International Journal of Applied Operational Research
Vol. 2, No. 2, pp. 13-24, July 2012

Journal homepage: www.ijorlu.ir

Investigation of the market efficiency of emerging stock markets in the East-European region

I. Ivanov*, B. Lomev, B. Bogdanova

Received: January 4, 2012; **Accepted:** May 9, 2012

Abstract The presence of stock market efficiency is a distinctive characteristic of the effectively functioning market economy. Investigation of the market efficiency of seven emerging East-European stock exchanges is carried out as their major stock indices (BELEX15, BET, CROBEX, ISE100, PFTS, RTSI, SOFIX) are studied in respect of long-range dependence (LRD), persistency, and forecasting possibilities, based on historical information. If the so enlisted characteristics are present, this would mean that the weak form of the Efficient Market Hypothesis (EMH) is rejected. The results obtained indicate definitely that we have strong evidence for deviation from market efficiency at East-European Financial Markets.

Keywords Financial Markets Efficiency, Long-Range Dependence, Hurst Exponent.

JEL classification: G14

1 Introduction

The current paper investigates the market efficiency of emerging stock exchanges from the East-European region. Seven countries are included in the research – Bulgaria, Croatia, Romania Russia, Serbia, Turkey and Ukraine. Most of the investigated capital markets have history dating back more than a century ago, but after the World War II the markets stopped their functioning and were re-established in the last ten years of the 20th century, only the Istanbul Stock Exchange is functioning since 1986. The markets are still young and in this respect it is reasonable to ask whether they have reached the stage of efficient functioning. On one hand the stock market efficiency is an important feature of a well-organized market economy. On the other hand if inefficiency is present, the market would provide new opportunities to the investors. Besides, market efficiency is of great importance to the portfolio and risk management since the asset pricing models as well as the derivative pricing models assume presence of certain statistical characteristics of the data that are closely related to the efficient functioning of the market.

* Corresponding Author. (✉)
E-mail: i_ivanov@feb.uni-sofia.bg (I. Ivanov)

I. Ivanov
Professor, Dr. Hab., Department of Statistics and Econometrics, Faculty of Economics and Business Administration, Sofia University.

B. Lomev
PhD, Department of Statistics and Econometrics, Faculty of Economics and Business Administration, Sofia University.

B. Bogdanova
Ph.D. Candidate, Department of Statistics and Econometrics, Faculty of Economics and Business Administration, Sofia University.

The East-European stock exchanges have already been investigated to some extent. Cajueiro and Tabak [1] investigate the short and long-run predictability of the major stock indices of nine European transition stock markets including the market of Bulgaria, Croatia, Russia, and Ukraine. The major findings are that the indices are characterized by long-range dependence. Anyway for the Ukrainian Stock Exchange is proven convergence to efficiency and the random walk hypothesis is accepted for the stock indices of Bulgaria and Ukraine. Angelov [2] investigates the Bulgarian Stock Exchange for the period Oct-2000 – Nov-2006. An interesting result is that the market is closer to efficient functioning in the first sub-period of the sample (Oct-2000 – Oct-2003) than in the second one (Oct-2003 – Nov-2006). Also Lomev and co-writers [3-5] investigate the Bulgarian Stock Exchange and find indications for market inefficiency. Balaban, Kandemir, and Kunter [6] analyze the Turkish capital market for the period Jan-1989 – Jul-1995 and conclude that the aggregate stock prices do not fully reflect publicly available information. Batroshina [7] confirms that the Ukrainian stock market as a whole is efficient in the sense of the weak form of EMH. Pele and Voineagu [8] analyze the BET Index for the period Sep-1997 – Sep-2007 and conclude that the EMH for the Romanian capital market could not be rejected but Moldovan [9] demonstrates the absence of weak form market efficiency for the same market. Cvetkovic [10] investigates the market efficiency of the Belgrade Stock exchange and rejects the weak form market efficiency. Heininen and Puttonen [11] study the major stock indices of twelve Central and Eastern European stock exchanges including the stock exchanges of Bulgaria, Croatia, Romania, and Russia for the period Jan-1997 – Feb-2008. The main conclusions are that there is an evidence for the predictability of the stock returns in Croatia, Romania and Russia but during the sample period in all of the examined countries the weak form efficiency has increased steadily. Lomev, Ivanov, and Bogdanova [12] investigate the major stock indices of Bulgaria, Croatia, Romania, Russia, Serbia, Turkey, and Ukraine in terms of LRD and conclude that except for ISE100, all of the examined indices are long-range dependent.

Other similar researches dealing with some of the East-European stock exchanges are available. The major issue is that on one hand these researches are performed over different periods of time and on the other hand, the applied research methods differ significantly. Thus for the same markets contradictory results have been documented. From this perspective, the goal of the current investigation is to study the seven capital markets over a long period of time applying classical as well as new methods in order to assure robustness of the results to the research tools as well as to enable comparison of the seven markets.

The paper is structured as follows. The second part of the paper presents a brief overview of the concept of market efficiency. The third part describes the methodologies that are utilized for the detection of market inefficiencies. The fourth part presents the dataset and in the fifth part are summarized the empirical results. The sixth part concludes the paper.

2 Market efficiency

According to Fama [13] an efficient security market is one in which prices always fully reflect all the available information. Roberts [14] introduces the classic taxonomy of information sets which is applied by Fama [13] for the definition of the weak, semi-strong and strong form of the EMH.

The weak form of the market efficiency implies that security prices reflect all the available historical information i.e. the information set consists of past prices and volumes. The weak form of EMH manifested itself in its restricted version according to which the successive logarithmic returns are assumed to be independent and identically (normally) distributed. This means that the security prices follow a random walk process. In this respect it is reasonable to examine whether price series deviate from the random walk process in order to conclude or reject weak form market efficiency. Although in the last few decades numerous researches have utilized random walk tests, the topic is still of present interest since a lot of contemporary researches are engaged with it. For example Koustas, Lamarche, and Serletis [15] re-examines the validity of the RWH to the US stock market. Parto and Wu [16] reject the RWH for many developed stock markets. Mateus [17] concludes predictability of stock returns for 13 EU accession countries. Henry [18] investigates the German, Japanese, Taiwanese, and South Korean stock exchanges in terms of long-range dependence. Oskoee, Li, and Shamsavari [19] conclude that for the Iran stock market is valid the RWH and hence it is weak form efficient.

The current paper is also testing the validity of the RWH for the seven East-European markets. In particular, the investigated time series are tested for presence of long-range dependence (LRD), persistency, and possibility for forecasting on the basis of past information on prices.

Since the semi-strong and strong form of EMH are out of the scope of the current paper, it is just briefly mentioned that the semi-strong form of EMH implies that prices incorporate all the publicly available information which includes historical information, annual reports, announcements, etc. The strong form suggests that prices fully reflect all the available information – public and private.

3 Deviations from random walk

3.1 Fractal Processes and Persistency

Bachelier [20] introduced for the first time the idea that security prices follow a random walk process. Brownian motion is the random walk limit and Bachelier found that it is a proper model for stock price fluctuations. By definition the continuous stochastic process $Y(t)$ is said to be Brownian motion if for any time change Δt, the process defined as $\Delta Y(t) = Y(t + \Delta t) - Y(t)$ is Gaussian, with zero mean, and variance proportional to Δt, and the successive changes $\Delta Y(t)$ and $\Delta Y(t + \Delta t)$ are uncorrelated. A generalization of the Brownian motion is proposed by Mandelbrot [21, 22]. He defines a fractal process $\{y(t)\}$ by the introduction of an additional parameter – the Hurst exponent $H, H \in (0,1)$. In the generalized case its variance is proportional to Δt^{2H} and it is easily seen that for $H = 1/2$ the process is Brownian motion. The correlation coefficient between successive changes in the fractal process $\{y(t)\}$ is not dependant on the time change Δt and is defined as follows:

$$2^{2H} = 2 + 2\rho \quad (-1/2 < \rho < 1)$$

With regard of the latter formula, the correlation of a fractal process with $H > 1/2$ is positive and than the process is said to be persistent. This means that positive values are likely to be followed by positive values and negative values are likely to be followed by negative values. When $H < 1/2$, then the investigated process is anti-persistent which means that the probability of positive values to be followed by negative values is greater than 0.5 and vice versa. The presence of persistency is a kind of deviation from the random walk process. Numerous tests are developed to estimate the value of the Hurst exponent H, amongst them is the R/Sn method, which is the oldest and the best known technique.

The R/Sn method is initially developed by Hurst [23] and is later improved by Mandelbrot [21, 22]. The R/Sn method is based on the self-similar property of fractal processes. The essence of the self-similarity is that if $\{y(t)\}$ is a fractal process with Hurst exponent H, then for any constant $c > 0$ the corresponding rescaled process is statistically the same as $\{y(t)\}$. I.e. the fractal process $\{y(t)\}$ and any other fractal process $\{y_c(t)\} = \left\{\frac{1}{c^H} y(ct)\right\}$ are statistically equivalent. The range of the fractal process $\{y(t)\}$, corresponding to the interval Δt is denoted by $r(\Delta t)$ and is expressed as follows:

$$r(\Delta t) = \max(y(t)) - \min(y(t)),$$

where $t \in \Delta t$. $R(t)$ is the mean of all ranges $r(\Delta t)$ defined for consecutive non-overlapping intervals of length Δt. Due to self-similarity, the expected range of the fractional process $\{y(t)\}$ and the expected range of any fractional process $\{y_c(t)\}$ over all of the intervals will be the same. In particular the range of $\{y_c(t)\}$ over an interval of length Δt is to be c^{-H} times the range of $\{y(t)\}$ over an interval of length $\frac{\Delta t}{c}$. Substituting $\frac{\Delta t}{c}$ with Δt the following formula is derived:

$$R(\Delta t) = c\Delta t^H$$

The latter expression holds when the time periods are long enough since for short periods the number of observations required for the range calculation would be insufficient. As a result, the range would be underestimated and $R(\Delta t)$ would grow faster than $c\Delta t^H$ which leads to systematical overestimation of H. One of the approaches diminishing the short interval influences is rescaling the range by dividing it by the standard deviation $S(\Delta t)$ of $y(t)$ corresponding to the interval Δt, i.e. calculate $R / S(\Delta t)$.

Introducing the discrete time $t = \pm 1, \pm 2, \pm 3 \pm \cdots$ and taking the logarithm on both sides of the latter expression H is estimated by linear regression:

$$\log\left(R / S(t)\right) = \log c + H \log t$$

3.2 Long-Range Dependence and FARIMA

The LRD processes, called also long memory processes exhibit correlations that do not decay at a sufficiently fast rate which formally is expressed via:

$$\sum_{k=-\infty}^{\infty} \rho(k) = \infty \text{ or } \rho(k) \approx C_\rho k^{-\alpha}, \ \alpha \in (0,1)$$

The LRD is measured by the exponent of Hurst and LRD is present if $H > 1/2$. The LRD processes cannot be modeled properly with the classical ARIMA (p,d,q) processes which is due to the very slow decay of the autocorrelation function. In the early 1980s, Granger and Joyeux [24] and Hosking [25] introduced fractional ARIMA models (FARIMA) in order to model the LRD effects. Distinctive characteristic of the FARIMA models is the fractional differentiation, i.e. d is real. The fractional differing operator is derived through binomial expansion:

$$\nabla^d = (1-B)^d = \sum_{k=0}^{d} \binom{d}{k} (-1)^k B^k$$

where $\binom{d}{k} = \dfrac{\Gamma(d+1)}{\Gamma(k+1)\Gamma(d-k+1)}$.

The general form of FARIMA(p,d,q) is expressed as

$$\Phi(B)\nabla^d X_t = \Theta(B) Z_t,$$

where $\Phi(B) = 1 - \phi_1 B - \phi_2 B^2 - \ldots - \phi_p B^p$, $\Theta(B) = 1 + \theta_1 B + \theta_2 B^2 + \ldots + \theta_q B^q$, B is the backshift operator and Z_t is discrete white noise.

If the fractional parameter of FARIMA is positive, i.e. $d > 0$ then LRD is present. The relation of d and the Hurst exponent H is $d = H - 1/2$.

Different approaches are developed for the estimation of the long memory parameter, most of which are spectral based or apply time domain techniques, but there are also methods based on the wavelet transform. In the current paper two approaches are applied for the estimation of the long memory parameter – the first one is the well-know Whittle method, which is based on spectral analysis. The second approach utilizes wavelet based weighted regression. A brief discussion on both of the methods is provided below.

3.2.1 Whittle Maximum Likelihood Estimator

A theoretically appealing from statistical inference standpoint maximum likelihood estimator (MLE) is developed by Sowell [26] for the general class of FARIMA models, which involves simulations estimation of both long- and short-memory parameters. The major disadvantage of the exact MLE is that it is computationally exhaustive for large data sets and thus for practical purposes is used an approximated MLE. The Whittle approximated MLE is generalized for fractionally integrated processes [27]. According to Whittle approach the ratio of the normalized periodogram $\widetilde{I}_n(\omega)$ and the power transfer function $g(\omega, \beta)$ are minimized in respect of β, i.e.:

$$\hat{\sigma}_n^2 = \frac{2\pi}{n} \sum_j \frac{\widetilde{I}_n(\omega_j)}{g(\omega_j, \beta)},$$

where $\omega_j = 2\pi j / n \in (-\pi, \pi)$ are Furrier frequencies,

$$\widetilde{I}_n(\omega) = \left(\sum_{t=1}^{n} X_t^2\right)^{-1} \left|\sum_{t=1}^{n} X_t e^{-i\omega t}\right|^2, \quad -\pi \le \omega \le \pi,$$

$$g(\omega, \beta) = \left|\frac{\Theta\left(e^{-i\omega}, \beta\right)}{\Theta\left(e^{-i\omega}, \beta\right)\left(1 - e^{-i\omega}\right)^{d(\beta)}}\right|^2, \quad -\pi \le \omega \le \pi \text{, and}$$

$$\beta = \left(\phi_1, \phi_2, \ldots, \phi_p, \theta_1, \theta_2, \ldots, \theta_q, d\right),$$

which is an array of unknown parameters of the FARIMA(p,d,q) process.

3.2.2 Wavelet-based Weighted Least Squares Estimator

The following paragraph is briefly mentioned the idea behind the discrete wavelet transform (DWT). Generally the DWT of the process $\{X(t)\}$ results in the sequence of wavelet coefficients (called also details) $\{w_{j,k}\}$, for $j,k \in Z$, which are derived as follows:

$$w_{j,k} = \int_R X(t)\psi_{j,k}(t)dt,$$

where

$$\psi_{j,k}(t) = \frac{1}{2^{j/2}}\psi(2^{-j}t - k)$$

is the dilated by factor 2^j and translated by $2^j k$ version of the mother wavelet $\psi(t)$, where 2^j is called scale, j is called octave with possible values $j = 1,2,...,J$, where $J = \log_2 N$, N is the number of the observations available on the investigated process. The mother wavelet $\psi(t)$ is a function of time, satisfying the admissibility condition, defined as:

$$C_\psi = \int_0^\infty \frac{|\Psi(\nu)|}{\nu} d\nu < \infty,$$

where by $\Psi(\nu)$ is denoted the Fourier transform of $\psi(t)$, and normalized frequencies are used. A secondary condition imposed on the mother wavelet is unit energy, which is formally defined as:

$$\int_R |\psi(t)|^2 dt = 1.$$

The interested reader might find a detailed discussion on the topic in [28].

In [29] is available the proof of the fact that for LRD processes the variance of the wavelet coefficients $\{w_{j,k}\}$, corresponding to scale 2^j might be expressed as follows:

$$Ew_{j,k}^2 \sim c_g 2^{j\gamma} \int_R |\nu|^{-\gamma} |\Psi(\nu)|^2 d\nu ,$$

when $j \to +\infty$ and where $d = \frac{\gamma}{2}$. The latter expression together with the admissibility condition gives as a result the following representation:

$$Ew_{j,k}^2 \sim K 2^{j\gamma} \text{, when } j \to +\infty ,$$

where K is a finite constant. After taking logarithm on both sides of the last expression the following result is obtained:

$$\log_2\left(Ew_{j,\cdot}^2\right) \sim C + \gamma j .$$

Based on the last expression, an estimate of γ might be obtained through linear regression, where the explanatory variable is the octave $j \in [j_1, j_2]$; by $[j_1, j_2]$ is denoted the interval where LRD is present. The mean standard error of the estimate $\hat{\gamma}$ is significantly reduced if weighted least squares regression (WLS) is utilized compared to ordinary least squares regression. In [29] is proposed the following WLS estimator:

$$\hat{\gamma} = \frac{\sum_{j=j_1}^{j_2} y_j (Sj - S_1)/\sigma_j^2}{SS_2 - S_1^2} \equiv \sum_{j=j_1}^{j_2} a_i y_j ,$$

where $y_j = \log_2\left(\frac{1}{n_j}\sum_{k=1}^{n_j} |w_{j,k}|^2\right) - g(j)$, $g(j)$ is a corrective term, $n_j = N/2^j$, N is the number of observation. With σ_j^2 is denoted the variance of y_j and the weights S, S_1, S_2 are expressed as $S = \sum_{j=j_1}^{j_2} 1/\sigma_j^2$, $S_1 = \sum_{j=j_1}^{j_2} j/\sigma_j^2$, $S_2 = \sum_{j=j_1}^{j_2} j^2/\sigma_j^2$.

The current investigation utilizes the so described WLS estimator in order to obtain an estimate of the LRD parameter.

3.3 Possibility for Forecasting Based on the Historical Information

According the Random walk hypothesis the best forecast one step ahead is the previous value of the prices and the sign of the increments is unpredictable – we have 50% chance to face increase and 50% to have decrease.

In this work we use two approaches to test the possibility for forecasting. The first approach is direct implementation of the persistence notion. We measure the probability of positive increments to be followed by positive and negative increments by negative thus using the last increment sign as a forecast for the next innovation sign.

The second approach is based on Back Propagation Neural Networks as a method for increments sign forecasting. Application of Back Propagation Neural Networks for stocks prices prediction is a frequently used approach [30]. In this work we are focused on principal possibility to forecast the sign of the future increments one step ahead. A wide range of neural networks structures is implemented with dimension of the hidden layer from 1 to 10 and input size from one week to two months. The data are divided in two thirds to one third sets for training and testing. The probability for correct sign forecasting is measured on the test set.

4 The data

The current paper investigates the major stock indices of seven East-European stock markets in respect of persistency presence, LRD presence, and possibility for forecasting on the basis of historical information. Table 1 presents the details on the indices utilized in the investigation.

Table 1 Summary of the data

Index	Country	Number of stocks	Period	Data Source
BELEX15	Serbia	15	Oct 2005 – Aug 2010	http://www.belex.rs
BET	Romania	10	Oct 2000 – Aug 2010	http://www.bvb.ro
CROBEX	Croatia	25	Oct 2000 – Aug 2010	http://zse.hr
ISE100	Turkey	100	Oct 2000 – Aug 2010	http://www.ise.org
PFTS	Ukraine	20	Oct 2001 – Aug 2010	http://www.pfts.com
RTSI	Russia	50	Oct 2000 – Aug 2010	http://www.rts.ru
SOFIX	Bulgaria	15	Oct 2000 – Aug 2010	http://www.bse-sofia.bg; http://www.investor.bg

The time span of the investigation is from 20-Oct-2000 to 31-Aug-2010. As a start date of the analyzed period is chosen SOFIX basis date. BELEX15 and PFTS are exceptions, since the basis date of BELEX15 is 01-Oct-2005. PFTS is registered in 1997, but it is the year of 2001 when publicly available register with historical information on the index is created.

The raw data consist of the daily closing values of the investigated indices. The actual data analyzed are the logarithmic returns derived from the raw data as follows:

$$R_t = \ln \frac{P_t}{P_{t-1}}, \quad t = 2,3,\ldots,N,$$

where the index value in moment t is denoted by P_t.

5 Empirical results

5.1 Hurst exponent

The Hurst exponent H is estimated by the R/Sn method for all of the investigated indices and the results are summarized in table 2.

Table 2 Estimates of the Hurst exponent, the R/Sn method

BELEX15	BET	CROBEX	ISE100	PFTS	RTSI	SOFIX
H=0.6315	H=0.5673	H=0.5703	H=0.5287	H=0.5981	H=0.5550	H=0.5941

The results confirm that all of the investigated indices are persistent, i.e. the probability of positive values being followed by positive values and negative values being followed by negative values is greater than 0.5000, which is an indication of market imperfectness.

5.2 LRD

The long-memory parameter is estimated for all of indices of interest by the Whittle MLE and by the wavelet based WLE and the results are presented in tables 3 and 4 respectively:

Table 3 Estimates of the fractional differencing parameter, the Whittle method

BELEX15	BET	CROBEX	ISE100	PFTS	RTSI	SOFIX
			FARIMA(0,d,0)			
d=0.2689	d=0.0727	d=0.0555	d=0.0079	d=0.0750	d=0.0599	d=0.0463
			FARIMA(1,d,0)			
d=0.1504	d=0.0274	d=0.0631	d=-0.0116	d=0.1498	d=0.0149	d=0.1312
			FARIMA(0,d,1)			
d=0.0875	d=0.0285	d=0.0616	d=-0.0138	d=0.1380	d=0.0076	d=0.1208

Table 4 Estimates of the fractional differencing parameter, the wavelet-based WLS method

BELEX15	BET	CROBEX	ISE100	PFTS	RTSI	SOFIX
d=0.2185	d=0.0512	d=0.0421	d=0.0030	d=0.0566	d=0.0569	d=0.0503

The results obtained clearly state that for all of the examined indices but ISE100 LRD is present. In the case of ISE100 additional test is required in order to draw conclusion.

5.3 Possibility for Forecasting

5.3.1 Persistence

The empirical probabilities positive increments to be followed by positive and negative increments by negative for the studied indexes is presented on the Table 5.

Table 5 Probability of positive increments to be followed by positive increments and negative increments to be followed by negative increments

BELEX15	BET	CROBEX	ISE100	PFTS	RTSI	SOFIX
61.15%	54.88%	52.18%	50.49%	52.88%	52.41%	55.73%

We see that except for ISE100 for all other indexes we have probabilities substantially higher than 50%. These results are in accordance with the previous findings for the Hurst exponent and the coefficient of the Long-range dependence.

5.3.2 Prediction with Neural Networks

Following the aim to investigate the principal possibility for increments sign forecasting we present in Table 6 only the higher results obtained.

Table 6 Principal possibility for forecasting increments sign by neural network

BELEX15	BET	CROBEX	ISE100	PFTS	RTSI	SOFIX
60.58%	56.13%	54.21%	54.10%	55.91%	54.47%	54.72%

Again we have probabilities substantially higher than 50% and even for the ISE100 index the result does not differ from the results for the other indexes.

6 Conclusions

For all of the examined indices there is clearly an indication for deviation from Random walk hypothesis and thus the studied markets manifest inefficiency. For BELEX15 the value of the Hurst exponent is significantly higher than for the rest of the indices. The Hurst exponent for ISE100 has the lowest value, but it is still greater than 0.50. Both of the utilized approaches for the estimation of LRD parameter confirm that for all the indices but ISE100 LRD is present. Additional tests are required for ISE100 in order to claim with certainty any result. The tests performed regarding the possibility for forecasting definitely confirm the inefficiency of the investigated emerging markets.

7 Acknowledgements

This research was supported in part by a Sofia University "St. Kl. Ohridski" research project for the 2012 year.

References

1. Cajueiro, D., Tabak, B., (2006). Testing for predictability in equity returns for European transition markets. Economic Systems, 30, 56-78.
2. Angelov, N., (2009). Testing the weak-form efficiency of the Bulgarian stock market. Bulgarian National Bank: DP/71/2009.
3. Lomev, B., Ivanov, I., Bogdanova, B., (2009). Investigation of market efficiency of stock markets of Bulgaria and Russia through frequency domain methods. Sixth Scientific Conference "Management and Entrepreneurship", Plovdiv, Bulgaria, 95-100.
4. Lomev, B., Ivanov I., Tuyova, E., (2008). Long range dependence in SOFIX index of the Bulgarian stock exchange. Economics and Management, University of Ruse, Bulgaria, 47, 6.1, 29-32.
5. Lomev, B., Ivanov, I., (2009). Self-similarity, heavy tails and long-range dependence as measures for financial market inefficiency-the case of Bulgaria. The 9th Hellenic European Research on Computer Mathematics and its Applications Conference, Athens, (a conference talk).
6. Balaban, E., Kandemir, H., Kunter K., (1996). Stock market efficiency in a developing economy: evidence from Turkey. The Central Bank of Republic of Turkey: DP/ 9612/1996.
7. Batroshina, A. , (2006). The efficiency of Ukraine's Stock Market. UDC 336.761, 103-122.
8. Pele, D., Voineagu, V., (2008). Testing market efficiency via decomposition of stock return. Application to Romanian capital market. Romanian Journal of Economic Forecasting – 3/2008, 63-79.
9. Moldovan, D., (2010). Testing the efficiency of the Romanian stock market. Development, Energy, Environment, Economics, 378-381.
10. Cvetkovic, T., (2007). The market efficiency of the stock market in Serbia. http://edissertations.nottingham.ac.uk/919/1/07MAlixtc4.pdf.
11. Heininen, P., Puttonen, V. Stock market efficiency in transition economies through the lens of calendar anomalies. http://www.hse.ru/data/090/182/1235/Heininen_Puttonen_paper.pdf.
12. Lomev, B., Ivanov, I., Bogdanova, B., (2010). Investigation of market efficiency of emerging stock markets from the East-European region through discrete wavelet transform. Economics and Management ,University of Ruse, 49, 5.1, 194-198.
13. Fama, E. F., (1970). Efficient capital markets: a review of theory and empirical work. Journal of Finance, 25(2), 383–417.
14. Roberts, H., (1967). Statistical versus clinical prediction of the stock market. Unpublished manuscript.
15. Koustas, Z., Lamarche, J.F., Serletis, A., (2008). Threshold random walks in the US stock markets. Chaos, Solutions & Fractals. 37, 43-48.
16. Parto, D.K., Wu, Y., (2004). Predictability of short-horizon returns in international equity markets. Journal of Empirical Finance, 11, 553-584.
17. Mateus, T., (2004). The risk and predictability of equity returns of the EU accession countries. Emerging Markets Review, 5, 241-266.
18. Henry, O.T., (2002). Long memory in stock returns-some international evidence. Applied Financial Economics, 12, 725-729.
19. Oskoee, S. A. P., Li, H., Shamsavari, A. (2010). The Random walk hypothesis in emerging stock market. International Research Journal of Finance and Economics, 50, 51-61.
20. Bachelier, L., (1964). Theory of Speculation. In Cootner, ed. The random character of stock market prices, MIT Press, MA.
21. Mandelbrot, B. B., Wallis, J., (1969). Some long-run properties of geophysical records. Water resources Res. 5, 321-340.
22. Mandelbrot, B. B., Van Ness, J., (1968). Fractional Brownian motions, fractional noises and applications. SIAM Rev. 10, 422-437.
23. Hurst, H. E., (1951). Long-term storage capacity of reservoirs. Trans. Am. Soc. Civil Eng. 5, Part 1, 519-577.

24. Granger, C. W., Joyeux, R., (1980). An introduction to long-memory time series models and fractional differencing. J. Time Series Analysis, 1, 15-29.
25. Hosking, J. R. M., (1981). Fractional differencing. Biometrika, 68, 165-176.
26. Sowell, F. B., (1992b). Modelling long run behaviour with the fractional ARIMA model. Journal of Monetary Economics, 29, 277-302.
27. Kokoszka, P. S., Taqqu, M. S., (1996). Parameter Estimation for Infinite Variance Fractional ARIMA. Ann.Statist, 24, 1880-1913.
28. Gençay, R., Selçuk, F., Whitcher, B., (2002). An introduction to wavelets and other filtering methods in finance and economics. Academic Press, New York.
29. Abry, P., Flandrin, P., Taqqu, M. S., Veitch, D., (2003). Self-similarity and long-range dependence through the wavelet lens. Theory and Applications of Long-range Dependence, Birkhäuser, 527-556.
30. Azzof, E. M., (1994). Neural network time series forecasting of financial markets. John Wiley, New York.