estimate of the spectral density; simulated results show that this estimator of d performs better than the GPH estimator. Both estimators are asymptotically normally distributed with mean d. The rejection of the null hypothesis of $d = 0$ against one sided alternative $d > 0$ indicates the presence of long-range positive dependence in stock returns. When the null hypothesis of $d = 0$ against one sided alternative $d < 0$ is rejected, the series displays long-range negative dependence.

3. EMPIRICAL STUDY

This empirical study identify possible dependencies in Romanian stock returns, with consequences upon the information efficiency of the market respectively of models useful to forecast returns. There are taken under study 16 daily stock returns: returns calculated from the BET index, respectively time series returns of 15 individual stocks from Bucharest Stock Exchange. There were selected stocks with important share in market capitalization. The five stocks SIF1 - SIF5 belong to financial investments companies. The data are provided starting from the 5th of January 2000, with the exception of titles not yet rated at the beginning of the period; in this respect, we have considered prices starting from the date when they were rated. The last date of all individual series is the 21th of February, and for BET returns the 20th of March 2008. Certain companies have not been rated in all the days from the given period.

Descriptive statistics. Descriptive statistics concerning returns are provided in table 1. The mean returns are positive for all stocks. The high standard deviation with respect to the mean return indicates a high volatility. For 7 of the 16 stock returns the skewness coefficient is negative. The kurtosis coefficients are all bigger than three, while distributions are leptokurtic; however, this characteristic is common to many financial series (Todea [20]). Jarque-Bera test rejects the normality hypothesis, for all series.

Linear Correlation in stock returns. Table 2 provides the Ljung-Box Q-statistics (EViews 5 software was used for statistical tests applied to detect serial correlation and nonlinear behaviors), used to detect linear correlations in stock returns. However, for most of the assets one can observe a significant positive first-order autocorrelation, which indicates predictability of returns. The values of the Q statistics, reported for m equal 20 respectively 30, bring mainly evidence against market efficiency, the null hypothesis of no autocorrelation is rejected for 11 of the 16 stock returns series, at 5% significant level. To compute adjusted returns, as well as to separate false correlations induced

TABLE 2. Ljung-Box Q-statistics for observed and adjusted returns. Note : *** Significant at 1% level; ** Significant at 5% level; * Significant at 10% level.

Stock	Returns		Adjusted returns	
	$Q(20)$	$Q(30)$	$Q(20)$	$Q(30)$
BET Index	82,999***	102,38***	29,379*	49,087**
ALR	240,09***	241,98***	239,99***	241,84***
ART	77,964***	91,980***	54,534***	77,823***
ATB	45,680***	68,406***	41,369**	63,486***
BCC	25,588	31,043	–	–
BRD	51,677***	63,784***	47,551***	60,102***
IMP	35,482**	60,718***	26,169	49,403**
RRC	26,517	32,379	–	–
SIF1	36,787**	50,744**	29,026*	45,038**
SIF2	38,761***	56,606***	24,204	42,390*
SIF3	29,533*	34,452	–	–
SIF4	40,694***	53,709***	24,325	36,853
SIF5	23,429	32,551	–	–
SNP	61,044***	66,497***	24,539	30,842
TEL	15,900	21,208	–	–
TLV	89,464***	96,680***	88,344***	95,949***

TABLE 3. Estimated $ARMA(p,q)$ models and Mcleod-Li statistics. Note : *** Significant at 1% level; ** Significant at 5% level; * Significant at 10% level.

Stock	$ARMA(p,q)$	$LM(15)$	$LM(20)$	$LM(30)$
BET Index	$ARMA(1,0)$	554,38**	564,76**	614,09**
ALR	$ARMA(11,2)$	4,135	4,148	4,167
ART	$ARMA(3,0)$	871,69**	1022,4**	1294,9**
ATB	$ARMA(3,4)$	1,946	1,950	2,118
BCC		102,59**	111,01**	130,83**
BRD	$ARMA(4,2)$	196,68**	196,74**	198,17**
IMP	$ARMA(4,1)$	216,35**	216,94**	227,19**
RRC		134,46**	136,19**	139,01**
SIF1	$ARMA(2,3)$	314,26**	330,56**	431,93**
SIF2	$ARMA(1,1)$	361,57**	391,92**	440,39**
SIF3		294,38***	300,94***	369,99***
SIF4	$ARMA(1,0)$	294,63**	332,99**	433,23**
SIF5		327,99**	328,99**	347,98**
SNP	$ARMA(3,3)$	204,42**	206,73**	208,51**
TEL		40,500**	42,812***	61,521***
TLV	$ARMA(3,0)$	21,778**	21,889**	22,080**

by the thin trading, it is used the method proposed by authors Miller, Muthuswamy and Whale (1994). Thin trading determines a false negative autocorrelation corresponding to an individual stock respectively a positive one in case of the index (Todea [19]). We underline that most stocks haven't strong negative first-order autocorrelation. Linear correlations were eliminated by adjustment for SIF4, SNP and partially for SIF2.

Nonlinear Behavior Tests. The McLeod-Li test and the BDS test requires filtration (extraction) of linear dependencies from the returns series. An $ARMA(p,q)$ model is typically fitted to the series, to capture linear correlations, and tests are applied upon estimated residuals. The $ARMA(p,q)$ models identified and estimated, for stocks defined by linear dependencies, are shown in table 3. For the five series returns, were there were no obvious linear dependencies, the McLeod-Li and BDS tests were applied to returns observed.

The McLeod-Li statistics $LM(m)$, displayed in table 3 for m equal 15, 20 respectively 30, points out the existence of autocorrelations in squared ARMA residuals, for 14 of the 16 series returns. Excepting the ALR and ATB returns, all the other stock returns manifest nonlinearity.

TABLE 4. BDS statistics, for $m = 2, 3, \ldots, 6$ and $\varepsilon/\sigma = 1$. Note: * Significant at 1% level.

ε/σ	m	BET	ALR	ART	ATB	BCC	BRD	TLV	IMP
1,0	2	12,8*	12,4*	12,9*	17,5*	6,0*	13,2*	12.93*	12,7*
1,0	3	15,6*	14,0*	15,8*	18,3*	8,3*	15,6*	15.74*	14,5*
1,0	4	17,0*	16,6*	18,6*	18,7*	9,4*	17,5*	16.85*	15,8*
1,0	5	18,6*	17,7*	21,6*	19,0*	10,1*	19,1*	18.07*	17,1*
1,0	6	20,8*	18,1*	25,1*	19,4*	11,2*	20,7*	18.94*	18,7*
ε/σ	m	SIF1	SIF2	SIF3	SIF4	SIF5	RRC	SNP	TEL
1,0	2	13,8*	11,4*	10,2*	11,2*	11,4*	6,7*	10,9*	5,36*
1,0	3	17,2*	13,7*	12,5*	13,7*	13,2*	7,4*	13,0*	5,93*
1,0	4	19,5*	15,6*	14,2*	15,6*	14,8*	7,9*	15,1*	7,85*
1,0	5	21,9*	17,1*	15,9*	17,2*	16,5*	8,3*	16,9*	9,64*
1,0	6	24,1*	18,9*	17,7*	19,1*	18,2*	8,8*	19,3*	11,2*

TABLE 5. KPSS statistics for stock returns. Note: ***, **, * Significant at 1%, 5% and 10% level. EViews 5 package was used; spectral estimation method: Bartlett kernel, Newey-West bandwidth.

Stock	KPSS	Stock	KPSS
BET Index	0.289	SIF1	0.146
ALR	0.070	SIF2	0.110
ART	0.197	SIF3	0.108
ATB	0.107	SIF4	0.093
BCC	0.429*	SIF5	0.103
BRD	0.135	SNP	0.269
IMP	0.367*	TEL	0.479**
RRC	0.206	TLV	0.267

The $B(m, \varepsilon)$ statistics were calculated for a large range of embedding dimension $m = (2, 3, \ldots, 6)$ and $\varepsilon/\sigma = (0.5; 1; 1.5)$, where σ is the standard deviation of the series; these values are commonly used in the application of the test. Results obtained after the application of the BDS test are summarized in table 4, for $\varepsilon/\sigma = 1$; for $\varepsilon/\sigma = 0.5$ respectively 1.5 the test leads to the same conclusions, and corresponding calculations can be obtained from the authors. Regardless of the values for m and ε the test represents evidence for the existence of nonlinear dependencies in all returns. Simulation studies show that BDS test is productive when used as a ″nonlinearity screening test″ (Ashley and Patterson [1]).

The tests used prove clearly the existence of linear and nonlinear dependences in most of stock returns series. There is a strong evidence of some form of non-linearity in all series. Relatively to the BET returns we can notice a strong non-linear structure and also a serial linear correlation. The Romanian stock market is not weak-form efficient, like most of the emerging equity markets.

Testing for long memory in stock returns. Although often used as stationary test, the KPSS test seems to be consistent against stationary long memory alternatives, like $I(d)$ for $d \in (-0.5, 0.5)$, with $d \neq 0$ (Lee and Schmidt [12]). Table 5 displays the results obtained, under the null hypothesis of stationary level. The test identifies weak signals of long memory, in 3 of the 16 time series. For most series, there is no evidence against the null hypothesis, the time series of the rates of returns being at stationary level.

Table 6 reports the spectral regression estimates for the fractional differencing parameter d, according to Geweke and Porter-Hudak method respectively the Reisen [16] method. The rejection of null hypothesis of $d = 0$ against one sided alternative $d > 0$ indicates the presence of long-memory in stock returns. When the null hypothesis of $d = 0$ against one sided alternative $d < 0$ is rejected, the series is characterized by anti-persistence. Are displayed GPH estimates for $T^{1/2}$ frequencies included in the spectral regression, respectively Reisen estimates for exponent of the bandwidth used in the regression equation 0.5 and exponent of the bandwidth used in the lag Parzen window 0.9. There are also provided asymptotic standard deviations of the fractional estimator d and t-statistics.

According to both methods, the long-term memory parameter $\widehat{d}$ variates between -0.191 and 0.216. The series are covariance stationary, the fractional parameter estimates are placed below the 0.5. The Reisen method detects better the minor long memory. At the 10% significance level the given test points out clear evidence of long-range positive dependence in 4 of the 16 time series returns. A long-range negative dependence (or intermediate memory) is detected in 4 of the 16 returns. For the other stocks, including BET returns, fractional differencing parameter d is not significantly different from zero, series having short memory.

For stocks where it was identified a long memory behavior the fractionally integrated ARFIMA models could be used to predict the returns.

TABLE 6. Long memory tests results. Note: ***, **, * significance for the null hypothesis $d = 0$ against the alternative $d > 0$, and ″″″, ″″, ″ against the alternative $d < 0$, at 1%, 5%, 10% levels. R-package was used.

Stock	GPH estimates			Reisen estimates		
	$\widehat{d}$	St. dev.	t	$\widehat{d}$	St. dev.	t statistic
BET Index	-0.032	0.088	0.0364	0.009	0.035	0.257
ALR	-0.191	0.097	-1.969″″	-0.185	0.039	-4.743″″″
ART	-0.049	0.107	-0.457	0.073	0.043	1.697**
ATB	0.057	0.901	0.063	0.028	0.035	0.800
BCC	0.163	0.116	1.405*	0.118	0.047	2.51***
BRD	0.142	0.094	1.511*	0.053	0.037	1.432*
IMP	0.009	0.091	0.098	0.015	0.035	0.428
RRC	-0.124	0.114	-1.088	-0.050	0.046	-1.087
SIF1	0.041	0.089	0.460	-0.044	0.034	-1.294″
SIF2	0.035	0.089	0.393	-0.046	0.035	-1.314″
SIF3	0.033	0.089	0.371	-0.023	0.035	-0.657
SIF4	-0.032	0.089	-0.359	-0.058	0.035	-1.657″″
SIF5	0.075	0.089	0.843	0.018	0.035	0.514
SNP	0.216	0.097	2.227**	0.125	0.039	3.205***
TEL	0.014	0.149	0.093	0.011	0.063	0.175
TLV	0.009	0.089	0.101	-0.029	0.035	0.828

4. CONCLUSIONS

The used statistical tests find evidence of stochastic dependencies for all stock returns. There is strong evidence of some form of linearity and/or non-linearity in series. Corresponding to the BET returns there are identified a strong non-linear structure and also serial linear correlation, however not a long memory as well. The Romanian stock market is not weak-form efficient, like most of the emerging equity markets.

The null hypothesis of no linear autocorrelation is rejected for 11 of the 16 stock returns series. The BDS test finds evidence of nonlinear dependencies in all returns. The fractional differencing parameter $\widehat{d}$ variates between -0.191 and 0.216. At the 10% significant level the GPH method in the Reisen's variant gives evidence of long-range positive dependence in 4 series returns. Also, 4 of the 16 returns display a long-range negative dependence. To our knowledge, fractional integration approach has not been yet used to test the existence of long memory in the asset returns, for the Romanian capital market.

The results of the empirical study are useful as guidance in order to choose an adequate stochastic model to forecast returns. If the stock returns are linearly correlated, we can identify linear autoregressive moving average ARMA models and use them to generate forecasts. Where nonlinear dependencies were detected in returns, nonlinear time series models can be used, such as TAR models in the case of additive nonlinearity, respectively GARCH models for multiplicative nonlinearity, to improve forecasts. If a long memory behavior was identified, the fractionally integrated ARFIMA models could be used to predict the returns.

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