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LONG MEMORY IN THE RETURNS OF STOCK INDICES AND MAJOR STOCKS LISTED IN THREE CENTRAL AND EASTERN EUROPEAN COUNTRIES

Abstract. *This article aims to investigate whether the return series of stocks and stock indices of three Central and Eastern European countries (i.e. of Slovenia, the Czech Republic and Hungary) exhibit long memory. The returns of the stocks and the stock indices are modeled as ARFIMA (Autoregressive Fractionally Integrated Moving Average) processes and different methods of calculating long memory parameters are applied to prove if the estimates are sensitive to the method chosen. The main findings of the paper can be summarized as follows. First, the Slovenian stock index returns do exhibit long memory, whereas the Czech and Hungarian stock indices returns are stationary. Second, the returns of majority of the stocks listed in Slovenian stock market were found to be characterized with a long memory property, while in the Czech and Hungarian stock markets almost all of the investigated stocks' returns were found to be stationary. Third, different methods of the fractional differencing parameter* d *yielded similar conclusions regarding long memory evidence. Fourth, the results of the long memory tests reject the weak-form efficiency hypothesis for the Slovenian stock market, while the hypothesis of weak-form efficiency for the Czech and Hungarian stock market cannot be rejected.*

Keywords: *stock markets, long memory, Central and Eastern Europe, efficient-market hypothesis.*
JEL classification: **G14, G15**

1 Introduction

Long memory (or long-term dependence) describes the correlation structure of a series at long lags (Mandelbrot, 1977). Sibbertsen (2004) noted that the correlation of a process with a long memory decays slowly by a hyperbolic rate and there is persistent temporal dependence even between distant observations. The presence of long-memory in asset returns has important implications for many of the paradigms used in modern financial economics (Maheswaran and Sims, 1992). Optimal consumption/savings and portfolio decisions would become extremely sensitive to the investment horizon if stock returns were long-range dependent. Problems arise in the pricing of derivative securities with martingale methods, since the continuous time stochastic processes most commonly employed are inconsistent with long-term memory (Sims, 1984; Maheswaran and Sims, 1992). Furthermore, LeRoy (1989) shows that the CAPM and the APT are not valid, because the usual forms of statistical inference do not apply to time series that exhibit such persistence.

The presence of long memory in a stock return series would also provide evidence against the weak-form of financial market efficiency, since it would imply nonlinear dependence in the first moment of the distribution and hence a potentially predictable component in the time series dynamics (Barkoulas and Baum, 1996). According to Fama (1970), financial markets can only be called efficient if the security prices always fully reflect the available information. The weak-form of financial market efficiency, which in empirical studies is the most commonly tested financial market efficiency hypothesis, asserts that the only relevant information set to the determination of current security prices is the historical prices of that particular security. In this regard, investors cannot expect to find any patterns in the historical sequence of stock prices or returns that will provide insight into future price movements and allow them to earn abnormal rates of returns.

Due to their flexibility, ARFIMA (Autoregressive Fractionally Integrated Moving Average) models have often been used to model financial time series. They have been applied to interest rates (e.g. Harmantzis and Nakahara, 2006; McCarthy et al., 2004; Tkacz, 2001), exchange rates (e.g. Jin et al., 2006; Karuppiah and Los, 2005), prices of financial derivatives (e.g. Fang et al., 1994), and returns and volatilities of stocks and stock indices. The results for stock returns and their volatilities are mixed. Studies, supportive of long memory in stock market returns or their volatility include: Ding et al. (1993) for the S&P500, Lobato and Savin (1998) for the S&P500 and Ray and Tsay (2000) for the companies listed in the S&P500 index. Barkoulas et al. (2000) found significant and robust evidence of positive long-term persistence for the stocks traded on the Athens stock exchange. Assaf and Cavalcante (2005) provide empirical evidence of the long-range dependence in the returns and volatility of the Brazilian stock market. Supportive evidence of long memory is also provided by Ozdemir (2007) and Chan and Feng (2008) for the DJI, the S&P500, the FTSE, DAX and NIKKEI (for different time periods), Bilel and Nadhem (2009) for G7 countries stock indices and Mariani et al. (2010) for international stock indices.

Mixed results were obtained by Henry (2002), after investigating nine developed stock market indices. He only found strong evidence for long memory in the South Korean returns and some evidence of long memory in the German, Japanese, and Taiwanese returns. Tolvi (2003), investigating the stock market indices of 16 OECD countries, only found evidence of long memory in stock indices returns for three smaller stock markets: in Finland, Denmark, and Ireland. Jagric et al. (2005) reported of mixed evidence of long memory presence in the stock indices of six Central and Eastern European (CEE) countries: strong long range dependence was identified in the returns of the Czech, Hungarian, Russian, and Slovenian stock markets, whereas there was weak or no long range dependence in the returns of the Slovakian, and Polish stock markets. Another study, investigating the fractal structure of CEE stock market returns was by Kasman et al. (2009a). Their results point to the existence of long memory in five of the eight studied markets. Furthermore, Kasman et al. (2009b), investigating four CEE stock markets, found significant long memory in the return series of the Slovak Republic, weak evidence of long memory for Hungary and the Czech Republic, and no evidence for Poland.

Studies that found no evidence of long memory presence in stock market returns and return volatility are Barkoulas and Baum (1996) for the Dow Jones index returns, sectoral stock returns, and stock returns included in the Dow Jones Industrials index; Chow et al. (1996), who examined 22 international stock indices; Lux (1996), for the DAX and some individual shares in the DAX; Grau-Carles (2005), for the S&P500 and Dow Jones Industrial; and Oh et al. (2006) for stock indices in seven developed countries.

The majority of the empirical studies on long memory testing have used returns series on stock indices, whose construction entails a great deal of aggregation. As argued by Barkoulas and Baum (1996), if fractal structure does exist in individual stock returns series, its presence may be masked in aggregate returns series. It is therefore important to test for long memory presence in individual stock returns as well as for the returns of stock indices.

This study aims to answer whether the time series of stock indices returns of three Central and Eastern European (these are Slovenian, Czech and Hungarian) stock markets exhibit long range dependence (fractal structure). Different methods for calculating long range (long memory) parameter are applied to prove if results are sensitive to the method chosen: the Kwiatkowski-Phillips-Schmidt-Shin (KPSS) (1992) test, the method of Geweke and Porter-Hudak (GPH), the method of detrended fluctuation analysis (Peng et al. 1994), the method of Higuchi (1988) and the Robinson´s (1995) method of local Whittle approximation. As the fractal structure of the individual stock returns may be masked in the fractal structure of the stock index returns incorporating the stock, the fractal structures of returns of individual stocks in the stock markets are also calculated. The results of the paper are informative of the weak-form efficiency hypothesis of the stock markets and individual stocks listed in the investigated stock markets.

2 The long memory property of time series

The long memory property of a time series can be defined in the time domain by a hyperbolically decaying autocovariance function. Alternatively, it can be defined in the frequency domain by a spectral density function that approaches infinity at near zero frequencies.

Let X_t be a stationary process with an autocovariance function γ_τ (τ is time lag). The long memory is present in the process, if its autocovariance function decays hypebolically (DiSario et al., 2008)

$$\gamma_\tau \approx |\tau|^{2d-1} \text{ as } |\tau| \to \infty, \tag{1}$$

where $d \in (0,0.5)$ is a long memory parameter. The spectral density function $\omega(\lambda_s)$ of such a process, where $\lambda_s \in (-\pi,\pi)$, has the following property:

$$\omega(\lambda_s) \approx c|\lambda_s|^{-2d} \text{ as } \lambda_s \to 0, \tag{2}$$

where $c > 0$ and $d \in (0,0.5)$.

The subject of the long-memory time series was brought to prominence by the seminal work of hydrologist Hurst (1951). The works of Mandelbrot (1965, 1971) extended the study of long memory to economic and financial time series. Two measures are commonly used in estimating the strength of the long memory (long-range dependence). The parameter *H*, known as the Hurst or self-similarity parameter, was introduced to applied statistics by Mandelbrot and van Ness (1968) who focused on self-similar processes such as fractional Brownian motion and fractional Gaussian noise. The other measure, the fractional integration parameter, d, arises from the generalization of the Box-Jenkins ARIMA(p,d,q) models from integer to non-integer values of the integration parameter *d* (Autoregressive Fractionally Integrated Moving Average – ARFIMA models) and were introduced by Granger and Joyeux (1980) and Hosking (1981)[1].
A general class of fractional processes ARFIMA(p,d,q) is described as (Sadique and Silvapulle, 2001):

$$\Phi(B)(1-B)^d X_t = \Theta(B)\varepsilon_t \quad , \tag{3}$$

[1] The fractional integration parameter d is also the discrete time counterpart to the self-similarity parameter H, and the two are related by the simple formula $d = H - 0.5$ (Rea et al., 2007).

where X_t is a time series, $\Phi(B) = 1 - \varphi_1 B - \ldots - \varphi_p B^p$ and $\Theta(B) = 1 + \theta_1 B + \ldots + \theta_1 B^q$ are autoregressive and moving average polynomials in the lag operator B with all roots of $\Phi(B)$ and $\Theta(B)$ being stable, and ε_t is a Gaussian white noise $\varepsilon_t \sim \boldsymbol{IID(0,\sigma^2)}$. For $d = 0$ the process is stationary, and the effect of a shock to ε_t on X_t decays geometrically with time. For $d = 1$, the process is said to have a unit root, and the effect of a shock to ε_t on X_t persists into infinity.

When $p = q = 0$, X_t becomes a simple fractional differenced process, proposed by Hosking (1981). The function $(1-B)^d$ can be defined for non-integer values of d:

$$(1-B)^d X_t = \varepsilon_t, \qquad (4)$$

where B is a lag operator, innovation is a Gaussian white noise $\varepsilon_t \sim \boldsymbol{IID(0,\sigma^2)}$, d a fractional integration parameter varying in the interval ($-0.5, 0.5$), and $(1-B)^d$ is the fractional differencing operator.

Hosking (1981) showed that for $-0.5 < d < 0.5$ the process X_t is stationary and invertible. An ARFIMA process with the parameter $0 < d < 0.5$, is stationary, but the effects of a shock in ε_t on X_t decay at a much slower rate than for a process integrated of order zero. The process with parameter d in range $0 < d < 0.5$ is said to exhibit long memory as well as a process with parameter $-0.5 < d < 0$.[2] The autocovariance function for zero integrated processes decays geometrically, while the autocovariance function for a fractionally integrated process decays hyperbolically with the sign of the autocovariances being the same as the sign of d (Pons Fanals and Suriñach Caralt, 2002). When d is positive the sum of autocorrelations diverges to infinity, and collapses to zero when d is negative (Lo and MacKinlay, 2001). A process with parameter $d \geq 0.5$ is not stationary and a shock in ε_t on X_t decays even more slowly.

3 Methodology

Simulation studies (Taqqu and Teverovsky, 1996; Rea et al., 2007) show that different methods of estimating the fractional integration parameter can lead to different conclusions regarding the fractal structure of a time series. It is therefore advised to estimate the fractional integration parameter using more different methods, since this can provide a better perspective on the structure of the time series (Taqqu and Teverovsky, 1996).

[2] Processes with the parameter $-0.5 < d < 0$ are also called antipersistent (this terminology is applied by Mandelbrot in numerous works, by Rea et al. (2007) and Kunze and Strohe (2010).

In our study, the fractal structure parameter d is calculated by these methods: i) the Kwiatowski-Phillips-Schmidt-Shin (KPSS; 1992) test, ii) the detrended fluctuation analysis (Method of Peng et al. (1994)), iii) the method of Higuchi (1988), iv) the GPH estimator and v) the Robinson´s (1995) method of local Whittle approximation.

3.1 KPSS test in combination with unit root tests

Lee and Schmidt (1996) proposed the test of Kwiatkowski-Phillips-Schmidt-Shin (KPSS; 1992) to test the null hypothesis of $I(0)$ against the fractional alternative. The KPSS test assumes that a time series (X_t) can be decomposed into three components, a deterministic time trend (ct), a random walk (r_t) and a stationary error (ε_t) (Kwiatkowski et al., 1992):

$$X_t = r_t + ct + \varepsilon_t \, , \tag{5}$$

where r_t is a random walk $r_t = r_{t-1} + v_t$, v_t is $IID(0, \sigma_v^2)$. The null hypothesis of stationarity implies $H_0 : \sigma_v^2$. Under the alternative hypothesis $\sigma_v^2 > 0$ the time series X_t is a fractionally integrated process. This test may be conducted under the null hypothesis of either trend stationarity or level stationarity. Using the residuals from the regression of X_t on intercept and time (or on intercept only in case of level stationarity), the test statistic is computed as:

$$KPSS = \sum_{t=1}^{T} \frac{(s(t))^2}{s_{nw}^2 T^2} \, , \tag{6}$$

where $s(t) = e_1 + ... + e_t$, e is a vector of residuals, s_{nw}^2 is the Newey-West estimator of the long-run variance σ^2 of the errors ε_t and T the sample size.

According to Lee and Schmidt (1996), the two KPSS tests (trend stationarity or level stationarity) are consistent against an $I(d)$ alternative, and can be used in conjunction with usual stationarity tests, like the Augmented Dickey-Fuller (ADF) test and the Phillips-Perron (PP) test, to investigate the possibility that a series is fractionally integrated (i.e. neither $I(1)$) nor $I(0)$).The combination of the KPSS, ADF and PP test results suggests these deductions:

1. The rejection of the null hypothesis for the ADF and PP test and the non-rejection of the null hypothesis of the KPSS test lead to the conclusion of no unit-root in a time series. The alternative hypothesis of stationary time series ($I(0)$ can be accepted.

2. Non-rejection of the null hypothesis of the ADF and PP test and the rejection of KPSS test leads to the conclusion of a unit root in time. The time series is integrated to the order 1 ($I(1)$).

3. When the null hypothesis of the ADF, PP test and KPSS test are not rejected we cannot draw a conclusion about the non(stationarity) of a time series.

4. The rejection of the null hypothesis of the ADF, PP and KPSS test leads to the conclusion that the time series is neither $I(1)$ nor $I(0)$ wherefrom it follows that parameter d takes some non-integer value (i.e. the time series is fractionally integrated).

3.2 Method of Higuchi

Higuchi (1988) proposed a method for estimating the fractal dimension for the length of a curve in a time domain. Let us consider a finite set of time series observations, j $(j = 1,2,...,N)$. From a given time series, k new time series, X_k^m, are formed

$$X_k^m : X(m), X(m+k), X(m+2k),...,X(m+\left[\frac{N-m}{k}\right]k), \tag{7}$$

where $m = 1,2,...,k$; m and k are integers and indicate the initial time and the time interval, respectively. [ ] denotes the Gauss' nearest integer function. The length of the curve associated to each time series, $L_m(k)$, is defined as (Higuchi, 1988):

$$L_m(k) = \left(\sum_{i=1}^{\left[\frac{N-m}{k}\right]} \left| X(m+ik) - X(m+(i-1)k \right| \right) \frac{N-1}{\left[\frac{N-m}{k}\right]k^2} . \tag{8}$$

The term $\left[\frac{N-m}{k}\right]k^2$ represents the normalization factor for the curve length of subset time series. The length of the curve for the time interval k, $\langle L(k) \rangle$, is the average value over k sets of $L_m(k)$. For the long range dependent time series $\langle L(k) \rangle \propto k^{-(2-H)}$, where H is Hurst parameter. The slope of the linear least squares fit of $\log\langle L(k) \rangle$ versus $\log(k)$ produces an estimate of $2-H$. To estimate H, we apply an algorithm proposed by Taqqu et al. (1995). The maximal time interval, k , is set to $\frac{N}{5}$. The fractional differencing parameter, d, is then obtained by equation $d = H - 0.5$ (Rea et al., 2007).

This estimator has two main drawbacks. On one hand, there is no result for its asymptotic distribution and properties; on the other, it can only be useful with quite a long series because of its bias with small sample sizes (Cecchinato, 2008).

3.3 Detrended fluctuation analysis

The detrended fluctuation analysis (DFA) is another time domain method of the Hurst parameter estimation.

Given the time series $X(i)$, $x = 1,2,...,N$, a new time series $Y(k)$ is formed by integrating the time series $X(i)$:

$$Y(k) = \sum_{i=1}^{k} (X(i) - X_{ave}) , \tag{9}$$

where X_{ave} is the average of the time series $X(i)$. Next, the integrated time series is divided into l nonoverlapping time intervals (time windows) of length n ($\frac{N}{n} = l$). In each interval, a least-squares line is fitted (the fitting line in the time interval j is denoted by $Y_j(k)$) and then the time series $Y(k)$ is locally detrended, by linear trend filtering[3] ($Y(k) - Y_j(k)$).

For a given interval length, n, a root mean-square fluctuation of integrated and detrended time series (i.e. residual variance) is calculated for every time interval j:

$$F(n, j) = \sqrt{\frac{1}{n} \sum_{k=1}^{n} [Y((j-1)n + k) - Y_j(k)]^2} \tag{10}$$

and the fluctuation function $F(n)$ is obtained by taking the average over all time intervals. The above computation is repeated over different possible interval lengths[4] to provide a relationship between $F(n)$ and n. The relationship between the detrended series and interval lengths can be expressed as $F(n) \propto n^H$. The slope of the linear least squares fit of $\log F(n)$ versus the $\log(n)$ produces an estimate of

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[3] The procedure is then labeled as DFA-1. If the order of filtering was s, these would be a DFA-s analysis (Hu et al. 2001).

[4] We estimated 50 different lengths for the time interval, setting a minimum interval length size $\max(10, \log N^2)$ and then time intervals increasing for equal logarithmic distances between $\log(\max(10, \log N^2))$ and $\log(\frac{N}{5})$.

H. Again, the fractional differencing parameter, d, is obtained by the equation $d = H - 0.5$ (Rea et al. 2007).

Taqqu et al. (1995) provided a proof that the DFA is asymptotically unbiased. In simulations the bias was never large, but even at a sample size of 10,000 observations the estimator cannot be considered unbiased.

3.4 The local Whittle estimator of Robinson

Robinson (1995) proposed an asymptotically unbiased estimator for d that is based on the approximation of the spectrum of a long-memory process in the Whittle approximate maximum likelihood. An estimator of the fractional integration parameter d is obtained by solving the Gauss objective function, as first proposed by Künsch (1987):

$$Q_m(G,H) = \frac{1}{m}\sum_{s=1}^{m}\left[\log(G\lambda_s^{1-2H}) + \frac{\lambda_s^{2H-1}}{G}P_x(\lambda_s)\right], \tag{11}$$

where $\lambda_s = \frac{2\pi s}{N}$, $s = 1,2,...,N$ and $G \in (0,\infty)$. The estimator depends on the choice of bandwidth, m, which is generally chosen in the range $N^{0.5} \le m \le N^{0.8}$ (Baillie and Kapetanios, 2009). However, when there is substantial persistence in short run dynamics, the value of m should be reduced, so that more weight is placed on ordinates of the periodogram associated with the low frequency components.

The Hurst parameter is estimated by solving the minimization problem:

$$\hat{H} = \underset{H \in [\Delta_1, \Delta_2]}{\arg\min}\, R(H), \tag{12}$$

where $R(H) = \log\left(\frac{1}{m}\sum_{s=1}^{m}\lambda_s^{2H-1}P_x(\lambda_s)\right) - (2H-1)\left(\frac{1}{m}\sum_{s=1}^{m}\log(\lambda_s)\right)$; Δ_1 and Δ_2 are numbers picked such that $0 < \Delta_1 < \Delta_2 < 1$. Robinson (1995) proved that under some regularity conditions the estimator $\hat{H}$ is asymptotically normally distributed: $\sqrt{m}(\hat{H} - H_0) \xrightarrow{d} N(0,\frac{1}{4})$ (H_0 is the true value of the Hurst parameter, while $\hat{H}$ is estimated). The fractional differencing parameter, d, is obtained from the Hurst estimate by equation $d = H - 0.5$.

4 Data and empirical results

The returns of stocks and stock indices are calculated as the differences of logarithmic daily closing prices (or stock indices) ($\ln(P_t) - \ln(P_{t-1})$, where P is a closing price). The following indices were considered: LJSEX (Slovenia), PX

(Czech Republic), BUX (Hungary). The stocks included were those that are included in the calculation of the investigated stock indices and are regularly traded on their respective exchanges. The first date of observation for the Slovenian stock market was April 4, 1996, for the Hungarian stock market it was April 1, 1997 and for the Czech stock market it was January 1, 1995. The data of stock (stock indices) prices were obtained from the web pages of the respective stock exchanges.
Tables 1 through 3 present some descriptive statistics of the data. The data appear extremely non-normal. The majority of the return distributions are negatively skewed (especially for the Hungarian and Czech stock markets), possibly due to the large negative returns associated with the financial crises in the observed period[5].

Table 1: Descriptive statistics for returns series of stocks listed at Ljubljana stock exchange and its representative stock index

Stock/ stock index	Period of obser.	Min	Max	Mean	Std. d.	SK	KU	J-B stat
Aerodrom Ljubljana	8.10.1997-20.7.2010	-0.1557	0.1656	0.0002	0.0196	-0.05	9.81	6,167.71***
Gorenje	2.6.1998-20.7.2010	-0.0955	0.1045	0.0001	0.0161	0.12	7.45	2,504.87***
Intereuropa	12.1.1998-20.7.2010	-0.1016	0.1542	-0.0004	0.0163	0.31	12.15	10,955.89***
Krka	10.2.1997-20.7.2010	-0.2679	0.1984	0.0004	0.0179	-0.38	38.39	17,3381,37***
Laško	1.2.2000-20.7.2010	-0.1504	0.1263	-0.0002	0.0200	-0.16	9.41	4,476.48***
Luka Koper	20.11.1996-20.7.2010	-0.0965	0.1281	0.0001	0.0172	-0.03	7.95	3,474.08***
Mercator	4.4.1996-20.7.2010	-0.1751	0.1554	0.0006	0.0188	0.23	13.94	17,803,66***
Petrol	5.5.1997-20.7.2010	-0.102	0.1328	0.0003	0.0162	0.33	11.09	9,062.37***
Sava	6.1.2000-20.7.2010	-0.1274	0.1535	0.0003	0.0181	0.01	9.84	5,120.06***
LJSEX (index)	4.4.1996-20.7.2010	-0.1161	0.1893	0.0003	0.0118	0.35	34.16	144,220.93***

Notes: SK = skewness, KU = kurtosis, J-B stat. = Jarque-Berra statistics. Jarque-Bera test: *** indicates that the null hypothesis (of normal distribution) is rejected at the 1% significance.

The data also reveals a high degree of excess kurtosis. Such skewness and kurtosis are common features in asset return distributions, which are repeatedly found to be leptokurtic (Henry, 2002). The Jarque-Bera test rejects the hypothesis of normally distributed returns for all stocks as well as stock indices.

[5] These are the Russian financial crisis (in 1998), the dot-com crisis (in 2000), the Internet bubble burst (2002), the Middle East financial crisis (in 2006) and the Global financial crisis (2007-2008).

Table 2: Descriptive statistics for returns series of stocks listed at Budapest stock exchange and its representative stock index

Stock/ stock index	Period of obser.	Min	Max	Mean	Std. d.	SK	KU	J-B stat.
ANY	8.12.2005-12.5.2010	-0.1316	0.1214	0.0002	0.0203	-0.43	10.37	2,534.35***
Egis	1.4.1997-12.5.2010	-0.3567	0.1944	0.0002	0.0268	-0.97	20.41	41,904.65***
Fotex	1.4.1997-12.5.2010	-0.3365	0.2346	0.0003	0.0328	0.40	13.60	15,419.85***
MOL	1.4.1997-12.5.2010	-0.2231	0.1403	0.0006	0.0245	-0.21	9.70	6,153.19***
MTelekom	14.11.1997-12.5.2010	-0.1257	0.1199	-0.0001	0.0214	-0.20	6.67	1,769.98***
OTP	1.4.1997-12.5.2010	-0.2513	0.2092	0.0009	0.02782	-0.22	10.80	8,321.11***
Pannergy	1.4.1997-12.5.2010	-0.2076	0.2343	-0.0002	0.0267	0.20	11.68	10,304.38***
Raba	17.12.1997-12.5.2010	-0.2501	0.1999	-0.0004	0.026	-0.14	12.56	11,794.59***
Richte	1.4.1997-12.5.2010	-0.231	0.2178	0.0004	0.0262	-0.63	16.39	24,698.68***
Synergon	5.5.1999-12.5.2010	-0.1625	0.1526	-0.0006	0.0299	0.41	8.63	3,724.70***
TVK	1.4.1997-12.5.2010	-0.2231	0.2068	0.0001	0.0276	-0.15	11.84	10,683.4***
BUX (index)	1.4.1997-12.5.2010	-0.1803	0.1362	0.0005	0.0192	-0.64	13.18	14,367.97***

Table 3: Descriptive statistics for returns series of stocks listed at the Prague stock exchange and the representative stock index

Stock/ stock index	Period of obser.	Min	Max	Mean	Std. d.	SK	KU	J-B stat.
Auto Group	26.9.2007-12.5.2010	-0.1777	0.383	-0.0018	0.0377	1.69	25.23	13,760.99***
CETV	26.9.2007-12.5.2010	-0.237	0.3075	-0.0018	0.0480	0.28	9.01	991.58***
CEZ	10.1.1995-12.5.2010	-0.1539	0.204	0.0006	0.0241	-0.32	8.52	4,626.25***
ECM Real Estate	1.11.1997-12.5.2010	-0.2707	0.3381	-0.0028	0.0405	0.64	17.94	5,895.57***
Erste Group Bank	26.9.2007-12.5.2010	-0.1836	0.1632	-0.0009	0.0375	-0.11	7.37	521,34***
Komerční Banka	10.1.1995-12.5.2010	-0.2076	0.1594	0.0002	0.0268	-0.32	7.62	3,263.82***
ORCO	26.9.2007-12.5.2010	-0.3185	0.2646	-0.0043	0.0507	-0.07	9.55	1,169.40***
Philip Moris	10.1.1995-12.5.2010	-0.1634	0.1263	0.00020	0.0244	-0.31	6.94	2,386.91***
Telefonica	28.3.1995-12.5.2010	-0.1281	0.1299	0.0001	0.0218	-0.02	6.93	2,316.04***
Unipetrol	26.8.1997-12.5.2010	-0.1704	0.1799	0.0001	0.0263	-0.13	7.61	2,829.18***
PX (index)	09.1.1996-12.5.2010	-0.1619	0.1236	0.0003	0.0149	-0.41	14.88	21,256,18***

For the Slovenian stock market unit root tests (ADF and PP tests) clearly reject the null hypothesis of unit root in a time series; the results are robust to model specifications (see Tables 4 through 6). The null hypothesis of the KPSS test (i.e. the time series is stationary) is rejected for some stocks: Aerodrom Ljubljana, Intereuropa, Laško, Luka Koper, and also for the stock index LJSEX, meaning that these time series are fractionally integrated.For the Hungarian and the Czech stock market the null hypotheses of ADF and PP test can also be rejected, proving that the return time series of investigated stocks and stock indices are not unit root. The KPSS model with a constant is given advantage over the KPSS model with a constant plus trend since the trend is not significant for any of the time series. Combining the unit root test results and the KPSS test show that the returns of stock and the stock index in the Hungarian stock market are stationary ($d = 0$), while in the Czech stock market some evidence of long memory is found for one stock share listed in the PX index.

Table 4: Results of stationarity tests for the Slovenian stock market

	KPSS test (a constant + trend)	KPSS test (a constant)	PP test (a constant + trend)	PP test (a constant)	ADF test (a constant + trend)	ADF test (a constant)
Aerodrom Ljubljana	0.284*** (4) trend is significant	0.468** (3)	-61.261*** (1)	-61.260*** (3)	-61,264*** (L=0)	-61.234*** (L=0)
Gorenje	0.132* (11) trend is significant	0.540** (12)	-53.600*** (11)	-53.573*** (12)	-53,452*** (L=0)	-53,377*** (L=0)
Intereuropa	0.259*** (14) trend is significant	1.211*** (16)	-48.647*** (11)	-48.562*** (13)	-48,832*** (L=0)	-48.651*** (L=0)
Krka	0.175** (6)	0.191 (6)	-54.188*** (3)	-54.198*** (3)	-54,209*** (L=0)	-54,218*** (L=0)
Laško	0.388*** (6)	0.645** (4)	-61,268*** (4)	-60.560*** (1)	-60,563*** (L=0)	-60.514*** (L=0)
Luka Koper	0.265*** (10)	0.515** (11)	-57.735*** (10)	-57.699*** (11)	-57,736*** (L=0)	-57,695*** (L=0)
Mercator	0.069* (6)	0,3484 (5)	-58,518*** (1)	-58.492*** (1)	-39,853*** (L=2)	-39,826*** (L=2)
Petrol	0.232*** (7)	0.336 (7)	-54.061*** (5)	-54.036*** (6)	-54,111*** (L=0)	-54.096*** (L=0)
Sava	0.202** (0)	0.314 (1)	-55.183*** (4)	-55.172*** (4)	-55,066*** (L=0)	-55,059*** (L=0)
LJSEX (index)	0.192** (20) trend is significant	0.413* (20)	-50.760*** (17)	-50.768*** (17)	-50,465*** (L=0)	-50,410*** (L=0)

Notes: All tests are performed for a model with a constant and for the model with a constant plus trend. Bartlett Kernel estimation method is used with Newey-West automatic bandwidth selection. Optimal bandwidth is indicated in parentheses under the statistics. The number of lags (L) to be included for ADF test were selected by SIC criteria (30 was a maximum lag). Exceeded critical values for rejection of the null hypothesis are marked by *** (1% significance level), ** (5% significance level) and * (10% significance level). If trend is significant, this is denoted in the table.

Table 5: Results of stationarity tests for the Hungarian stock market

	KPSS test (a constant + trend)	KPSS test (a constant)	PP test (a constant + trend)	PP test (a constant)	ADF test (a constant + trend)	ADF test (a constant)
ANY	0.165** (7)	0.389 (8)	-37.264*** (8)	-37,128*** (9)	-27.939*** (L=1)	-27.880*** (L=1)
Egis	0.062 (11)	0.074 (11)	-56.797*** (11)	-56.803*** (11)	-56.787*** (L=0)	-56.792*** (L=0)
Fotex	0.070 (16)	0.069 (16)	-57,117*** (16)	-57.125*** (16)	-56.858*** (L=0)	-56.867*** (L=0)
MOL	0.080 (24)	0.086 (24)	-54.941*** (26)	-54.947*** (26)	-54.932*** (L=0)	-54.939*** (L=0)
MTelekom	0.072 (15)	0.122 (15)	-55.274*** (16)	-55.268*** (16)	-55.240*** (L=0)	-55.237*** (L=0)
OTP	0.047 (3)	0.186 (2)	-53.888*** (6)	-53.874*** (6)	-35.421*** (L=2)	-35.395*** (L=2)
Pannergy	0.093 (4)	0.260 (5)	-57.432*** (4)	-57.420*** (5)	-57.433***(L=0)	-57.420*** (L=0)
Raba	0.063 (12)	0.118 (12)	-54.580*** (13)	-54.576*** (13)	-54.569*** (L=0)	-54.566*** (L=0)
Richte	0.034 (26)	0.034 (26)	-53.708*** (26)	-53.716*** (26)	-34.532*** (L=2)	-34.538***(L=2)
Synergon	0.102 (11)	0.229 (11)	-48.336*** (9)	-48.330*** (9)	-48.150*** (L=0)	-48.136*** (L=0)
TVK	0.038 (14)	0.114 (14)	-58.984*** (13)	-58.976*** (13)	-58.972*** (L=0)	-58.967*** (L=0)
BUX (index)	0.065 (9)	0.066 (9)	54.522*** (10)	-54.530*** (10)	-54.580*** (L=0)	-54.590*** (L=0)

Table 6: Results of stationarity tests for the Czech stock market

	KPSS test (a constant + trend)	KPSS test (a constant)	PP test (a constant + trend)	PP test (a constant)	ADF test (a constant + trend)	ADF test (a constant)
Auto Group	0.054 (2)	0.749*** (6)	-27,928*** (4)	-27.657*** (7)	-16.551*** (L=1)	-16.288*** (L=1)
CETV	0.096 (10)	0.198 (11)	-23. 568*** (10)	-23.860*** (10)	-23.457*** (L=0)	-23.437*** (L=0)
CEZ	0.173** (11)	0.264 (12)	-64.643*** (12)	-64.634*** (12)	-64.484*** (L=0)	-64.481*** (L=0)
ECM Real Estate	0.064 (8)	0.314 (7)	-23.159*** (9)	-23.101*** (8)	-23.226*** (L=0)	-23.170*** (L=0)
Erste Group Bank	0.086 (5)	0.316 (6)	-22.141*** (2)	-22.013*** (4)	-22.134*** (L=0)	-22.075*** (L=0)
Komerčni Bank	0.088 (2)	0.112 (2)	-58.662*** (3)	-58.666*** (3)	-58.655*** (L=0)	-58.660*** (L=0)
ORCO	0.066 (16)	0.304 (15)	-21.428*** (21)	-21.441*** (19)	-21.652*** (L=0)	-21.601*** (L=0)
PhilipMoris	0.077 (10)	0.225 (9)	-72.949*** (2)	-72.160*** (3)	-50.268*** (L=1)	-50.251*** (L=1)
Telefonica	0.056 (5)	0.074 (5)	-65.918*** (1)	-65.920*** (1)	-65.916*** (L=0)	-65.919*** (L=0)
Unipetrol	0.172** (10)	0.0305 (10)	-54.966*** (11)	-54.937*** (10)	-41.626*** (L=1)	-41.599*** (L=1)
PX (index)	0.127* (6)	0.129 (6)	-55.242*** (3)	-55.250*** (3)	-55.333*** (L=0)	-55.341*** (L=0)

Robinson's local Whittle estimator of the fractional differencing parameter d depends on the choice of bandwidth, m , which is generally chosen in the range $N^{0.5} \le m \le N^{0.8}$ (Baillie and Kapetanios 2009). We chose bandwidths with the sizes $m=[N^{0.5}]$, $m=[N^{0.7}]$, and $m=[N^{0.8}]$. Higuchi's estimator of parameter d is calculated, setting the maximal value of the time interval, k, to $\frac{N}{5}$. The results are displayed in the Tables 7 through 9.

Table 7: Higuchi's, DFA, and local Whittle estimator results of the parameter *d* for the Slovenian stock market

Stocks	Higuchi's estimator	DFA estimator	Local Whittle estimator of Robinson		
			$m=[N^{0.5}]$	$m=[N^{0.7}]$	$m=[N^{0.8}]$
Aerodrom Ljubljana	0.1495 (0.0101)	-0.012 (0.0273)	0.2773*** (0.0668)	0.0685** (0.0297)	0.0160 (0.0198)
Gorenje	0.1291 (0.0044)	0.0421 (0.0168)	0.2243*** (0.0674)	0.0822*** (0.0303)	0.0675*** (0.0203)
Intereuropa	0.1262 (0.0115)	0.0036 (0.0237)	0.2445*** (0.0674)	0.0780*** (0.0299)	0.0386** (0.02)
Krka	0.1143 (0.0038)	0.0362 (0.0197)	0.0574 (0.0662)	0.04062 (0.0293105)	-0.0294 (0.0195)
Laško	0.0768 (0.0096)	-0.0775 (0.0273)	0.0872 (0.0700)	0.0282 (0.03188)	-0.0279 (0.0215)
Luka Koper	0.1049 (0.0055)	0.0181 (0.022)	0.2201*** (0.0657)	0.0656** (0.0290)	0.0297 (0.0193)
Mercator	0.0884 (0.0058)	-0.0278 (0.0174)	0.0682 (0.0651)	0.0075 (0.0286)	-0.0692*** (0.0190)
Petrol	0.1327 (0.0049)	0.0516 (0.0201)	0.1605** (0.0662)	0.0692** (0.0294)	0.0190 (0.0196)
Sava	0.1099 (0.0096)	-0.0212 (0.0209)	0.2322*** (0.0700)	0.0453 (0.0318)	-0.0001 (0.0215)
LJSEX (index)	0.1620 (0.0037)	0.0632 (0.0136)	0.1779*** (0.0651)	0.0948*** (0.0286)	0.0378** (0.0190)

Notes: In parentheses under parameter d estimates, OLS standard errors of the estimates are given. For the local Whittle estimator exceeded critical values for rejection of the null hypothesis of stationary time series ($d=0$) against alternative of long memory ($d \neq 0$) are marked by: *** (1% significance level), ** (5% significance level) and * (10% significance level).

Table 8: Higuchi's, DFA, and local Whittle estimator results of the parameter *d* for the Hungarian stock market

Stocks	Higuchi's estimator	DFA estimator	Local Whittle estimator of Robinson		
			$m=[N^{0.5}]$	$m=[N^{0.7}]$	$m=[N^{0.8}]$
ANY	0.1136 (0.0047)	0.0247 (0.0476)	0.1476* (0.0870)	0,0604 (0.0430)	-0.0461 (0.0303)
Egis	0.0855 (0.0027)	0.0588 (0.019)	0.0779 (0.0662)	0.0375 (0.0295)	0.0149 (0.0196)
Fotex	0.0893 (0.003)	0.0661 (0.0158)	0.0545 (0.0662)	0.0391 (0.0295)	0.0497** (0.0196)
MOL	0.0094	-0.0179	-0.0185	-0.0312	-0.0218

	(0.0056)	(0.015)	(0.0662)	(0.0295)	(0.0196)
MTelekom	-0.0064 (0.0041)	0.0033 (0.019)	-0.0734 (0.0674)	-0.0260 (0.0299)	-0.0223 (0.0200)
OTP	0.0527 (0.0037)	0.0534 (0.0256)	0.0036 (0.0662)	0.0174 (0.0295)	-0.0120 (0.0196)
Pannergy	0.0560 (0.0031)	0.0158 (0.0131)	0.0362 (0.0662)	0.0204 (0.0295)	0.0155 (0.0196)
Raba	0.0520 (0.0028)	-0.0277 (0.0228)	0.0047 (0.0674)	-0.0306 (0.0300)	0.0072 (0.0201)
Richte	0.0105 (0.0044)	0.0202 (0.029)	-0.0636 (0.0662)	-0.0580** (0.0295)	-0.0327* (0.0196)
Synergon	0.1189 (0.0021)	0.0866 (0.0321)	0.0236 (0.0693)	0.0620** (0.0313)	0.0707*** (0.0210)
TVK	0.0670 (0.0047)	0.0287 (0.0228)	-0.0522 (0.0662)	-0.0102 (0.0295)	0.0056 (0.0196)
BUX (index)	0.0644 (0.0039)	0.0564 (0.0219)	-0.0205 (0.0662)	0.0065 (0.0295)	0.0036 (0.0196)

Table 9: Higuchi's, DFA and local Whittle estimator results of the parameter *d* for the Czech stock market

Stocks	Higuchi's estimator	DFA estimator	Local Whittle estimator of Robinson		
			$m=[N^{0.5}]$	$m=[N^{0.7}]$	$m=[N^{0.8}]$
Auto Group	0.2365 (0.0045)	0.0603 (0.0654)	0.1508 (0.1)	0.1007* (0.0518)	0.0982*** (0.0375)
CETV	0.1604 (0.0055)	0.1331 (0.0686)	0.1446 (0.1)	0.1290** (0.0518)	0.1146*** (0.0374)
CEZ	0.0679 (0.0027)	0.0092 (0.0163)	0.0360 (0.0651)	0.0109 (0.0285)	-0.0239 (0.0189)
ECM Real Estate	0.1529 (0.0101)	0.0020 (0.0671)	0.0729 (0.1)	-0.0543 (0.0524)	-0.0205 (0.0380)
Erste Group Bank	0.1168 (0.0092)	0.0194 (0.0542)	0.1927* (0.1)	0.0727 (0.0518)	0.0415 (0.0375)
Komerční Banka	0.0257 (0.0034)	-0.001 (0.0151)	0.0436 (0.0645)	0.0066 (0.0285)	0.0109 (0.0189)
ORCO	0.1632 (0.0065)	0.0324 (0.0483)	0.1015 (0.1)	-0.0738 (0.0518)	0.0029 (0.0375)
Philip Moris	0.0326 (0.0027)	-0.0302 (0.0155)	0.0303 (0.0651)	0.0100 (0.0285)	-0.0200 (0.0189)
Telefonica	0.0228 (0.0056)	0.0215 (0.0216)	-0.0802 (0.0651)	-0.0180 (0.0285)	0.0167 (0.0189)
Unipetrol	0.0806 (0.0045)	0.0073 (0.0152)	0.0683 (0.0668)	-0.0067 (0.0297)	-0.0211 (0.0199)
PX (index)	0.0882 (0.0022)	0.0622 (0.0176)	0.0284 (0.0651)	0.0312 (0.0285)	0.0105 (0.0189)

Higuchi's and DFA estimators have some important drawbacks: the estimators for asymptotic distributions are not known and estimates obtained by the methods are biased (Rea et al., 2007; Cecchinato, 2008). The Local Whittle estimator is known for unbiasedness. However estimates of the parameter d via this method depend on the bandwidth size of the periodogram over which the parameter d is estimated. The results in Tables 7 through 9 convey that as the bandwidth is increased, the estimates for the parameter d are lowered. It is also evident that Higuchi's estimator systematically gives higher estimates for parameter d as the DFA estimator.

The Local Whittle estimator results show that the Slovenian stock market exhibits a long memory process, since the null hypothesis of stationarity for LJSEX index returns is clearly rejected. Most of the listed stocks in the LJSEX also exhibit long memory, at least at some periodogram bandwidths. The parameter d estimates for the PX and BUX indices and stocks listed in these indices are generally smaller than for the Slovenian stock market. Also, the null hypotheses of stationary returns time series are not rejected, except for the CETV and Auto Group stocks (in the Czech stock market) and Synergon (in the Hungarian stock market) returns. The results are consistent with the results of other long memory estimators.

The results of our study are in contrast to the findings of Jagric et al. (2005) who identified long memory in the returns of the Slovenian, Czech and Hungarian stock markets. Our findings are closer to those of Kasman (2009b), who found only weak evidence for long memory in Hungary and the Czech Republic. The differences in the findings may be due to the different methods used in these studies and the different time periods of observation.

Long memory found in the returns of the Slovenian stock market implies that stock returns follow a predictable behavior, which is inconsistent with the weak-form efficiency market hypothesis. The results of long memory tests for the Czech and Hungarian stock markets do not reject the weak-form efficiency hypothesis. Cajueiro and Tabak (2004) and Limam (2003)] argue that the liquidity of stocks (and stock markets) may explain differences in long memory tests. The greater efficiency of the Czech and Hungarian stock markets can thus be attributed to the fact that the Czech and Hungarian markets have attracted more large foreign investors, while the Slovenian market has struggled to do so. This has, in turn, increased the stock market turnover and liquidity of shares listed on the Prague and Budapest stock exchange as compared to the Ljubljana stock exchange.

5 Conclusion

This study aimed to answer whether the returns of three Central and Eastern European (the Slovenian, Czech and Hungarian) stock markets exhibit long memory. Since the fractal structure of individual stock return series may be masked in aggregate returns series, we tested for long memory presence in individual stock returns as well as in the stock index returns. After applying the KPSS test, the Higuchi’s estimator, the DFA analysis, and the local Whittle estimator of Robinson, we found that the Slovenian aggregated stock market returns (i.e. returns of the stock index) exhibit long memory, while the stock market returns of the Czech Republic and Hungary are stationary. The next finding is that the majority of Slovenian stock market stocks’ returns can be characterized with a long memory property, while returns of almost all the investigated stocks in the Czech and Hungarian stock markets were found to be stationary. Different methods of the fractional differencing parameter d yield similar conclusion regarding long memory evidence. Based on the results of long memory tests, the weak-form efficiency hypothesis for Slovenian stock market could be rejected, while the hypothesis could not be rejected for the Czech and Hungarian stock markets.

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