TESTING THE LONG RANGE-DEPENDENCE FOR THE CENTRAL EASTERN EUROPEAN AND THE BALKANS STOCK MARKETS

Pece Andreea Maria, Ludusan (Corovei) Emilia Anuta, Mutu Simona
Ph.D. student, Faculty of Economics and Business Administration/Department of Finance, Babeş-Bolyai University Cluj-Napoca, Romania
andreeapece@yahoo.com
Ph.D. student, Faculty of Economics and Business Administration/Department of Finance, Babeş-Bolyai University Cluj-Napoca, Romania
emilia_lud@yahoo.com
Ph.D., Teaching Assistant, Faculty of Economics and Business Administration/Department of Finance, Babeş-Bolyai University Cluj-Napoca, Romania
simona.mutu@ubbcluj.ro

Abstract: *In this study we tested the existence of long memory in the return series for major Central Eastern European and Balkans stock markets, using the following statistical methods: Hurst Exponent, GPH method, Andrews and Guggenberger method, Reisen method, Willinger, Taqqu and Teverovsky method and ARFIMA model. The results obtained are mixed. The Hurst Exponent showed the existence of long memory in all indices, except PX. After applying the GPH method, the results showed that BET, ATHEX, SOFIX and CROBEX have a predictable behavior. The ARFIMA model results support the existence of long memory for BUX, SAX and BELEX. The predictable behavior of index returns may suggest that the CEE and Balkans stock markets are not weak form efficient.*

Keywords: *emerging markets, long memory, market efficiency, ARFIMA model*

JEL Classification: *C14, C58, G14*

1. Introduction

The efficient market hypothesis has major implications for the capital markets, investors behavior and trading strategies. According to Fama (1965) the random walk hypothesis implies that price changes do not have memory, which means that the past cannot be used to predict the future. For this reason, is essential to identify the presence of long memory in index returns, which is manifested through the existence of correlations for high lags. In a case of a shock on the capital market, it will not be assimilated quickly in the course and will pass a longer period of time to reach the equilibrium, which will lead to a higher risk on the market.
In the case that the return series have a long memory, it means that the returns are not independent. In this conditions, the efficient market hypothesis in weak-form is not valid, the return series do not follow a random walk process. The indices have a predictable behavior, which can offer the investors the opportunity to predict the future evolution of index courses using past information for the market and to obtain abnormal profits.
There is a large literature regarding the existence of long memory on the capital markets. A number of studies are carried out for the emerging markets of Central and Eastern Europe. Necula C. and Radu A. (2012) conducted a survey in which

they took into consideration the capital markets from Romania, Hungary, the Czeck Republic, Poland, Bulgaria, Slovenia, Slovakia and Croatia. Using non-parametric methods (R/S statistic and GPH method) and ARFIMA-FIGARCH models, the authors concluded that all markets surveyed present long memory in returns, except Slovakia. In another study made by Festic M. et al. (2012) for the Hungarian and Croatian capital markets are used Lo's (1991) modified rescaled range (R/S) test and the wavelet ordinary least squares (WOLS) estimator of Jensen (1999). The R/S test results indicated the possible presence of long memory in Croatia, while there is no evidence against the null hypothesis of long memory in Hungary. The WOLS estimator showed the existence of long memory for CROBEX, while on the other hand, there is no long memory for BUX. However, it is found that there is long memory for some stocks in its composition. Moreover, Kasman S. et al (2009) has tested the existence of long memory for Czech Republic, Hungary, Poland and Slovakia using a semi-parametric method of Geweke Porter Hudak and the parametric method of Sowell. They concluded that all the capital markets analyzed present long memory, except Poland. There are also studies for both long memory in returns and volatility. Kasman A. and Torun E. (2007) examined the existence of long memory for the Turkish capital market during 1988-2007. They used ARFIMA, GARCH, IGARCH, FIGARCH and ARFIMA-FIGARCH models. In order to test the existence of dual long memory, the authors estimated ARFIMA-FIGARCH models, both for normal distributions, and for Student distributions. Long memory coefficients are significant, both for mean and variance, thus showing the presence of dual long memory for Turkish capital market. They found that the models performance that used Student distribution is superior to those models that used normal distribution. Another research for Turkey was conducted by Korkmaz T. et al (2009), taking into account the period 1988-2008. Using the ICSS method proposed by Inclan and Tiao (1994), they identified four structural breaks. The ARFIMA-FIGARCH models signaled the existence of long memory in volatility. Dajcman S. (2012) investigates the long range dependence for eight capital markets in Europe. Unlike other studies, in order to detect the long memory, the author use a dinamic approach. In this sense, the author uses a rolling window method to show that the long memory parameter is variable in time. The results have pointed out that the increase of the long memory parameter coincided with the major financial market disruptions which characterized the capital markets during the period October 1999 – April 2011.

Other studies were developed for Asian capital markets. Maheshchandra J.P. (2012) has analyzed the Indian capital market using daily returns of BSE and NSE during 2008-2011. In order to detect the existence of long memory in volatility are estimated several models: ARMA-GARCH, ARMA-IGARCH, ARMA-FIGARCH. The results highlighted the presence of long memory in the conditional variance. Tan S.H. et al (2009) has analyzed the Malaysian capital market during 1985-2009, taking into account both growth and recession periods, finding the existence of long memory and the possibility of forecasts the courses, especially before the crisis of 1997. Gabjinova et al. (2008) has analyzed two indices: KOSPI1 (Korea 1995-2002) and KOSDAQ1 (Korea, 1997-2004) and six exchange rates EURO, GBP(UK), JPY (Japonia), SGD (Singapore), CHF (Suedia) and AUD (Australia). The possible existence of long memory has been investigated using DTA method (Detrended Fluctuation Analysis) and some models: AR(1), GARCH(1,1) and FIGARCH. As a result, it is concluded that there is insignificant long memory in returns and only the volatility is characterized by long memory.

Further, there are studies for stock markets in Africa. Onour I. (2010) has realized a study for Tunisia, Egypt and Morocco during the period 2002-2006. Using the GPH method and ARFIMA model, it was concluded that this capital markets have short memory. Following the results of FIGARCH model, it was found that the shocks are not likely to persist for long periods on the markets. Boubaker A. and Makram B. (2012) explore the presence of long memory for capital markets in North Africa (Morocco, Egypt and Tunisia), finding that the return distributions can be modeled more adequate through the alpha distribution than by normal distribution. As a result of ARFIMA and FIGARCH models estimations, it was concluded that there is long memory both in returns and volatility.
The South American capital markets have been studied by Assaf A. and Cavalcante J. (2005) which used Lo's (1991) modified rescaled range (R/S) test, V/S statistic proposed by Giraitis et al. (2003), Robinson method and FIGARCH model and signaled the presence of long memory in volatility and a low evidence in returns.
Also, there are studies for groups of emerging and developed countries. Bhattacharya S. N. and Bhattacharya M. (2012) have studied the long memory for ten emerging markets (Hungary, China, Brazil, Chile, Malaysia, Korea, Russia, Mexico, India and Taiwan) during 2005-2011, using the following methods: Hurst-Mandelbrot's Classical R/S statistic, Lo's statistic, GPH method and GPH method modified by Robinson (1995) applied both for absolute and squared returns. The conclusions were that there is a long memory for all countries surveyed, with the exception of Malaysia (the existence of long memory was rejected by Lo's statistical method and by the Robinson method for $T^{0.65}$). Bentes S. and Mendes da Cruz (2009) have analyzed the G7 capital markets from 1999 to 2009. The results have shown the existence of long memory in volatility in Germany, Italy and France, while in Japan it appears to be the least visible and most low intensity. Consider thin trading that characterizes the emerging capital markets, Limam I. (2003) examine the presence of long memory for fourteen capital markets (United Kingdom, Japan, USA, Brazil, India, Mexico and the eight Arab countries) with different degrees of development. By using the GPH and MLE methods and ARFIMA model, the author has detected the existence of short memory for developed capital markets, while the long memory is associated with emerging markets.
The objective of this study is to examine the existence of long memory in returns for nine indices in CEE and the Balkans emerging stock markets: BET (Romania), BUX (Hungary), SAX (Slovakia), PX (Czech Republic), PFTS (Ukraine), BELEX (Serbia), SOFIX (Bulgaria), ATHEX (Greece) and CROBEX (Croatia). The existence of long memory for emerging markets implies that the future evolution of indices is predictable and will influence the investors behavior on these markets. This study comes to rich the financial literature in the field of long memory. Previous studies have focused on the EU emerging markets, but there are quite a few studies that include the Balkans capital markets. Also, in order to check the existence of long memory in return series, this study uses the method proposed by Willinger, Taqqu and Teverovski (1999), that has not been used previously in other research carried out for Balkan markets. The paper is organized as follows. Section 2 presents the empirical methods and models used to identify long memory in return series. Section 3 outlines the characteristics of the sample analyzed. Section 4 provides a synthesis of the results obtained. Section 5 concludes.

2. Methodology

The statistical methods used in this study for the detection of long memory are: Hurst Exponent estimated by R/S statistics, Hurst Exponent determined by the method proposed by Willinger, Taqqu and Teverovski (1999), Geweke Porter Hudak (1983) method, Andrews and Guggenberger (2003) method, Reisen method (1994) and ARFIMA (1980, 1981) models. Furthermore, will be presented briefly these methods. The Hurst Exponent is determined through the classical R/S analysis, which because of its simplicity is the most popular method used to detect long memory. Let *X(t)* be the course of a stock market index at time t and R_t the logarithmic return, determined by the equation:

$$R_t = \ln\left(\frac{X_{t+1}}{X_t}\right) \quad (1)$$

The R/S statistic is the range of partial sums of deviations of time series of its mean, rescaled by its standard deviation. It is take into consideration a sample of continuously compounded returns $\{R_1, R_2, ..., R_\tau\}$ and let $\overline{R}_\tau$ denote the sample mean $\frac{1}{\tau}\sum_{t=1}^{\tau} R_\tau$, where τ is the period of time considered. The R/S statistic is given by:

$$(R/S)_\tau = \frac{1}{s_\tau}\left[\max \sum_{t=1}^{\tau}(R_t - \overline{R}_\tau) - \min \sum_{t=1}^{\tau}(R_t - \overline{R}_\tau)\right] \quad (2)$$

where s_τ represents the usual standard deviation estimator. Hurst (1951) has shown that the rescaled range, R/S, for many records in time is described by the following equation $(R/S)_\tau = (\tau/2)^H$ (Cajueiro, D.; Tabak, B., 2004).

Willinger, Taqqu and Teverovsky (1999) proposed a new R/S analysis in determing the long memory, which involves the use of equally weighted returns. It is recommended to use EW series over blocks of size 10 and 20. The authors consider the analysis proosed by Lo accept too easily the null hypothesis of no long-range dependence in the time series. In order to remove the ”extra” short-range dependence and isolating hibriden „pure” long-range dependence effects, the authors proposed partitioning of time series into non-overlapping blocks of size m, e.g. $m = 10,20,50$, and „shuffle” the observations within each block, so that is a random permutation of the time indices. The effect of such a shuffiling experiment is to destroy any particular structure of the autocorrelation function below lag m, but to leave the high lags essentially unchanged (Willinger, Taqqu, Teverovsky, 1999).

In order to estimate the parameter of fractional integration d, can be used both parametric and semi-parametric methods. In this study the parameter d is estimated by the Geweke and Porter Hudak (GPH 1983), which is a semi-parametric method. The GPH method is based upon the estimation of the spectral density function, as follows:

$$\ln\left[I(\lambda_j)\right] = c - d\ln\left[4\sin^2(\lambda_j/2)\right] + \eta_j, \forall j = 1,...,n \quad (3)$$

where: $\lambda_j = 2\pi j / T (j = 1,...,T-1)$ represents the harmonic frequencies and

$$I(\lambda_j) = (1/2\pi T) | \sum_{t=1}^{T} e^{itw} (x_t - \bar{x}) |^2 \quad (4)$$

is the periodagram x_t at these frequencies. Considering the number of observations used in the estimation of the regression is: $n = g(T) = T^{\lambda}$, where $0 < \lambda < 1$ (Kasman, S. et al., 2009). In order to improve the method proposed by Geweke Porter and Hudak (1983), Andrews and Guggenberger (2003) proposed a simple biased-reduced log-periodogram regression estimator, $\hat{d}_r$, of a long parameter, d, that eliminates the first and higher order biases of the GPH (1983) estimator. The bias reduced estimator is the same as the GPH estimator, except that uses additional regressors in the pseudo-regression model that yields the GPH estimator. The reduction in bias is obtained using assumptions on the spectrum only in the neighborhood of the zero frequency. In order to define the biased reduced estimator $\hat{d}_r$, it is consider a semiparametric model for a statioary Gaussian long-memory time series $Y_t : t = 1,...,n$ and the spectral density of the time series is given by $f(\lambda) = |\lambda|^{-2d} g(\lambda)$ (5), where d is a long-memory parameter, $g(.)$ is an even function on $[-\pi, \pi]$ that is continuous at zero with $0 < g(0) < \infty$ and $f(\lambda)$ is an integrable over $(-\pi, \pi)$. The authors use the regressor X_j, as in Robinson (1995a). Because the parameter d, proposed by Geweke and Porter-Hudak (1983) was criticized due to its finite-sample bias, Andrews and Guggenberger (2003) proposed a new bias-reduced log-periodogram estimator $\hat{d}_r$ of the long-memory parameter d. The estimator $\hat{d}_r$ is defined to be the least squares (LS) estimator of the coefficient on $-2\log\lambda_j$, and $\lambda_j^2, \lambda_j^4, ..., \lambda_j^{2r}$, for $j = 1,...,m$, where r is a (fixed) nonnegative integer. The authors take m, such that $m \to \infty$ and $m/n \to 0$ as $n \to \infty$. When r is 0, corresponds to the GPH estimator, $\hat{d}_{GPH}$. The bias-reduced log-periodogram estimator $\hat{d}_r$ is defined by:

$$\hat{d}_r = \left(X^{*'} M_{Q^*} X^* \right)^{-1} X^{*'} M_{Q^*} \log I \quad (6),$$

where $M_{Q^*} = I_m - Q^* (Q^{*'} Q^*) Q^{*'}$, $X^* = X - 1_m \bar{X}, Q^* = Q - 1_m \bar{Q}'$ (7)

represents the deviation from column mean regressor vector X^*, and matrix Q^*, $\log I, X, Q_k$ denote column $m-$vectors whose jth elements are $\log I_j, X_j, Q_{k,j}$ and $Q_{k,j} = \lambda_j^k$, for $j = 1,...,m$ and $k = 1,2,...,$ Q denote the mxr matrix whose k th column is Q_{2k} for $k = 1,...,r$ and 1_m denote a column m vector of ones and $\bar{X} = \frac{1}{m} X' 1_m$, $\bar{Q} = \frac{1}{m} Q^1 1_m$. Andrews and Guggenberger recommend the use of

$r=1, r=2$ in order to get better results for the biased-reduced log-periodogram estimator, $\hat{d}_r$, of a long-memory parameter d (Andrews and Guggenberger, 2003).

Another method used in this study is that proposed by Reisen (1994). Compared to the method proposed by Geweke Porter and Hudak (1983), there is a replacement of the periodogram function by its smoothing version based on the Parzen lag window. The truncation point in the Parzen lag window is denoted by $m=T^{\beta}$, for $0<\beta<1$ (Reisen, et al., 2006).

Taking into account the studies made by Granger and Joyeaux (1980) and Hosking (1981), an ARFIMA process (p, d, q) can be expressed as follows:

$$(1-L)^d \phi(L)x_t = \theta(L)\varepsilon_t \quad \varepsilon_t \sim iid(0,\sigma_\varepsilon^2) \quad (8)$$

where $\phi(L);\theta(L)$ are the autoregressive and moving average polynomials of order *p* and *q*, *L* is lag operator. When parameter d takes value between (-0.5; 0.5) the process is stationary and invertible. For $-0.5<d<0$ the series have long-range negative dependence or anti-persistence. For $0<d<0.5$, the series have long memory, the autocorrelations are positive and decay slowly at a hyperbolic rate. For $d>0.5$, the series is covariance non-stationary, but mean-reverting. If $|d|>1$, the series does not revert to its mean (Kasman, S. et al., 2009).

3. Data

In this study, the sample consists daily returns of the nine stock indices for the CEE and the Balkans countries: Romania (BET), Hungary (BUX), Slovakia (SAX), Czech Republic (PX), Ukraine (PFTS), Serbia (BELEX), Bulgaria (SOFIX), Greece (ATHEX), Croatia (CROBEX), during january 2005-november 2012. The daily logarithmic returns were determined using the following equation: $r_t = \frac{I_t}{I_{t-1}}$ where r_t - index return at time t, I_t, I_{t-1} - represents the index prices at time t and $t-1$. The statistical properties of the indices are provided in Table 1.

Table 1: Descriptive statistics

Index	Mean	Median	Maximum	Minimum	SD	Skewness	Kurtosis	ADF
BET	0.000019	0.00044	0.10564	-0.13116	0.01892	-0,59820	9.27951	-40.566***
BUX	0.000108	0.00032	0.13177	-0.12648	0.01817	-0.07453	8.66019	-33.120***
SAX	-0.00026	0.00000	0.11880	-0.14810	0.01179	-1.63963	29.4877	-46.045***
PX	0.000439	0.00056	0.13856	-0.13466	0.01854	0.11462	11.1150	-24.589***
PFTS	0.000089	0.00085	0.13517	-0.15183	0.01897	-0.31408	11.3544	-32.728***
BELEX	-0.000368	0.00000	4.64918	-4.67282	0.65855	0.00689	20.23822	-18.003***
SOFIX	-0.000322	0.00007	0.07292	-0.11360	0.01383	-0.87362	11.83066	-25.282***
ATHEX	-0.000615	0.00000	0.13431	-0.10214	0.01925	0.04555	6.87466	-42.846***
CROBEX	0.000044	0.00022	0.14779	-0.10763	0.01423	0.04419	16.1925	-22.902***

Source: (Authors' calculations)

Notes: ADF represents Augmented Dickey Fuller (1979) unit root test, H_0: the series has a unit-root, H_1:the series is stationary; the lag length was chosen according to the Schwarz Information Criterion. The critical values for the test with constant are those of MacKinnon (1991): 3.43 (1%), 2.9 (5%), 2.57 (10%), ***denotes significance at 1%.

The mean returns are positive for Romania, Hungary, Czech Republic and Ukraine. In the case of Slovakia, the mean return is negative. The Balkans capital markets registered negative mean returns, except Croatia. All the capital markets manifested a high volatility, in particular Serbia, which registered the highest standard deviation from the mean returns. The skewness coefficients are negative for Romania, Hungary, Slovakia, Ukraine and Bulgaria, which reflects that there is a tail of the returns distribution to the right, compared to the normal distribution, this because of positive extreme values. Similar results for BET index were obtained by Lazar D. et al. (2009). In the case of Czech Republic, Serbia, Greece and Croatia the skewness coefficients are positive, indicating a greater probability of growth, than decline. The results are in accordance with those obtained by Festic et al. (2012) for Hungary. All kurtosis coefficients register values higher than three, meaning that the returns distribution is more sharp than the normal distribution, indicating leptokurtosis. The results of the Jarque Bera test indicate that the normality hypothesis is rejected for all the markets. The results of the ADF test show that all of the return series are stationary. This characteristics are similar to those obtained by Kasman et al. (2009) for Hungary, Czech Republic and Slovakia.

4. Empirical results

In order to detect the long range dependence the Hurst Exponent, GPH method, Andrews and Guggenberger method, Reisen method, Willinger,Taqqu and Teverovski method and ARFIMA model are used. The estimation results are presented in the tables below.

Table 2: Tests for long term persistence using the Hurst Exponent and Reisen method

Index	Hurst Exponent-R/S Statistics	Hurst Exponent-R/S with EW returns	Hurst Exponent-R/S with shuffled returns	Reisen Method $\hat{d}$
BET	0.6049	0.5853	0.6675	0.3019*** (0.0553)
BUX	0.5711	0.5852	0.5852	0.2607*** (0.0431)
SAX	0.5967	0.6353	0.5904	0.1729*** (0.0568)
PX	0.4800	0.6314	0.5454	0.3448*** (0.0341)
PFTS	0.6668	0.6568	0.6881	0.2010*** (0.0525)
BELEX	0.5511	0.5952	0.6019	0.2422*** (0.0441)
SOFIX	0.7180	0.6390	0.6796	0.2421 (0.5980)
ATHEX	0.5941	0.5759	0.6283	0.4153*** (0.0333)
CROBEX	0.6624	0.6113	0.6260	0.2884*** (0.0473)

Source: (authors' calculations)

Notes:() standard deviation in parenthesis; EW-equally weighted ***,**,* Significant at 1%, 5%, 10% level, respectively.

The Hurst Exponent estimated by R/S analysis, registered values higher than 0.5, indicating the presence of long memory for all the capital markets, except Czech Republic. The return series present long term dependencies and have a predictable behavior. For Czech Republic, the Hurst Exponent is less than 0.5, showing an anti-persistent behavior. In the case of R/S analysis with equally weighted returns, all Hurst Exponents have values higher than 0.5, indicating the existence of long memory for all indices. Also, it has been calculated a Hurst Exponent using the R/S analysis with shuffled returns. In the table above, it can be seen that all indices register values between 0.5 and 1, which indicate a persistent long-term dependence. The results of Reisen method detect the existence of long memory for all indices, except SOFIX.

Table 3: Estimation of long memory parameter d using GPH (1983) and Andrews and Guggenberger (2003) methods

Index	$\hat{d}_{GPH}\,(r=0)$	$\hat{d}_1\,(r=1)$	$\hat{d}_2\,(r=2)$
BET	0.2241** (0.1115)	0.1934 (0.1847)	0.4989** (0.2517)
BUX	0.0853 (0.1136)	0.1475 (0.1847)	0.2170 (0.2517)
SAX	0.2019 (0.1528)	-0.0433 (0.1847)	0.2231 (0.2517)
PX	0.0518 (0.1319)	0.1476 (0.1847)	-0.1288 (0.2517)
PFTS	0.1618 (0.1105)	0.1450 (0.1847)	0.2864 (0.2517)
BELEX	-0.2894*** (0.1027)	0.1206 (0.1905)	0.2778 (0.2605)
SOFIX	0.2878*** (0.0824)	0.3813** (0.1847)	0.3578 (0.2517)
ATHEX	0.1683* (0.0964)	0.2234 (0.1820)	0.3389 (0.2477)
CROBEX	0.2214** (0.0919)	0.3231* (0.1847)	0.3123 (0.2517)

Source: (Authors' calculations)
Notes: The number in parenthesis are the SE, are realized GPH estimates for $T^{1/2}$ ***,**,* Significant at 1%, 5%, 10% level, respectively

The results of GPH method indicate that the fractional differencing parameter estimated values are between 0 and 0.5, which means that BET, SOFIX, ATHEX and CROBEX exhibit long memory. For BELEX, the fractional differencing parameter d is less than 0, showing an anti-persistent behavior. The results of Andrews and Guggenberger test indicate that the value of long-memory parameter estimated with r=1, is statistically significant only for SOFIX and CROBEX. For r=2, the Andrews and Guggenberger test found presence of long memory only for BET Index. Similar results were obtained by Hiremath,G.and Kamaiah, B. (2011) for Chile and Brazil.

Table 4: ARFIMA model (1,d,1) estimates

	BET	BUX	SAX	PX	PFTS	BELEX	SOFIX	ATHEX	CROBEX
d	0.3317*** (0.0000)	0.3055*** (0.0000)	0.3639*** (0.0000)	0.5372*** (0.0000)	0.2935*** (0.0000)	0.2858*** (0.0000)	0.3024*** (0.0000)	0.2886*** (0.0000)	0.2862*** (0.0000)
ϕ	0.5130*** (0.0000)	0.4935*** (0.0000)	0.3873*** (0.0000)	0.3230*** (0.0000)	0.4342*** (0.0000)	0.3489*** (0.0000)	0.4710*** (0.0000)	0.3949*** (0.0000)	0.2934** (0.0194)
θ	-0.7203*** (0.0000)	-0.7407*** (0.0000)	-0.6842*** (0.0000)	-0.8215*** (0.0000)	-0.5836*** (0.0000)	-0.6724*** (0.0000)	-0.5766*** (0.0000)	-0.6506*** (0.0000)	-3.2686*** (0.0011)
Q(10)	4.305 (0.9326)	13.224 (0.2114)	10.799 (0.3733)	10.237 (0.4199)	2.832 (0.9851)	34.173*** (0.000)	5.469 (0.8577)	2.213 (0.9944)	3.497 (0.9671)
Q(20)	16.126 (0.7088)	21.314 (0.3789)	21.000 (0.3971)	21.722 (0.3558)	9.702 (0.9733)	67.199*** (0.000)	20.932 (0.4011)	11.508 (0.9319)	21.478 (0.3694)
Q(30)	24.709 (0.7391)	44.399** (0.0438)	34.056 (0.2786)	34.319 (0.2682)	22.864 (0.8208)	82.104*** (0.0000)	30.565 (0.4370)	20.562 (0.9010)	28.206 (0.5595)
Q(40)	43.152 (0.3381)	5.285* (0.0546)	54.490* (0.0630)	53.483* (0.0752)	34.709 (0.7070)	113.718*** (0.0000)	40.811 (0.4346)	37.141 (0.5996)	44.312 (0.2947)

Source: (authors' calculations)

Notes: ***,**,* Significant at 1%, 5%, 10% level, respectively; Q() – Ljung Box statistics

In the table above, it can be seen that the value of the parameter d is significant at a confidence level of 1%
for all indices. For all indices, except PX, the parameter d takes values between $0 < d < 0.5$, implying that the series have long memory, autocorrelations are positive and hyperbolic decline toward zero. Long memory refers to the fact that stock prices have a predictable behavior, showing that these capital markets are not weak-form efficient. Similar results in financial literature were obtained by Kasman and Torun (2007) for another emerging market, Turkey. So, ARFIMA models can be used by investors to predict returns and thus have the possibility of obtaining abnormal earnings. For PX, the estimated value of parameter d is higher than 0.5, which means that the process is mean-reverting, since there is no long term impact of the innovation variance on the process future values.

Table 5: ARFIMA model (1,d,1) estimates using Willinger, Taqqu and Teverovsky (1999) method

	BET	BUX	SAX	PX	PFTS	BELEX	SOFIX	ATHEX	CROBEX
H	0.5781*** (0.0000)	0.5377*** (0.0000)	0.5881*** (0.0000)	0.3204*** (0.0000)	0.6526*** (0.0000)	0.4348*** (0.0000)	0.5893*** (0.0000)	0.6966*** (0.0000)	0.5464*** (0.0000)
ϕ	0.1484 (0.2191)	0.1695 (0.2990)	0.4697*** (0.0042)	0.6388*** (0.0000)	0.2912 (0.2835)	0.6545*** (0.0000)	0.1173** (0.0190)	0.5665*** (0.0000)	0.4243*** (0.0000)
θ	-0.3132** (0.0269)	-0.2919 (0.1140)	-0.5394*** (0.0018)	-0.4769*** (0.0000)	-0.3199 (0.2551)	-0.6288*** (0.0000)	-0.1228** (0.0141)	-0.7444*** (0.0000)	-0.4561*** (0.0000)
IV	0.000129*** (0.0000)	0.000097 (0.0000)	0.000054*** (0.0000)	0.000106 (0.0000)	0.000115*** (0.0000)	0.1708*** (0.0000)	0.000067*** (0.0000)	0.000115*** (0.0000)	0.000067*** (0.0000)
EW=10									
H	0.5642*** (0.0000)	0.4991*** (0.0016)	0.6064*** (0.0000)	0.3224*** (0.0002)	0.5481*** (0.0000)	0.3449*** (0.0000)	0.7874*** (0.0000)	0.6944*** (0.0000)	0.7004*** (0.0000)
IV	0.000344*** (0.0000)	0.00028 (0.0000)	0.000157*** (0.0000)	0.000313*** (0.0000)	0.000635 (0.0000)	0.3827*** (0.0000)	0.000267*** (0.0000)	0.000317*** (0.0000)	0.00016*** (0.0000)
EW=20									
H	0.6461** (0.0223)	0.4946 (0.2558)	0.5895* (0.0546)	0.3583* (0.0534)	0.4599*** (0.0000)	0.4788 (0.1268)	0.5855*** (0.0000)	0.7208*** (0.0000)	0.6948** (0.0113)
IV	0.000780*** (0.0000)	0.000587* (0.0696)	0.000370*** (0.0000)	0.000445** (0.0303)	0.001262 (0.0000)	0.5576*** (0.0000)	0.000872*** (0.0000)	0.000777*** (0.0000)	0.000359*** (0.0000)

Source: (authors' calculations)
Notes: IV – innovation variance; EW – returns equally weighted; ***,**,* Significant at 1%, 5%, 10% level, respectively.

According to the results presented in Table 5, when EW series over blocks of size 10 are used, the Hurst Exponents record values higher than 0.5 for BET, SAX, PFTS, SOFIX, ATHEX and CROBEX, indicating a long term dependence in return series. On the other hand, in the case of BUX, PX and BELEX, the return series are anti persistent, which means that the performances from the past will change in the future. Similar results are obtained for blocks of 20 observations, except for the PFTS Index, in which case we obtain a Hurst Exponent <0.5.

5. Conclusions

Analyzing the existence of long memory in return series for nine indices from Central Eastern European (Romania, Hungary, Slovakia, Czech Republic, Ukraine) and Balkan emerging markets (Serbia, Bulgaria, Greece, Croatia) we have found mixed results depending on the statistical methods that are used. The Hurst Exponent estimated by classical R/S analysis, indicates the presence of long memory for all indices, except PX. According with the results obtained by GPH method, the return series for BET, ATHEX, SOFIX and CROBEX exhibits long memory, while the return

series for BELEX Index is anti-persistent. The results of Andrews and Guggenberger test are similar to those obtained by GPH method in the case of BET, SOFIX and CROBEX. Using Reisen method, we have found that SOFIX exhibits short memory. The results provided by Willinger, Taqqu and Teverovsky method, indicate a long range dependence for BET, SAX, PFTS, SOFIX, ATHEX and CROBEX. According with ARFIMA model estimates, all indices, except PX, have a predictable behavior, the investors can obtain abnormal profits, suggesting that these capital markets are not weak-form efficient.
As direction of future research is recommended the analysis of long memory in volatility of these indices, the detection of the structural breaks and the estimation of GARCH models for modeling volatility. It also should be investigated the causes that lead to the appearance of various degrees of predictability of returns and volatility and their impact on the construction of portfolios and trading strategies of investors.

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